Do Age-Verification Bills Change Search Behavior? A Pre-Registered Synthetic Control Multiverse

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Abstract

In January 2023, Louisiana enacted Act 440, requiring websites containing substantial adult content to verify users' ages through government-issued identification or commercial verification services. Since the passing of this legislation, 17 additional states have adopted similar laws. Using Google Trends data and a preregistered synthetic control design, this paper examines the impact of these age verification requirements on digital behavior across four key dimensions: searches for the largest compliant website, the largest non-compliant website, VPN services, and adult content generally.Three months after the laws were passed, Our analysis reveals a 51% reduction in searches for the dominant compliant platform, accompanied by significant increases in searches for both the dominant non-compliant platform (48.1%) and VPN services (23.6%). Through multiverse analyses that incorporate multiple specifications and control group constructions, we demonstrate the robustness of these behavioral changes. Our point estimates remain consistent with our pre-registered hypotheses across 3,200 point estimates. Our findings highlight that while these regulation efforts reduce traffic to compliant firms and likely a net reduction overall to this type of content, individuals adapt primarily by moving to content providers that do not require age verification. Our methodological approach offers a framework for real-time policy evaluation in contexts with staggered treatment adoption. Code and pre-registration information are available at the Open Science Foundation (`https://osf.io/vp9z6/`)
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Keywords: Internet regulation, age verification, synthetic control, Google Trends, multiverse analysis, policy evaluation, digital behavior

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1 Introduction

The emergence of the internet has fundamentally transformed the way individuals access and consume content, presenting challenges for regulators. While internet regulation has existed since the internet's earliest days, recent years have witnessed a significant shift toward stricter rules about what content people can access and how they can access it, particularly regarding age-restricted material such as online pornography. The regulation of online adult content, specifically pornographic websites, represents a complex policy challenge at the intersection of privacy rights, child protection, and digital governance.

Proponents of stricter internet content regulation argue that age verification requirements on pornographic websites are essential to protect minors from pornographic content, citing evidence that early exposure to such material through digital platforms can lead to detrimental psychosocial outcomes (Owens, Behun, Manning, and Reid, 2012; Flood, 2009). Critics of these verification requirements contend that such measures may be ineffective, potentially compromise user privacy, and could drive users toward less regulated, potentially more dangerous platforms (Electronic Frontier Foundation, 2024).

State-level policy initiatives have brought these debates into sharp focus, beginning with Louisiana's implementation of age verification requirements in January 2023 (*Act No. 440*, 2022). This marked a significant shift in the way states approach online content regulation, with other states quickly introducing similar legislation (see Table 1). These laws typically require online platforms hosting adult content to implement age verification systems using government-issued identification or other verifiable credentials, with substantial penalties for non-compliance. The constitutionality of such requirements has recently come under scrutiny in *Free Speech Coalition, Inc. v. Paxton*, in which the Fifth Circuit's decision to uphold Texas's age verification law potentially conflicts with earlier Supreme Court precedents on protected speech access (*Free Speech Coalition, Inc. v. Paxton*, 2025).

Given the rapid implementation of age verification policies across states, thorough evaluations using state-of-the-art methodologies are essential to determine their effects. Recent work examining the real-time evaluation of policy adoption provides important methodological insights for studying age verification requirements. Lang et al. (2023) analyzed Ohio's COVID-19 vaccine lottery initiative using preregistered synthetic control methods, demonstrating how rigorous policy evaluation can be conducted prospectively even during active implementation and adoption by other jurisdictions. This and related studies, which produced findings within two months of the lottery announcement, provide a valuable template for evaluating age verification laws (Barber and West, 2022). This is particularly crucial given the swift adoption across states and the need for timely evidence to inform these ongoing policy decisions; findings from early adopter states can inform roll-out strategies and deliberation for subsequent states considering similar policies.

The broader regulatory context and accelerating pace of digital policy implementation heighten the importance of robust policy evaluation. These requirements emerge against a backdrop of intensifying scrutiny of digital platforms and growing public pressure for comprehensive safeguards. The speed with which jurisdictions are advancing new regulatory frameworks necessitates both swift analysis and consideration of how individual policies fit within larger governance efforts. Regarding the focal policy of our paper, age verification requirements represent just one aspect of an increasingly diverse and complex digital regulatory landscape. These U.S. state-level laws coincide with broader internet regulation discussions worldwide, including Australia's Online Safety Act and the European Union's Digital Services Act. At the federal level, legislation requiring ByteDance's TikTok divestment highlights potential unintended consequences of digital platform governance, with more than 3,000,000 users migrating (albeit briefly) to alternative platforms like Xiaohongshu (also called "RedNote") within two days of the announcement (Dedezade, 2025). State initiatives like Florida's HB 3, which restricts social media access for minors younger than 16, show expanding youth-focused regulations (*CS/CS/HB 3: Online Protections for Minors*, 2024). Together, these developments reflect a significant shift in how governments approach digital content regulation, particularly regarding access controls for minors. While technology-focused regulations have advanced, a lack of empirical data with which to evaluate the efficacy of regulatory changes has limited policy evaluations and evidence-based policymaking in key areas (Byrne and Burton, 2017; Davis, Signé, and Esposito, 2022).

Against this backdrop of evolving digital regulation, the purpose of this paper is to examine the effects of state-level age verification requirements for adult content websites in the United States, contributing to our understanding of the effect of digital regulation on user adaptation. This paper leverages the staggered timing of state-level age verification laws to evaluate their effectiveness in modifying user behavior. Our analysis uses Google Trends data aggregated at the state level, providing high-frequency measures of search interest. This approach allows us to capture immediate behavioral responses to policy implementation while addressing traditional challenges in measuring adult content consumption patterns. Our research design builds on recent methodological advances in policy evaluation, particularly in the domain of synthetic control designs (Ben-Michael, Feller, and Rothstein, 2022). Here, we use synthetic controls in combination with a multiverse analysis to address concerns about researcher degrees of freedom with respect to model specification and analytical choices (Silberzahn et al., 2018; Steegen, Tuerlinckx, Gelman, and Vanpaemel, 2016). Pre-registering our preferred specification limits our ability to cherry-pick a result consistent with our hypotheses. Using a synthetic control design in combination with a multiverse is an explicit acknowledgment of the fact that other analysts may have investigated this subject with slightly different approaches and methodological bents (Huntington-Klein et al., 2021; Gelman and Loken, 2013). A multiverse approach is particularly valuable given the real-time nature of our evaluation, as it allows us to determine how robust the findings are to reasonable methodological variations.

2 Related Literature

Our work builds on and contributes to four primary streams of literature: internet regulation efforts, the effects of adult content, adult content access patterns, and methodological approaches to measuring digital behavior.

2.1 Evaluations of Internet Regulation

Research on internet regulation has evolved through three distinct phases, each characterized by different regulatory approaches and methodological challenges. The early 1990s saw a more hands-off approach to internet regulation, with minimal government intervention. Early efforts in the United States to restrict minor access to explicit online content and protect children's privacy online included the 1996 Communications Decency Act (CDA), the 1998 Children's Online Privacy Protection Act (COPPA), and the 1998 Child Online Protection Act (COPA). These laws had divergent legal outcomes. Although COPA never took effect and ultimately received a permanent injunction, the CDA was forced to be modified after certain provisions were deemed unconstitutional, with other provisions (e.g., Section 230) remaining in effect. COPPA, which required websites to obtain parental consent before collecting personal information from children under 13, has been in effect since its passage without significant legal challenges.Internet regulation has continued to shift, with the initial phase (1995-2005) focused primarily on content filtering and direct access restrictions. Seminal work by Deibert and Rohozinski (2010a) established a taxonomy of first-generation controls, documenting how governments mandated and implemented technical barriers to restrict online access and how users developed circumvention tools in response. As they observed, "No matter how restrictive the regulations or how severe the repercussions, communities around the world have exhibited enormous creativity in sidestepping constraints on technology in order to exercise their freedoms" (Deibert and Rohozinski, 2010b, p. 43) These early studies revealed consistent patterns of user adaptation, where technical barriers often led to rapid development and adoption of workaround solutions.

The second phase (2006-2015) saw research shift toward examining more sophisticated regulatory frameworks, particularly as governments moved beyond simple blocking to implement nuanced content control systems. Zittrain and Palfrey (2008) documented this evolution, noting how regulation increasingly focused on intermediary liability and platform-level controls. Studies during this period demonstrated how regulatory effectiveness often depended on cooperation from private sector actors, with varying degrees of success based on jurisdictional reach and technical implementation.

The current phase (2016-present) has produced the most methodologically rigorous evaluations of internet regulation effectiveness. Goldberg, Johnson, and Shriver (2024) employed synthetic control methods to evaluate the impact of the European Union's General Data Protection Regulation (GDPR), finding a reduction in user visits and revenue for websites after GDPR's implementation. Their work established new methodological standards for measuring regulatory impacts in digital contexts. Similarly, Peukert et al. (2022) documented how cookie consent requirements altered online advertising effectiveness and user engagement patterns, demonstrating both intended and unintended consequences of privacy regulations.

Recent work has particularly focused on platform-specific regulations, revealing consistent patterns of user substitution behavior. Research on China's Great Firewall showed how users shifted to VPN services when facing access restrictions (Chen and Yang, 2019). Studies of platform bans in various countries consistently find evidence of displacement effects, where restrictions on one platform lead to increased usage of alternatives (M. E. Roberts, 2018; M. E. Roberts, 2020). This literature suggests that digital regulation effectiveness must be evaluated not just in terms of direct compliance, but also considering displacement effects and circumvention strategies.

2.2 Effects of Adult Content

Internet regulatory efforts have generally focused on areas where there are perceptions of potential harms. While many proponents of age verification laws point to the harms of adult content, research on the effects of pornography in adults is mixed, making it difficult to substantiate broad claims. Studies investigating mechanisms of biological addiction, including problematic pornography use, identify altered reward processing as a potentially shared underlying feature (Brand, Snagowski, Laier, and Maderwald, 2016). However, experimental research on exposure to sexual images demonstrates physiological responses that differ from established substance addiction models, raising questions about whether problematic pornography use constitutes a biological addiction or reflects typical habituation (i.e., a *decrease* in conditioned response; (Prause, Steele, Staley, Sabatinelli, and Hajcak, 2015)). Additionally, reinforcement learning processes underlie all forms of conditioned responses; although repeated exposure strengthens associations between sexual arousal and specific explicit imagery, their broader implications for cognition and behavior remain unclear (Gola et al., 2017). Importantly, pornography use is not universally harmful; motivations such as sexual curiosity and use with intimate partners can be associated with positive outcomes, including improved sexual satisfaction and reduced sexual distress (B the et al., 2022). These findings underscore the complexity of pornography's effects, highlighting the importance of individual motivations, usage patterns, and contextual factors in shaping outcomes.

Research examining the effects of pornography exposure on children and adolescents is primarily correlational due to ethical and legal concerns around exposing minors to explicit content in experimental studies, limiting the ability to draw causal claims within this age group (Owens et al., 2012). Studies support associations between adolescent exposure to online pornography and lower self-esteem, body image concerns, depressive symptoms, and emotional problems (Löfgren-Mårtenson & Månsson, 2010; Ybarra & Mitchell, 2005; Tsitsika et al., 2009). Adolescent pornography exposure is also associated with heightened risk-taking, deficits in self-control, and increased acceptance of aggressive sexual scripts in adolescents—which may normalize sexual aggression in intimate contexts (Owens et al., 2012; Peter and Valkenburg, 2016). However, the directionality of these relationships remain unclear, as these may be preexisting vulnerabilities that predispose certain adolescents to engage with pornographic content. These associations also depend on broader contextual factors; adolescents with access to comprehensive sexual education and strong parental communication demonstrate a greater ability to critically evaluate pornographic content and mitigate potential negative outcomes (Owens et al., 2012; Peter and Valkenburg, 2016); (Löfgren-Mårtenson and Månsson, 2010); (Wright, Paul, and Herbenick, 2021)).

2.3 Adult Content Access Patterns

While the consumption of adult content has long been a topic of scholarly inquiry, how the public accesses it has shifted considerably. Research on adult content access patterns reveals near-universal adoption of digital platforms as the primary consumption medium, with 91.5% of men and 60.2% of women reporting online consumption in a typical month (Solano, Eaton, and O'Leary, 2020). This dominance of digital access has introduced novel regulatory challenges, particularly around age verification (Marsden, 2023)

Digital trace data reveals consistent patterns in access methods and timing. Browser-based access accounted for a significant portion of traffic, with mobile devices rapidly increasing their share from 27% to 42% between 2014 and 2017 (Morichetta, Trevisan, and Vassio, 2019). Peak access periods demonstrate remarkable consistency across geographic regions, typically occurring during private hours such as late evenings. This clustering has important implications for platform infrastructure and the effectiveness of time-based restrictions (Morichetta et al., 2019).

Age-disaggregated data presents particular measurement challenges. Survey-based studies indicate first exposure typically occurs between ages 11-13, substantially earlier than pre-internet estimates (Robb & Mann, 2023). However, selection bias and social desirability bias limit the reliability of self-reported data. Digital trace studies face their own limitations, as age verification data is often unavailable or unreliable.

Access patterns show substantial heterogeneity across platforms and content types. Major platforms exhibit high but unstable market concentration, with the top five sites typically accounting for 75-85% of total traffic. This concentration appears sensitive to regulatory changes, with documented shifts toward smaller platforms following access restrictions or enhanced verification requirements (Happ, Harpenau, and Wiewiorra, 2024).

User adaptation to access restrictions demonstrates remarkable consistency across contexts. When faced with technical barriers, users typically respond through platform substitution, technical circumvention—including VPN usage—and modified search strategies. Recent data indicates that 46% of American adults use VPNs, with nearly 40% of users relying on them to prevent tracking from search engines or social media sites (Cruz, 2024). As noted by Novicoff (2025), the law is "toothless against websites that are hosted abroad, including the Czech porn giant XVideos, which hasn't complied at all with state age-verification rules, a fact that millions of teenagers in those states likely already know. Underage users can also evade the restrictions by employing virtual private networks to disguise their IP address." These adaptation patterns present significant challenges for measuring policy effectiveness and suggest potential unintended consequences of restrictive policies.

2.4 Measuring digital behavior

Measuring digital behavior poses unique methodological challenges that stem from both the nature of the data and the analytical methods required. Unlike traditional survey-based approaches, digital trace data—such as search queries, clickstreams, and social media interactions—are generated as a by-product of routine online activity rather than through systematic data collection (Lazer et al., 2009). This feature offers high-frequency, real-time insights but also introduces several complications. One challenge with such data is determining the real-world behavior onto which such data are mapped. Many digital data sources, including Google Trends, provide information on a relative or normalized scale rather than absolute counts. For example, Google Trends reports search interest on a 0–100 scale, where values reflect the proportion of searches relative to the peak period. Although this facilitates the detection of temporal patterns, it can obscure the true magnitude of behavioral changes and complicate comparisons between periods or regions. Furthermore, the anonymized and aggregated nature of these data limits the ability of researchers to disaggregate behavior by key demographic characteristics (e.g., age), which is especially important when evaluating policies that target particular groups, such as age verification. Despite its limitations, digital trace data can serve as a robust proxy for measuring large-scale behavioral trends. The reliability of digital trace data for tracking population-level behavioral patterns has been supported by several studies. For instance, Choi and Varian (2012) demonstrate that Google Trends data can effectively "predict the present" by correlating with real-time economic indicators, while Kristoufek, Moat, and Preis (2016) illustrate its usefulness in predicting public health outcomes (e.g. suicide).

Moreover, digital behavior is inherently dynamic and context-dependent. Users continuously adapt by shifting their activities across platforms, employing circumvention tools (e.g., VPNs), or altering search strategies in response to policy changes and broader environmental factors. The presence and adoption of privacy-enhancing technologies, particularly VPNs, further complicates measurement efforts. Khan et al. (2018) highlight how VPN services can fundamentally alter the observable characteristics of user traffic through varying implementations—from secure encrypted tunnels to basic TCP forwarding—creating different degrees of traffic opacity. This heterogeneity in VPN implementation can mask true behavioral patterns and introduce systematic measurement bias. Ikram, Vallina-Rodriguez, Seneviratne, Kaafar, and Paxson (2016) document how VPN services often implement traffic manipulation, tunneling, and redirection that can alter standard behavioral signals, while Ramesh, Vyas, and Ensafi (2023) find significant misalignment between users' perceived and actual privacy protections when using VPNs, suggesting that observed patterns may not accurately reflect underlying user intent.

Another significant challenge in measuring digital behavior is the fundamental difficulty of establishing causal identification when analyzing policy impacts. While techniques like synthetic control methods can help construct credible counterfactuals, several features of digital trace data complicate causal inference. Platform-level changes—such as modifications to search algorithms, content recommendation systems, or interface designs—may coincide with policy interventions, potentially confounding treatment effects. These changes are particularly problematic because platforms rarely provide detailed documentation of their internal modifications, forcing researchers to rely on imperfect proxy measures. Additionally, the granularity and completeness of available data can vary substantially across platforms and over time. This measurement challenge is compounded by the fact that many digital behaviors leave incomplete traces—users may access content through direct URLs rather than searches, switch between logged-in and anonymous browsing sessions, or utilize VPNs that mask their true location. These data limitations necessitate careful consideration of both model specification and interpretation when evaluating policy impacts.

3 Policy Implementation Details

3.1 Louisiana Implementation

Louisiana Act 440, implemented on January 1, 2023, serves as our primary case study as it represents the most comprehensive age verification requirement implemented to date. The law mandates that websites containing a "substantial portion" (i.e., more than 33.33%) of adult content must verify users' ages through government-issued identification or commercial age verification services. Key features of the Louisiana implementation include:

- Specific technical requirements for verification providers
- Clear definitions of covered content and websites
- Substantial penalties (not to exceed $5,000 for each day of violation; not to exceed $10,000 for failure to perform reasonable age-verification)
- Regular compliance auditing requirements

Notably, of the states that passed these laws, Louisiana was unique in that it was the only state that implemented age verification in a manner that plausibly preserved a user's anonymity while verifying age (Davidson, 2024). The age verification process was disintermediated by the state and its associated vendors such that only a coarse measure of a person's age was provided (i.e. over 18). In response to this law, compliant websites, such as Pornhub, enacted age verification protocols in accordance with the new regulation. However, noncompliant websites, such as XVideos, did not enact such protocols, leaving the user experience of accessing adult content unchanged.

3.2 Other Follow On States

In subsequently adopting states, the methods of age verification tended to be stricter, either requiring uploads of an individual's government identification, providing other PII data, or even presenting biometric data such as face scanning. While these laws also had provisions to require the deletion of the data, the capture of such data could have additional chilling effects. Additionally, some of these laws also required complying sites to engage in disclaimers and warnings regarding the potential harmfulness of adult content. In all additional 17 states except one (Georgia), Pornhub has exited the market entirely given the more invasive verification process, preventing access from any IP addresses located in those states. Similar to Louisiana, XVideos did not comply with follow on age verification laws. A timeline of all state laws can be found in Table 1.

4 Pre-registered Research Question and Hypotheses

We based our research question and hypotheses on the analysis conducted prior to pre-registration in Appendix B.The accompanying pre-registration documents and code can be found at the OSF (`https://osf.io/vp9z6/?view_only=f6695912a1c5487ca8a0f088ae0dc569`)

Title	Law Passage	Law Effective
Louisiana HB 142 (2022)	2022-06-15	2023-01-01
Utah SB 287	2023-03-14	2023-05-03
Mississippi SB 2346	2023-04-18	2023-07-01
Arkansas SB 66/Act 612	2023-04-11	2023-07-31
Virginia SB 1515	2023-05-12	2023-07-01
Montana SB 544	2023-05-22	2024-01-01
Texas HB 1181	2023-06-12	2023-09-19
North Carolina HB 8	2023-09-29	2024-01-01
Indiana SB 17	2024-03-13	2024-08-16
Idaho H 498	2024-03-20	2024-07-01
Florida HB 3	2024-03-25	2025-01-01
Kentucky HB 278	2024-04-05	2024-07-15
Nebraska LB 1092 (Online Age Verification Liability Act)	2024-04-16	2024-07-19
Georgia SB 351	2024-04-23	2025-07-01
Alabama HB 164	2024-04-18	2024-10-01
Kansas HB2592/SB394	2024-04-25	2024-07-01
Oklahoma SB 1959	2024-04-26	2024-11-01
South Carolina H 3424	2024-05-21	2025-01-01
Tennessee SB 1792	2024-05-28	2025-01-01

Table 1: State Age Verification Laws and Implementation Dates
Source: Adapted from Free Speech Coalition Action Center

and Github `https://github.com/davidnathanlang/internet_regulation_synth_project` respectively. Based on the Louisiana implementation of the law, it was clear that not all adult content providers would comply with regulatory changes. Among the top 20 websites visited in the United States (See Figure 1), two firms provided roughly 40% of adult content by monthly visitor counts (Semrush, 2025). Despite having substantial overlap in user interface, they took distinctly different approaches to complying with these laws. Pornhub and its parent company Aylo complied with the law in Louisiana or exited from states that passed these laws. Xvideos is based in the Czech Republic and access to this site remained possible in all of the states that passed these laws. Users in states that passed these laws could visit this site without participating in age verification or using technological workarounds. We postulated that despite both entities having been adjudicated by American Courts as doing business in the United States, enforcement actions and fines against an entity based in the Czech Republic would face additional administrative barriers and, therefore, be less likely to be enforced. Taken together, given its substantial market position and its divergent response to regulatory changes, XVideos offered a useful point of comparison to Pornhub in analyzing the effects of these laws on user behavior. Our research questions and hypotheses follow below:

4.1 RQ1

Research Question 1: Do online age-restriction policies cause shifts in internet behavior?

4.2 H1

The average treatment effect (ATT) of state-level age verification laws will be negative on Google Trends search volume for compliant adult content platform (Pornhub) in treated states relative to synthetic control states.

We speculate that the additional friction of age verification and readily available substitute sites will lead users towards other sites.

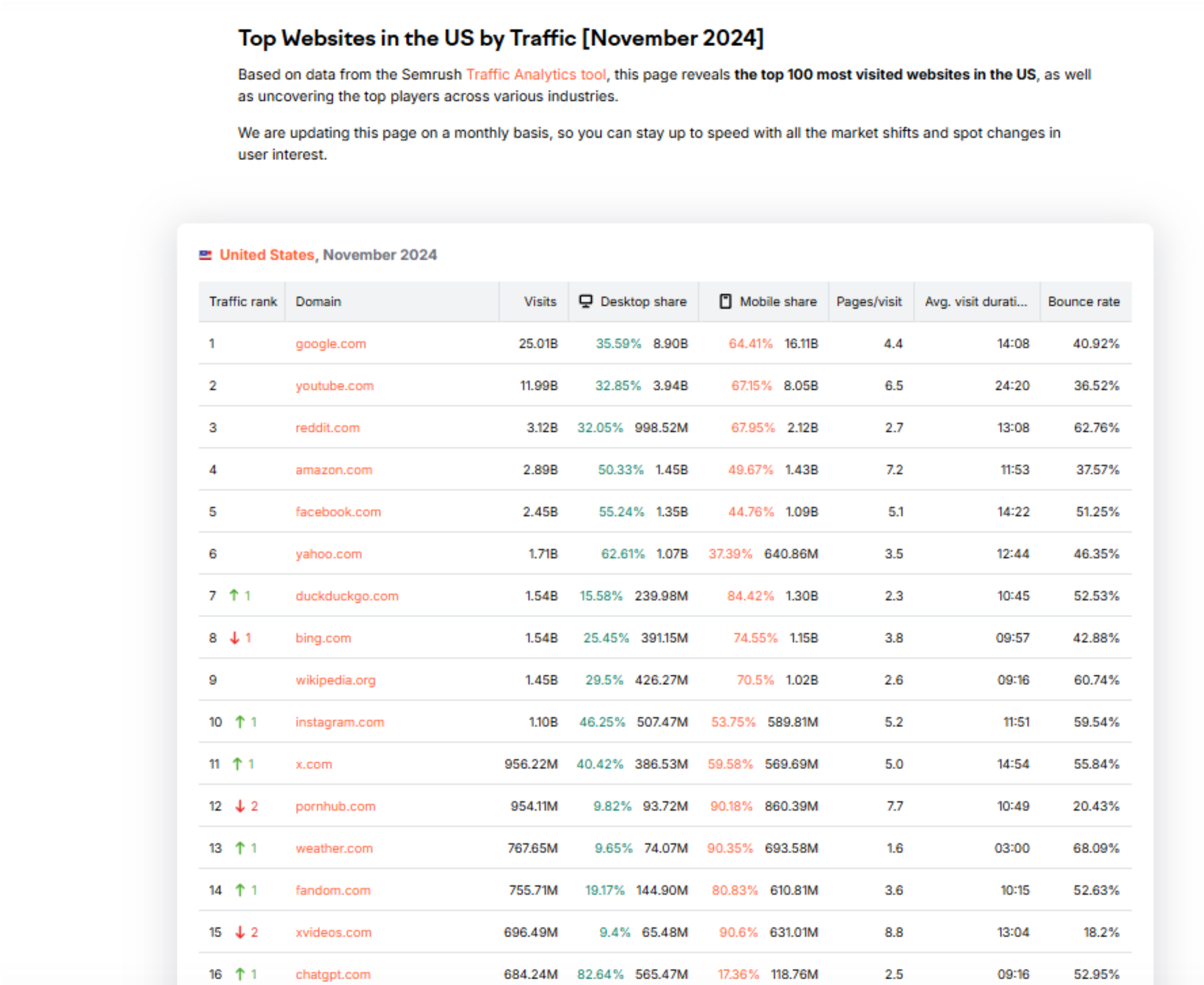
4.3 H2

The ATT of state-level age verification laws will be positive on Google Trends search volume for non-compliant adult content platform (XVideos) in treated states relative to synthetic control states.

Based on our first hypothesis, we believed non-compliant firms, which remained active and without any additional friction for access, would gain market share and new users.

4.4 H3

The ATT of state-level age verification laws will be positive on Google Trends search volume for virtual private networks (VPNs) in treated states relative to synthetic control states.



Top Websites in the US by Traffic [November 2024]

Based on data from the Semrush Traffic Analytics tool, this page reveals **the top 100 most visited websites in the US**, as well as uncovering the top players across various industries.

We are updating this page on a monthly basis, so you can stay up to speed with all the market shifts and spot changes in user interest.

United States, November 2024

Traffic rank	Domain	Visits	Desktop share		Mobile share		Pages/visit	Avg. visit durati...	Bounce rate
1	google.com	25.01B	35.59%	8.90B	64.41%	16.11B	4.4	14:08	40.92%
2	youtube.com	11.99B	32.85%	3.94B	67.15%	8.05B	6.5	24:20	36.52%
3	reddit.com	3.12B	32.05%	998.52M	67.95%	2.12B	2.7	13:08	62.76%
4	amazon.com	2.89B	50.33%	1.45B	49.67%	1.43B	7.2	11:53	37.57%
5	facebook.com	2.45B	55.24%	1.35B	44.76%	1.09B	5.1	14:22	51.25%
6	yahoo.com	1.71B	62.61%	1.07B	37.39%	640.86M	3.5	12:44	46.35%
7 ↑ 1	duckduckgo.com	1.54B	15.58%	239.98M	84.42%	1.30B	2.3	10:45	52.53%
8 ↓ 1	bing.com	1.54B	25.45%	391.15M	74.55%	1.15B	3.8	09:57	42.88%
9	wikipedia.org	1.45B	29.5%	426.27M	70.5%	1.02B	2.6	09:16	60.74%
10 ↑ 1	instagram.com	1.10B	46.25%	507.47M	53.75%	589.81M	5.2	11:51	59.54%
11 ↑ 1	x.com	956.22M	40.42%	386.53M	59.58%	569.69M	5.0	14:54	55.84%
12 ↓ 2	pornhub.com	954.11M	9.82%	93.72M	90.18%	860.39M	7.7	10:49	20.43%
13 ↑ 1	weather.com	767.65M	9.65%	74.07M	90.35%	693.58M	1.6	03:00	68.09%
14 ↑ 1	fandom.com	755.71M	19.17%	144.90M	80.83%	610.81M	3.6	10:15	52.63%
15 ↓ 2	xvideos.com	696.49M	9.4%	65.48M	90.6%	631.01M	8.8	13:04	18.2%
16 ↑ 1	chatgpt.com	684.24M	82.64%	565.47M	17.36%	118.76M	2.5	09:16	52.95%

Figur e 1: SEMRush: Top Websites in the United States

We speculate that users will begin searching for this technology in order to spoof their location so that they can access compliant content platforms without age verification and that the presence of age verification laws will raise the saliency of privacy-enhancing technology.

4.5 H4

The ATT of state-level age verification laws will be positive on Google Trends search volume for generic adult content searches ("porn") in treated states relative to synthetic control states.

We speculate that due to the 33.33% content clause of many of these regulations to trigger age verification, individuals may search for pornographic content on more diffuse and less concentrated platforms that are not as impacted by these laws.

5 Data

Google Trends data represents the relative search volume for specific terms or topics across time and geography on Google's search platform. When a user enters a search term, Google calculates how many searches have been done for that term relative to the total number of searches done on Google over a specified time period. These values are then normalized on a 0-100 scale, where 100 represents the peak search interest for the selected region and time period. For example, if a term shows a value of 50, this means the search term was half as popular as at its peak popularity. The data updates in near real-time and can be filtered by geographic region (country, state, or city level), time range (from 2004 to present), and search category (e.g., "Health," "News," "Shopping").

Our analysis uses Google Trends data to track changes in search behavior following age verification legislation. While proprietary web traffic data exists for this type of research, such data is often prohibitively expensive and subject to restrictive licensing agreements. Google Trends offers several key advantages as a data source: it is freely accessible, provides high-frequency observations, and allows for precise geographic disaggregation. The validity of Google Trends data for academic research has been well-established across multiple domains. Goldsmith-Pinkham and Sojourner (2020) demonstrate its predictive power for unemployment claims, while systematic reviews by Mavragani, Ochoa, and Tsagarakis (2018) and Nuti et al. (2014) confirm its reliability for tracking population-level behavioral patterns. Specifically relevant to our context, Mavragani and Ochoa developed a methodological framework validating Google Trends' effectiveness for monitoring changes in online behavior. Our own validation analysis (detailed in Appendix A) demonstrates strong correlations between Google Trends search data and actual web traffic data from SimilarWeb (r = 0.81 for XVideos and r = 0.84 for Pornhub), further supporting the use of search trends as a reliable proxy for site visitation patterns. Specifically relevant to our context, Mavragani and Ochoa developed a methodological framework validating Google Trends' effectiveness for monitoring changes in online behavior.

However, the data does have important limitations: measurements are relative rather than absolute, making cross-period and cross-region comparisons challenging, and the underlying sampling methodology is not fully transparent. This sampling methodology and the interval nature of the data inhibits our ability to investigate less frequently searched terms across the 50 states. Moreover, it cannot disaggregate search behavior by age, a key focus of these laws. Despite these constraints, Google Trends represents the most comprehensive publicly available data source for studying state-level, large-scale shifts in search behavior in response to policy changes.

We provide an example of these trends in Figure 2 , focusing on our focal compliant firm (Pornhub). The red line in each facet corresponds to Google Trends data prior to implementation of the age verification law. The blue line corresponds to Google Trends data following the passage of the law. In nearly all cases, there is a precipitous drop in Google Trends for the compliant firm when these laws become effective. The one exception is Texas where the law was stayed pending appeal, before it was ultimately implemented a few months later.

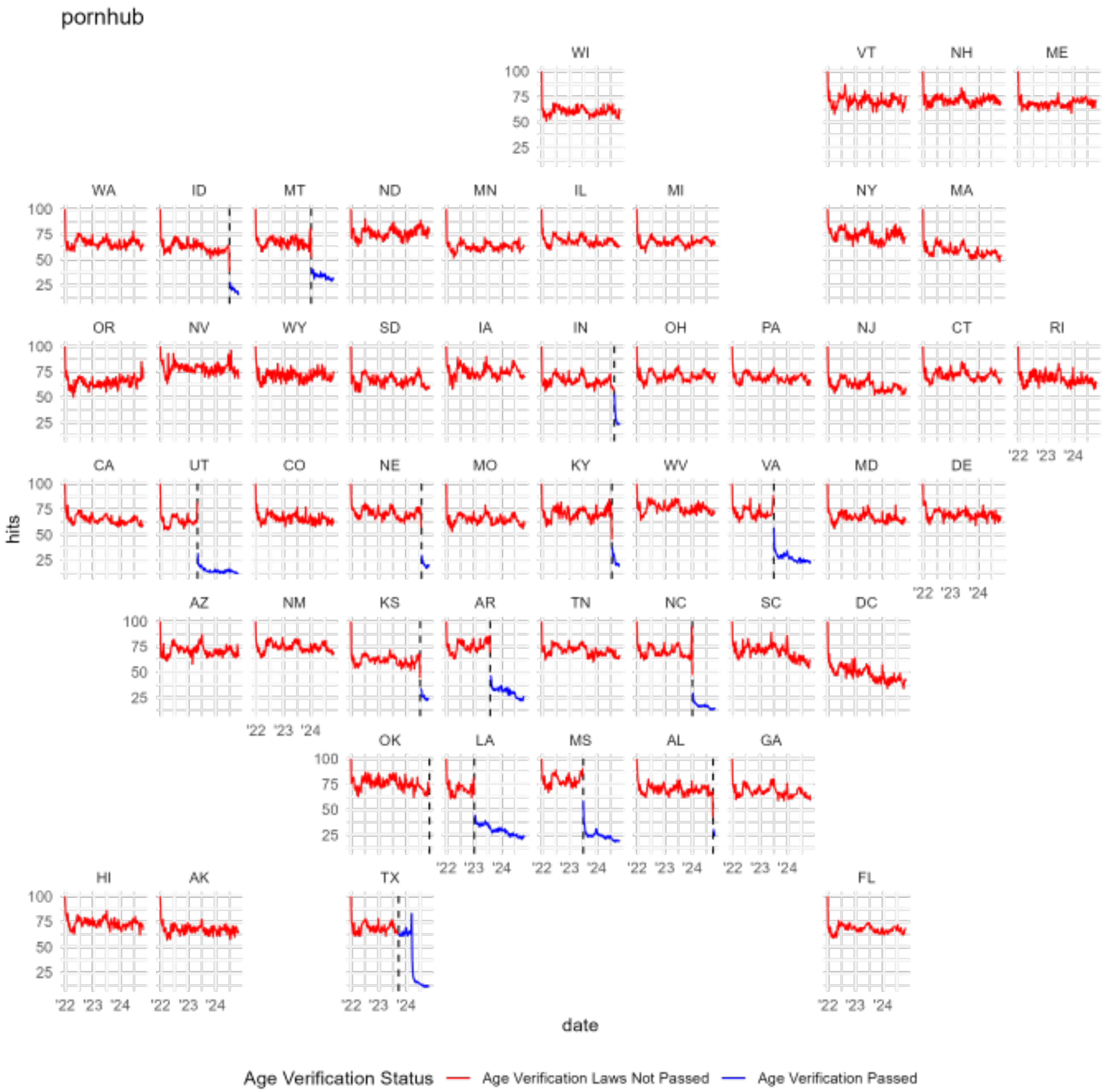


Figure 2: Google Trends Data For Pornhub 2022-01-01 to 2024-10-31

6 Methodology

We use a synthetic control methodology to analyze the impact of age verification requirements on digital behavior. Synthetic control is a technique that allows individuals to calculate their counterfactual estimate prior to seeing any outcome data (Abadie, 2021) [1] This technique is particularly well-suited for cases where a single aggregated unit, such as a state, receives a treatment (Abadie, Diamond, and Hainmueller, 2010). Direct comparison to other states is often ill-advised as comparator states may differ in many important characteristics and may not mirror the pre-intervention trends of the focal treated state. However, it is possible to construct a composite comparator state that mirrors the pre-treatment trends of the treated state. The synthetic control method allows us to construct a synthetic version of the treated state using a convex combination of other states (the donor pool) based on pre-treatment outcomes and relevant covariates. In short, we make a set of faux states that consists of states that did not adopt age verification laws but matched the pre-adoption paths of states that adopted these laws.

To build intuition around the method, we first discuss the case of a single state—in our case, Louisiana. We construct our synthetic control by minimizing the Mean Squared Predicted Error of our outcome variable in the pre-treatment period using the following expression:

$$\underset{w_j}{\text{minimize}} \quad \sum_{t=1}^{T_0} v_t \left(y_{1t} - \sum_{j=2}^{J+1} w_j y_{jt} \right)^2 \tag{1a}$$

$$\text{subject to} \quad \sum_{j=2}^{J+1} w_j = 1, \tag{1b}$$

$$w_j \geq 0 \tag{1c}$$

where y_1 corresponds to our vector of pre-treatment outcomes (search behavior metrics) for Louisiana, y_j corresponds to the pre-treatment outcomes and associated indices of other states in the donor pool, w_j corresponds to the unit weights (the associated weighting of each state in our synthetic construction), and v_t corresponds to a variable importance weight of the pre-treatment outcomes at time t, until the end of the pre-treatment period T_0. We minimize this expression subject to the constraints that both our unit weights and variable weights are non-negative and sum to unity. Once the counterfactual w_j weights are derived, estimating the counterfactual the Average Treatment on the Treated (ATT) would consist of just taking the average difference between Louisiana after it adopted the policy and its counterfactual state across the evaluation period:

$$\text{ATT} = \frac{1}{T_1 - T_0 + 1} \sum_{t \geq T_0}^{T_1} \left(y_{1t}^{\text{obs}} - \sum_{j=2}^{J+1} w_j y_{jt} \right) \tag{2}$$

To estimate treatment effects when treatment timing is staggered and there are multiple treated states, we utilize a technique known as generalized synthetic control (Xu, 2017). This technique is quite similar in intuition to classical synthetic control; however, the mechanism used to generate counterfactual outcomes are quite different.

The formula for ATT using the Generalized Synthetic Control (GSC) method is:

[1] Due to peculiarities in the interval nature of Google Trends, we did not compute the weights formally but instead pre-registered our specification and code.

$$ATT_t = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} \left[Y_{it}(1) - \hat{Y}_{it}(0) \right] \quad (3)$$

where:

- N_{tr} is the number of treated units,
- $Y_{it}(1)$ is the observed outcome for treated unit i at time t,
- $\hat{Y}_{it}(0)$ is the **GSC-estimated counterfactual outcome** for treated unit i at time t.

The counterfactual outcome is estimated as:

$$\hat{Y}_{it}(0) = X_{it}\hat{\beta} + \hat{\lambda}_i' \hat{f}_t \quad (4)$$

where:

- X_{it} represents observed covariates,
- $\hat{\beta}$ is the estimated coefficient vector from the control group,
- $\hat{\lambda}_i$ is the estimated factor loading for treated unit i,
- $\hat{f}_t$ is the estimated time-varying factor.

By using this approach to estimate counterfactual-outcomes, it is no longer the case that weights are restricted to be non-negative or to sum to unity.

Our pre-registered inference approach relies on a parametric bootstrap estimate. We collect a short-term and longer-term measure at one and three months of our estimates using the *cumuEff* function in the *gsynth* package. In our multiverse, we also use augmented synthetic control estimates, which allow for more traditional synthetic control weights while accommodating multiple treated units with staggered adoption times.

In Appendix B, we further elaborate on how to interpret results for the single-treated state of Louisiana where we trained our synthetic control model on the 52 weeks preceding the law's implementation using data starting in 2022. This analysis motivated our pre-registration and subsequent evaluation efforts.

While synthetic control methods have been widely used to evaluate various policy interventions, their application to digital behavior analysis represents a novel contribution to both the methodological literature and our understanding of internet regulation effectiveness. Given concerns about researcher degrees of freedom in synthetic control methodologies (Ferman, Pinto, and Possebom, 2020), we pre-registered the specification for our synthetic comparison group using data starting in January 2022. We further elaborate on deviations from our protocol in Appendix C.

We rely exclusively on pre-treatment outcome data to estimate our counterfactual. (Kaul, Klößner, Pfeifer, and Schieler, 2022) notes that this approach shrinks non-outcome variable importance weights to zero. As part of our multiverse analysis detailed in Section 8, we test the robustness of our results to the inclusion of additional covariates, including demographic variables.

7 Pre-registered Findings

We use the Generalized Synthetic Control (GSC) model to estimate treatment effects. This approach employs a latent factor model and uses cross-validation to select model parameters, optimizing the mean-squared prediction error of counterfactual outcomes. Instead of having an explicit linear combinations of weights, the generalized synthetic control estimates counterfactual outcomes using a latent factor model with time-varying factor loadings and unit-specific intercepts.

Our analysis found support for all four of our hypotheses, as highlighted in Table 2 and Figure 3. Table 2 contains the results for each search term as well as the absolute pre-treatment difference between the proposed synthetic control and the adopting states prior to enactment of age verification. In general, these models had good pre-treatment fit with the mean absolute error (MAE) being at most 2.3 google scale points across the four terms. The ATT is measured as the average of the twelve weeks after treatment has been implemented. We report standard 95% confidence intervals with their associated lower and upper bounds. The negative ATT estimate (-33.8) for the compliant platform (i.e. Pornhub) in states with age verification laws showed a decrease in usage compared to synthetic control states, supporting our first hypothesis (H1). In support of our second hypothesis (H2), we found a positive ATT estimate (27.9) indicating that users switched from compliant platforms to noncompliant alternatives (i.e. XVideos). We also found support for our third hypothesis, with Google Trends showing increased search interest for "VPN" in treated states relative to synthetic control states (ATT = 13.3). Lastly, our fourth hypothesis (H4) was supported, with significant findings (ATT = 3.5) indicating an overall increase in Google search interest for "porn" in treat states relative to synthetic control states.

search term	MAE	ATT	CI.lower	CI.upper	p.value
pornhub	0.70	-33.84	-34.97	-32.64	0.00
xvideos	1.17	27.85	26.83	30.43	0.00
vpn	2.29	13.33	10.00	16.73	0.00
porn	0.76	3.48	2.80	4.58	0.00

Tabl e 2: Pre-registered hypotheses by keyword

Carrying forward our pre-registered specification, we see largely similar effects across all states that adopted age verification laws as we saw in Louisiana. In Figure 3, we plot the generalized synthetic control results for the overall treatment population. Each panel corresponds to one of the four search terms we use and its corresponding hypothesis. The horizontal dotted line corresponds to the average treatment effect over the three month period following a law's implementation. Overall, the effects closely mirror what we see in Louisiana, with one notable exception: the search patterns for pornographic material (H4) are slightly larger relative to trend following launch.

Given that Google Trends scale points are somewhat opaque, we offer an easier-to-interpret framing of these effects. In Figure 4, we report the one month and three month Cumulative Average Treatment Effects (CATT) along with their standard errors. As a reminder, a Google Trends score of 100 would correspond to the week with the most search

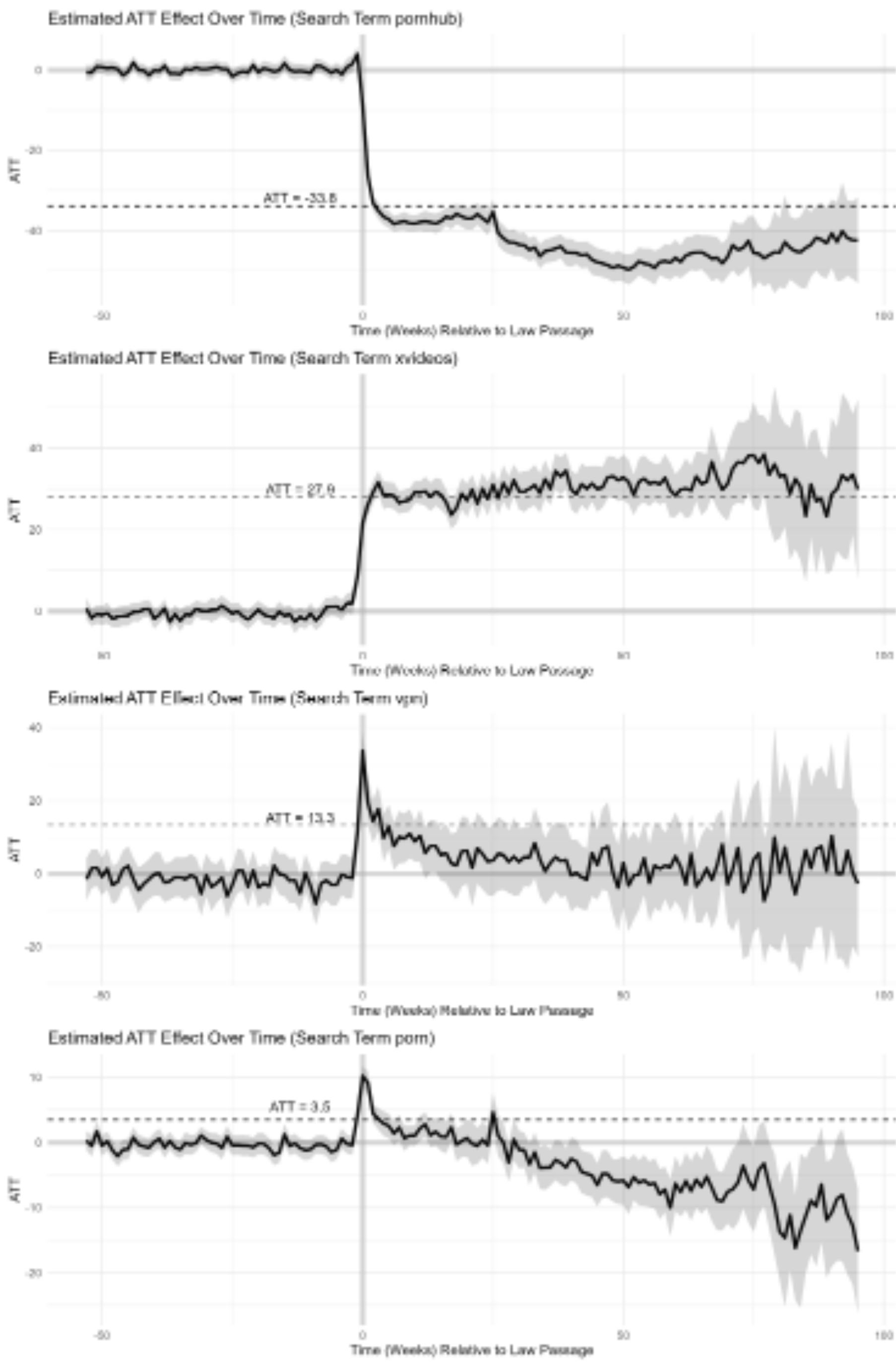


Figure 3: Change in Google Trends Relative to Synthetic Control. The figure shows the comparison of trends for Pornhub, Xvideos, VPN, and Porn.

traffic for a given search term within the specified time period (2022-01-01 to 2024-10-31). Thus, a week with a Google Trends value of 50 would reflect a 50% decrease in search traffic for that term relative to the peak traffic week. If we were to report a 200 scale point CATT, that would correspond to a search term gaining an additional two weeks of its highest relative search volume. In the one-month period following an age verification law

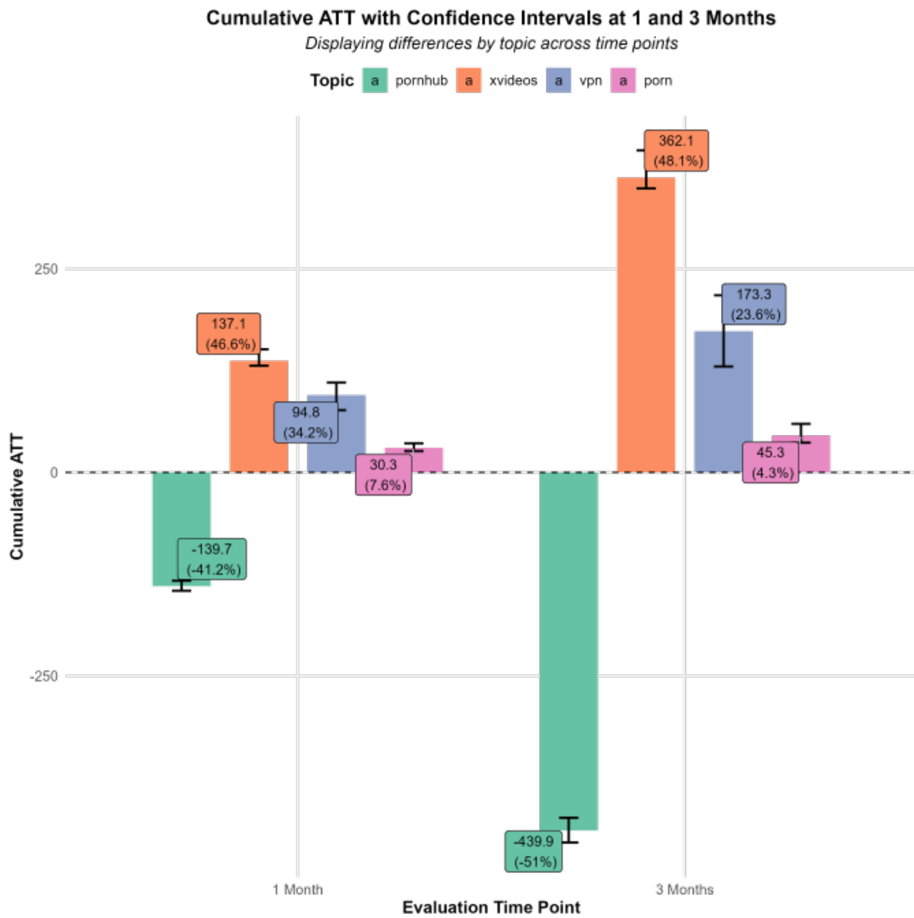


Figure 4: One Month and Three Month Cumulative Average Treatment Effects for Pornhub, Xvideos, VPN, and Porn.

becoming effective, we saw that the compliant firm (Pornhub) effectively lost 139.7 points, or more than a week of peak search traffic. The noncompliant firm (XVideos) gained a roughly equal magnitude increase in their search volume of 137 points, or more than a week of search traffic. Searches for "vpn" also spiked during this month by 94.8 points, yielding almost an additional week of search traffic. Searches for the term "porn" saw the smallest spike over the specified time period, gaining only 30 points over the one-month time period, representing substantially less than a week of peak search traffic.

Over a three-month evaluation period, we saw these effects continue to accumulate for the focal compliant firm and non-compliant firm. Pornhub lost more than a month of relative search volume (-439.9), and XVideos gained more than three weeks of peak relative search volume (362.1). The effects for VPN (173.3) and porn (45.3) searches accumulated in the same direction but not with the same level of magnitude.

As an alternative interpretation of these effects, we also annotate Figure 4 with the percentage change relative to the Google Trends counterfactual estimate. This interpretation makes it clear that Pornhub and XVideos saw larger percentage changes in relative search volume compared to the other search terms examined. Over the three months after the age verification law was passed, the focal compliant firm lost more than half their search traffic

(51%). The focal noncompliant firm saw relatively large magnitude gains in their search volume (48.1%). While we still see large gains in search traffic for VPN (23.6%) and porn (4.3%), these estimates are smaller in magnitude. Both framings help provide different senses of the magnitude of the change in more quantifiable ways than Google Trends points on their own.

7.1 Results by State

In Figure 5, we plot the synthetic control estimates relative to their actual difference for each state. In all cases we see a largely similar picture: when the law is implemented, there is a sharp and clear decrease in search volume for the compliant firm. The one exception is Texas, which had pending litigation and administratively stayed the law in question (*Free Speech Coalition, Inc. v. Paxton*, 2025). Following the reversal of that decision, Aylo and Pornhub left the state of Texas and the we hypothesized in (H1) followed shortly thereafter. When we examine the same plot for the non-compliant firm (Figure 6), we see a mirroring narrative with large increases in relative search volume once the law becomes effective. In both Figure 5 and Figure 6, we report the ATT only if there are at least three months of outcome data available. As more data become available with more states implementing similar laws, these estimates are subject to change and will be updated accordingly.

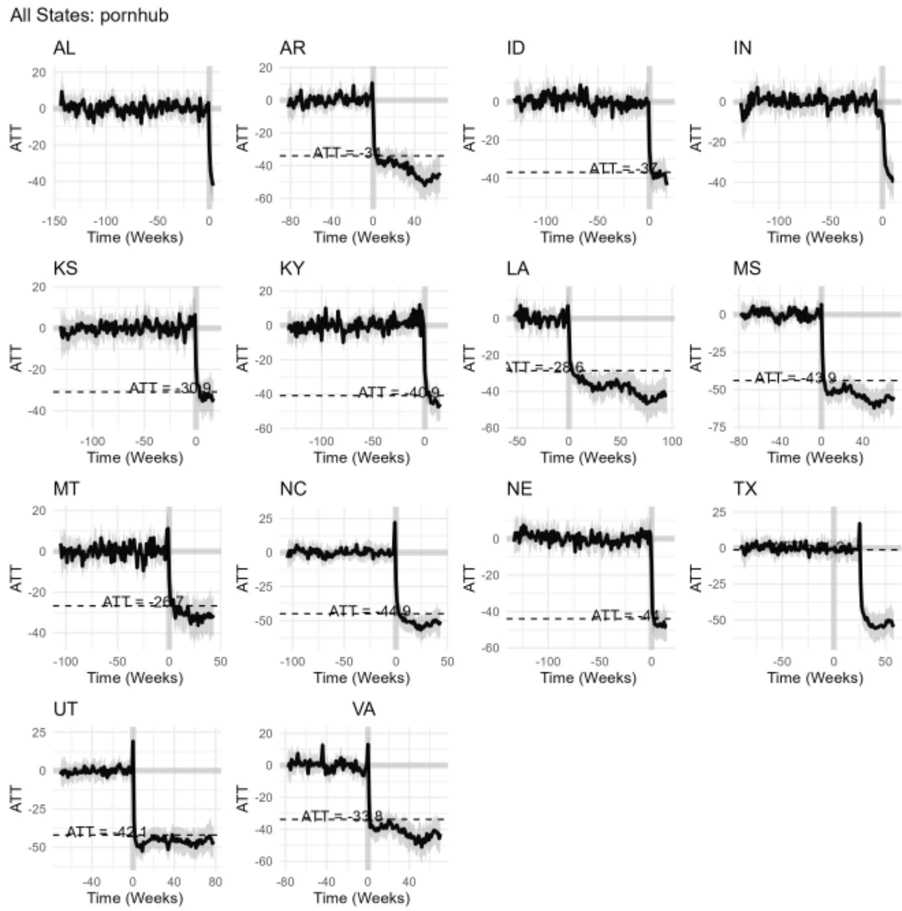
8 Multiverse Analysis

While we recognize that we chose an extremely parsimonious specification for our pre-registration, there are a number of additional paths we may have taken as researchers (Huntington-Klein et al., 2025). We utilize a multiverse analysis where we cross many of the steps and decisions we have taken as researchers with other plausibly valid approaches. Some of the choices that we examined are the following:

- **Start Date**- While we chose 2022-01-01 as our initial start date, we potentially could have chosen earlier or later start dates. We originally selected 2019-01-01 as an alternative start date. To fully cover the staggered adoption period, this will result in Google Trends data only being available at monthly frequency. We also note that the frequency of aggregation can reflect a trade-off between achieving good pre-treatment fit and potentially over-fitting to noisier high frequency data (Sun, Ben-Michael, and Feller, 2024).

- **Treatment Date** - In total, we examined two different instantiations of treatment date. While our primary specification focused on how behavior changed when the laws took effect, there is potential for anticipatory behavior or skepticism that these laws would be enacted or enforced. As such, we also added anadditional arms to our multiverse examining how our analysis would change if our treatment time weas the first day a law was passed.

- **Identity Verification**- Each state provides distinct mechanisms for verifying an individual's age. We re-estimated our model assuming that our treatment group consists of only states that comply with the stated method:



Figur e5: Change in Google Trends Relative to Synthetic Control for Pornhub (Compliant Firm)

  - Government ID
  - Digitized ID
  - Transaction Data
  - Database by Business or Government
  - Any identity verification method

- **Evaluation Window**- We assessed policy impacts using both one-month and three-month post-implementation windows. This allows us to distinguish between immediate effects and more persistent behavioral changes while avoiding contamination from subsequent policy adoptions. The one-month window captures immediate adaptation, while the three-month window reveals whether behavioral shifts persist or fade.

- **Identification Technique**- We compare results across two leading synthetic control extensions: generalized synthetic control (Xu, 2017) and augmented synthetic control (Ben-Michael et al., 2022). These methods make different assumptions about treatment effects and factor structures—generalized synthetic control allows for heterogeneous treatment effects through interactive fixed effects, while augmented synthetic

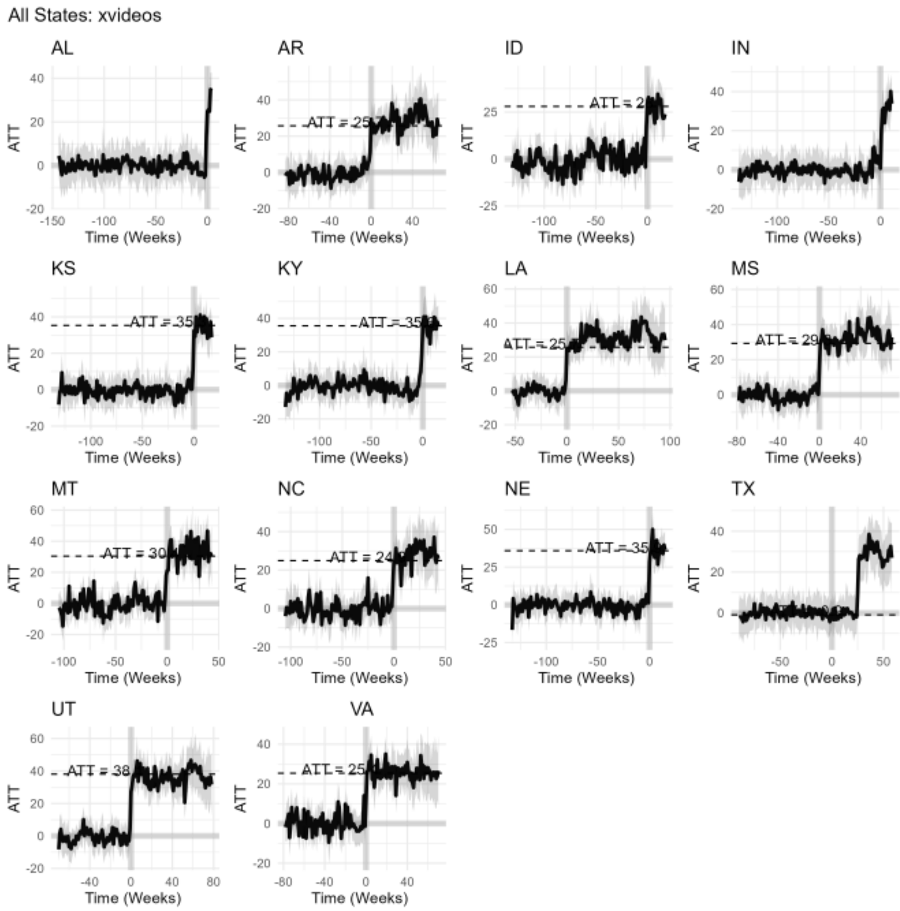


Figure 6: Change in Google Trends Relative to Synthetic Control for Xvideos (Non-compliant Firm)

control balances fit between individual treated units and the pooled average treatment effect.

While our multiverse is not fully crossed, in total for each keyword we generate 800 point estimates. We plot these point estimates in the violin plot in Figure 7. The red filled charts correspond to synthetic controls generated with gsynth, and the blue correspond to synthetic controls generated with the augmented synthetic control methods. The points correspond to either the minimum mean squared predicted error (MSPE) in the pre-treatment (blue) or the minimum cross-validation error in gsynth models. Looking only at the sign estimates of this multiverse, our results comply with H1 98% of the time, H2 complies 98.6% of the time, H3 complies 80.9% of the time, and H4 complies 100% of the time. We note that we saw no deviations from our pre-registered hypotheses when we defined our treatment date as the day the age verifications laws became effective. The only times we generated point estimates that were not consistent with our hypotheses was when we defined the treatment date as when the law was first passed.

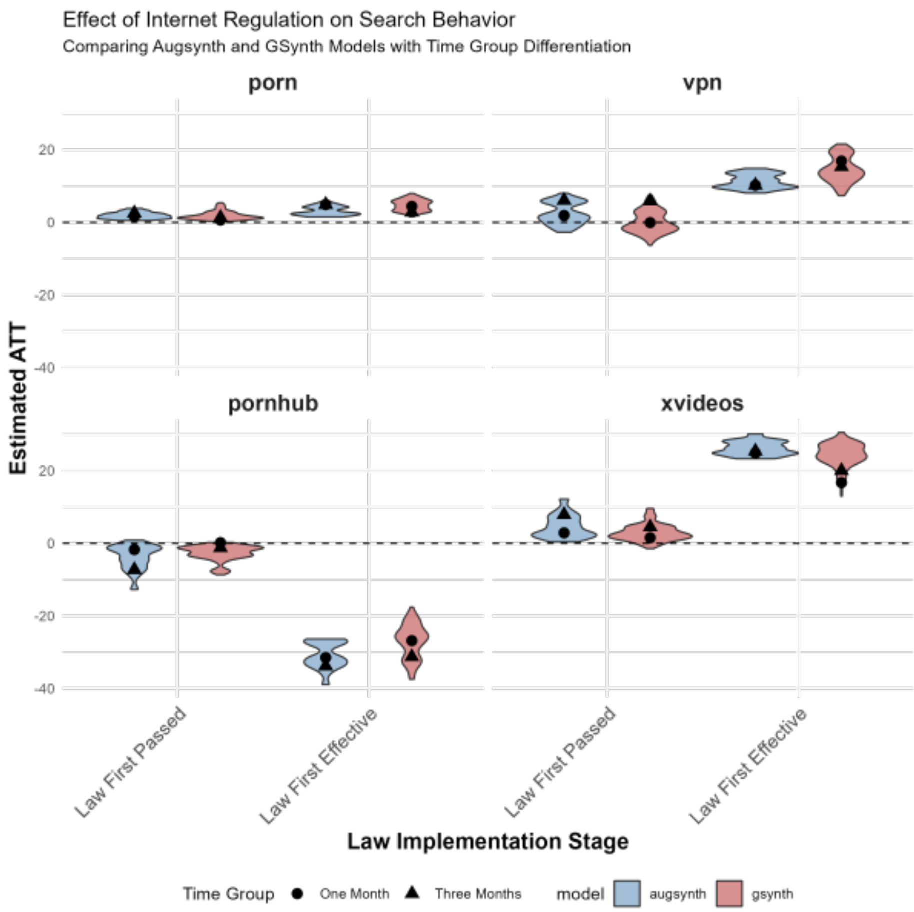


Figure 7: Multiverse Estimates

9 Limitations

Our analysis faces several important methodological limitations. First, while Google Trends data captures search behavior, it does not directly measure web traffic or actual site visits. This creates a construct validity challenge: we observe changes in search patterns but cannot definitively determine whether these changes translate to meaningful differences in site access. Second, we cannot compute the true extent to which these laws affect actual visitation to the targeted websites. While our findings suggest large decreases in search traffic, firms that complied with age verification laws have cited drops in traffic of 80% or more (Iovine, 2023). Additionally, users may access sites through direct URLs, bookmarks, or other means that bypass search engines entirely, meaning that our analysis potentially understates or misses important behavioral adaptations. Another potential limitation of our analysis is that the Stable Unit Treatment Value Assumption (SUTVA) may not hold perfectly in this context. Users in control states could potentially change their search behavior in response to nearby states implementing age verification laws, especially in border regions where cross-state internet access is common. Finally, a crucial limitation is our inability to differentiate users by age. Since Google Trends data is aggregated and anonymized, we cannot determine whether observed changes in search behavior are driven by the intended target of these regulations (i.e. minors) or reflect broader behavioral shifts across all age groups. This limitation is particularly relevant given that the primary policy objective is protecting minors from accessing adult content.

10 Discussion

Our analysis reveals several key insights about the effectiveness of state-level age verification requirements for adult content websites. The three-month results demonstrate a 51% reduction in searches for the largest compliant platform, accompanied by increases in searches for the next largest non-compliant platform (48.1%) and VPN (23.6%) services. These findings suggest that while age verification laws may successfully reduce search traffic to regulated platforms, they also appear to drive users to search for potentially less regulated alternatives. These results contribute to ongoing debates about the efficacy of digital content regulation. While proponents of age verification requirements argue that such measures are essential for protecting minors, our findings indicate that these policies may primarily shift user behavior rather than fundamentally alter access patterns. The observed increase in VPN-related searches suggests that users are actively seeking ways to circumvent these restrictions, potentially undermining the policies' intended protective effects. Anecdotal data from other states with different age verification regimes, such as Texas, have suggested similar circumvention behaviors (Fung, 2024).

While our findings demonstrate clear shifts in search behavior, quantifying the overall effectiveness of these laws requires careful consideration of market dynamics. Our analysis focused on the two dominant platforms in this space, where the compliant firm (Pornhub) historically commanded approximately three times the search volume of the non-compliant firm (XVideos) (see Figure 8). The observed effects—a 51% decrease for the compliant platform and 48.1% increase for the non-compliant platform—resulted in a net reduction in total search volume across these platforms, potentially suggesting some success in reducing overall access in the three months following the passage of these laws. Looking only at the impact on the compliant firm would tend to overestimate the impact of these laws. In Figure 8, we provide an estimate of the net impact of age verification on the search for adult content. Netting out the increase in our non-compliant firm's search volume would suggest that the reduction in searches for adult content is approximately two-thirds of what can be observed in direct reductions through the compliant firm. Additionally, despite the pre-existing market share disparity, after age verification passes, the compliant platform is now searched for less frequently than the non-compliant firm. We caveat this analysis with the fact that we only look at two firms that comprise about 40% of the market for adult content. Estimating a more precise substitution effect is outside the scope of this paper.However, this outcome highlights a complex policy dynamic: while the laws successfully reduced search traffic to regulated platforms, they may have inadvertently strengthened the market position of non-compliant firms among users who continue to seek such content. These findings underscore the importance of considering both direct and indirect effects when evaluating the effectiveness of digital regulation.

Our work is connected to several concurrent research efforts that examine the effectiveness of digital regulation. Studies of content moderation policies (S. T. Roberts, 2019),

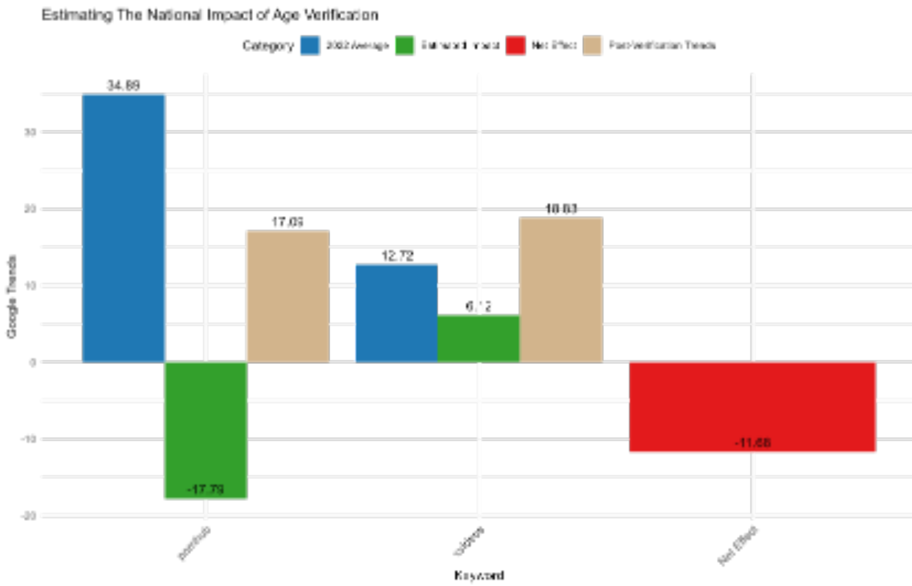


Figure 8: Estimated Nationwide Effect

platform-specific restrictions (Gorwa, Binns, and Katzenbach, 2020); (Horta Ribeiro et al., 2021), and digital privacy regulations (Goldberg et al., 2024) have consistently found evidence of substantial user adaptation and avoidance behaviors. Our results align with this broader literature while providing specific insights into how users respond to age-based access controls.

At the time of writing, multiple states are pending implementation of similar age verification laws, underscoring the urgency of understanding these behavioral responses (Ramkumar and Bobrowsky, 2025). The imminent expansion of these policies provides an opportunity to refine implementation strategies based on early evidence while highlighting the need for continued evaluation as the regulatory landscape evolves. The implications of these findings extend beyond the immediate context of adult content regulation. As states increasingly adopt digital access restrictions across various domains—from social media age verification to platform-specific bans—understanding how users adapt to such regulations becomes crucial for effective policy design. Our results suggest that policymakers should carefully consider the potential for displacement effects when implementing digital access controls.

Future research should address several key questions raised by our findings. First, studies using more granular data sources could help determine whether observed behavioral changes vary by age group, potentially illuminating the policies' effectiveness at protecting minors specifically. Second, comparative analysis of different implementation approaches across states could identify which verification methods most effectively balance access restriction with user privacy concerns. Finally, longer-term studies will be crucial for understanding whether initial adaptation patterns persist or evolve as users and platforms adjust to the new regulatory environment.

As states continue to expand digital access restrictions, our findings offer important lessons for policy design and implementation. Policymakers should anticipate and account for potential displacement effects when designing regulatory frameworks. The observed increase in circumvention-related searches also suggests a need for more comprehensive approaches that consider both technical and behavioral aspects of digital access control. Taken together, our results highlight the importance of monitoring unintended consequences, particularly the potential shift of users toward less regulated or potentially more dangerous platforms.

While our analysis cannot definitively resolve debates about the optimal approach to protecting minors online, it provides crucial empirical evidence about how users respond to current regulatory strategies. The substantial adaptation effects we document suggest that age verification requirements, while potentially valuable as part of a broader regulatory strategy, may have limited effectiveness as a standalone policy tool. Future regulatory approaches may need to balance traditional access controls with other mechanisms that account for the dynamic and adaptive nature of digital behavior.

For researchers studying digital regulation, our work demonstrates the value of combining pre-registered analyses with high-frequency behavioral data to evaluate policy effects in real-time. The rapid pace of both policy adoption and user adaptation in digital contexts makes such timely evaluation particularly crucial. We encourage future work to build on our methodological approach while incorporating additional data sources that can provide more nuanced insights into user behavior patterns.

In that spirit, we aim to update our study as planned based on the following events: 1) When the 19 states that have passed age verification laws currently have enacted them for at least 3 months; and 2) when the decision in *Free Speech Coalition, Inc. v. Paxton* is announced and an additional evaluation three months after the ruling has been implemented.

11 Acknowledgements

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A Appendix A: Validation of Google Trends as a Traffic Proxy

To validate our use of Google Trends data as a proxy for actual website traffic, we conducted a correlation analysis comparing worldwide Google Trends search interest with SimilarWeb traffic data from January 2020 to January 2025. This analysis serves to establish the construct validity of our primary metric.

We examined three key metrics:

1. Total traffic volume (daily visits) from SimilarWeb aggregated by week
2. Relative search volume from Google Trends aggregated by week
3. Platform-specific correlations between search volume and traffic

The analysis covers two major platforms:

- Pornhub (compliant with age verification laws)
- XVideos (non-compliant with age verification laws)

Our analysis reveals strong positive correlations between Google Trends relative search volume and actual SimilarWeb traffic data for both platforms (see Figure 9). These correlations suggest that Google Trends data serve as a reliable proxy for actual traffic patterns. The strength of these correlations is particularly noteworthy given that Google Trends provides relative rather than absolute measures.

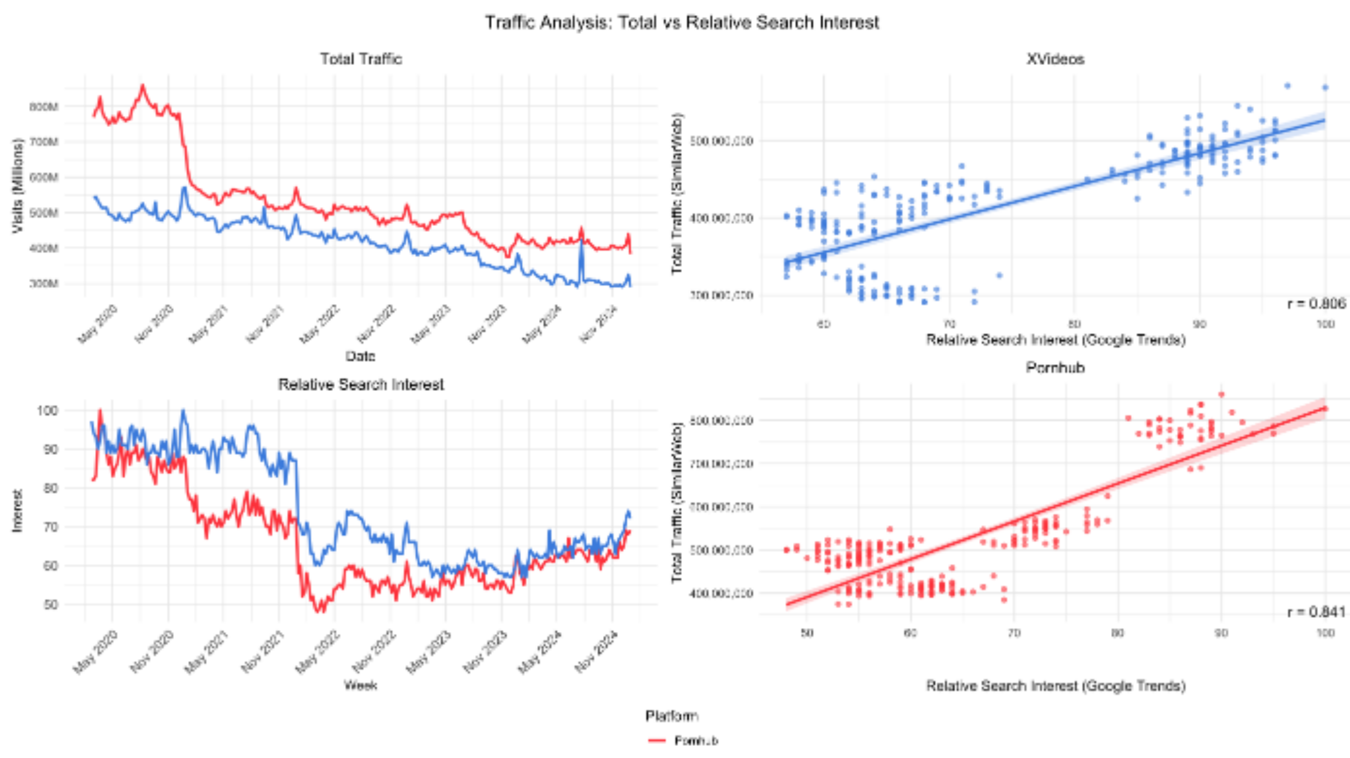

Figure 9: Validation of Google Trends as Traffic Proxy. Comparison of Google Trends search interest with SimilarWeb traffic data (2020-2024) (Source: Dewey Data)

- XVideos: $r = 0.81$
- Pornhub: $r = 0.84$

These findings support several key methodological choices in our primary analysis:

1. The strong correlations validate our use of Google Trends data as a proxy for actual traffic.
2. The stability of the relationship over time suggests our measure is reliable across our study period.
3. The similar correlation strengths across platforms indicates our metric is reasonably valid for both compliant and non-compliant websites.

B Appendix B: Analysis Conducted Prior to Pre-Registration

For classical synthetic control, the model weights tend to be largest for Arkansas, Alabama, Utah, Indiana, D.C., and Oklahoma (see Table 3). The generalized synthetic control weights generally are non-sparse and do not sum to one, making the face validity of the counterfactual harder to interpret. The exact weights vary depending on the outcome variable of interest. For instance, whereas Alabama weights are large for search volume for the term Pornhub, it has near-zero weight for other outcome variables.

state	pornhub_scm	pornhub_gsynth	xvideos_scm	xvideos_gsynth	vpn_scm	vpn_gsynth	porn_scm	porn_gsynth
AK	0.000	0.901	0.113	0.229	0.000	4.304	0.064	0.096
AL	0.305	1.358	0.036	-0.042	0.030	-1.664	0.006	0.363
AR	0.000	0.528	0.000	0.674	0.062	4.684	0.394	1.277
AZ	0.000	-0.261	0.000	0.016	0.000	-1.502	0.000	0.196
CA	0.007	1.257	0.000	-0.058	0.000	-3.355	0.000	-0.051
CO	0.000	1.302	0.018	0.041	0.000	-1.889	0.000	-0.021
CT	0.000	1.264	0.000	-0.078	0.000	-1.192	0.000	0.354
DC	0.000	-0.148	0.000	0.195	0.000	1.936	0.210	0.593
DE	0.128	0.662	0.000	0.175	0.000	2.268	0.000	-0.184
FL	0.000	0.797	0.000	-0.018	0.000	-3.088	0.000	0.207
GA	0.018	0.837	0.000	-0.102	0.000	-3.171	0.000	0.240
HI	0.000	0.403	0.000	0.304	0.113	4.265	0.000	-0.273
IA	0.000	0.398	0.000	0.150	0.095	-0.365	0.000	0.116
ID	0.000	0.655	0.000	0.529	0.024	0.107	0.000	0.174
IL	0.146	0.459	0.000	-0.214	0.000	-2.514	0.000	-0.336
IN	0.024	-0.221	0.000	0.252	0.214	-1.804	0.000	0.197
KS	0.000	0.486	0.000	0.135	0.000	-0.287	0.000	0.245
KY	0.000	0.761	0.000	0.456	0.000	-2.091	0.037	0.699
MA	0.053	0.301	0.000	-0.027	0.000	-2.762	0.102	-0.226
MD	0.152	1.187	0.000	0.071	0.000	-1.560	0.000	-0.206
ME	0.000	-0.078	0.000	0.176	0.009	0.520	0.000	-0.255
MI	0.000	0.743	0.000	0.034	0.000	-3.295	0.000	0.047
MN	0.000	1.603	0.000	-0.196	0.000	-1.498	0.000	0.086
MO	0.000	-0.242	0.000	-0.007	0.000	0.284	0.000	0.143
MS	0.000	0.034	0.000	0.731	0.000	0.619	0.149	1.197
MT	0.000	0.609	0.080	0.319	0.000	4.036	0.000	0.215
NC	0.000	0.646	0.000	-0.096	0.022	-3.183	0.000	0.720
ND	0.000	0.500	0.118	2.469	0.025	1.952	0.000	0.243
NE	0.000	0.915	0.000	0.267	0.039	2.571	0.000	-0.156
NH	0.000	0.831	0.029	0.538	0.000	1.892	0.000	0.036
NJ	0.000	-0.104	0.000	-0.102	0.000	1.747	0.000	-0.191

NM	0.000	0.828	0.000	-0.102	0.152	-1.085	0.000	-0.096
NV	0.000	0.901	0.000	-0.156	0.000	-0.872	0.000	0.525
NY	0.000	0.560	0.000	0.094	0.000	-0.276	0.000	-0.312
OH	0.000	0.102	0.000	0.046	0.000	-2.411	0.038	0.287
OK	0.160	1.090	0.000	-0.043	0.000	-0.597	0.000	0.593
OR	0.000	0.353	0.000	0.183	0.000	-1.253	0.000	-0.024
PA	0.006	1.079	0.000	-0.236	0.000	-2.335	0.000	0.125
RI	0.000	0.659	0.156	0.206	0.052	2.136	0.000	0.181
SC	0.000	1.275	0.000	-0.119	0.054	1.404	0.000	0.144
SD	0.000	1.024	0.132	2.389	0.000	3.803	0.000	0.213
TN	0.000	0.103	0.000	-0.220	0.000	-2.389	0.000	0.100
TX	0.000	0.668	0.000	0.140	0.000	-2.956	0.000	0.266
UT	0.000	0.453	0.208	1.252	0.108	6.257	0.000	0.630
VA	0.000	-1.095	0.110	0.487	0.000	0.592	0.000	0.903
VT	0.000	0.189	0.000	0.578	0.000	2.793	0.000	0.054
WA	0.000	0.272	0.000	0.082	0.000	-2.342	0.000	0.178
WI	0.000	0.128	0.000	-0.123	0.000	-2.326	0.000	0.188
WV	0.000	1.114	0.000	0.378	0.000	0.882	0.000	0.297
WY	0.000	-0.057	0.000	0.665	0.000	4.798	0.000	0.001

Table 3: Generalized Synthetic Control and Standard Synthetic Control Model Weights

For the single-state case we can then estimate the associated effect using conformal inference. In Table 4, p-values based on conformal inference procedures also suggest results consistent with the first three of our four hypotheses. We also provide estimates using the generalized synthetic control model in the same table. Overall, we find our point estimates to be relatively similar.

	Search Term	SCM			GSYNTH				
		Estimate	SE	P-Value	Estimate	SE	CI Low	CI Upper	P-Value
1	pornhub	-35.40	0.48	0.00	-36.54	2.17	-40.80	-32.28	0.00
2	xvideos	23.66	2.63	0.00	24.48	5.72	13.26	35.70	0.00
3	vpn	5.31	1.73	0.58	3.32	5.35	-7.16	13.80	0.53
4	porn	-0.06	0.85	0.92	0.47	1.98	-3.42	4.36	0.81

Table 4: Louisiana Results: Search terms with their estimates and standard errors for SCM and GSYNTH.

with respect to our pre-registered hypotheses. we illustrate them in Figure 10 . We see clear decreases for Pornhub by about 35.4 Google Trends points. We see a comparable increase of 23.66 for XVideos. We also see sharp spikes in VPN searches after an age-verification law's implementation, but that effect appears to fade out quickly. Searches for pornographic content show no clear effect.

While these findings are consistent with the first three of our four hypotheses, we note that this is only one state. There may be novelty effects such that these effects will not generalize when other states subsequently adopt such policies. We also note that there is substantial heterogeneity around subsequent state laws both in terms of fines, identification requirements, and enforcement mechanisms.

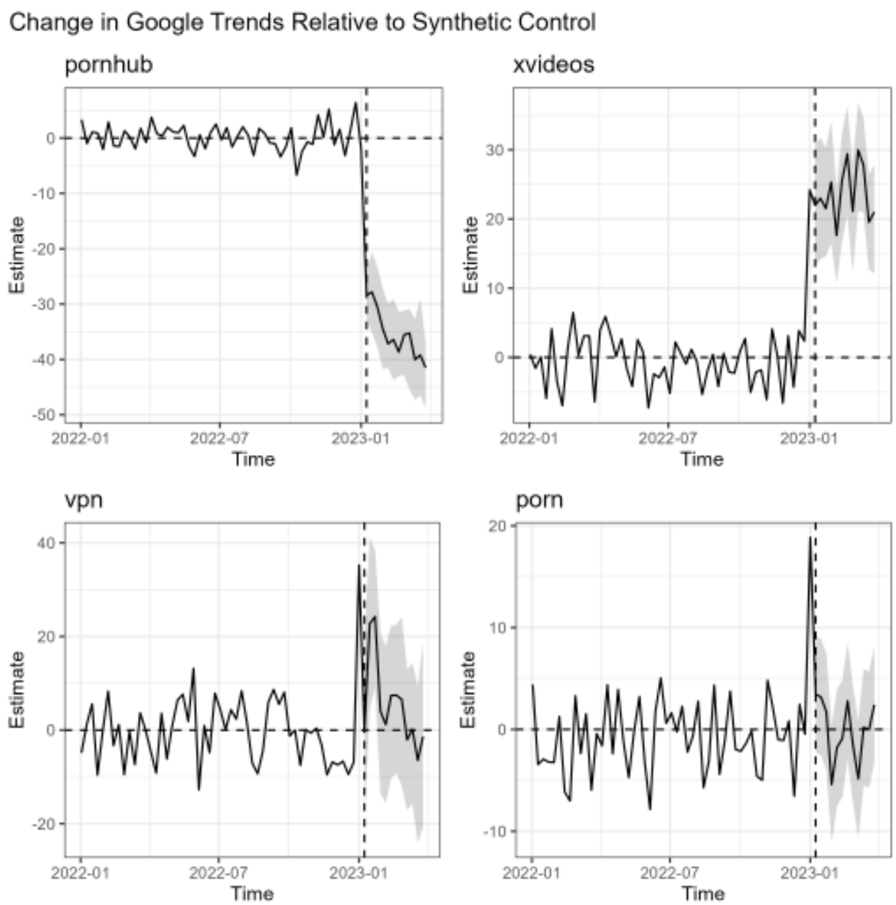

Figure 10: Louisiana Results: Change in Google Trends Relative to Synthetic Control. The figure shows the comparison of trends for Pornhub, Xvideos, VPN, and Porn.

We go through and compute the more standard permutation test for each term in Figure 11. Our results are also concordant for the more traditional permutation test. The ordinal rank for H1, H2, and H3 are either the first or second state, yielding a permuted p-value of less than 0.05. Our finding for H4 was null.

C Appendix C: Pre-Registration Deviations

This study was first pre-registered on May 23, 2023. Our primary research question explored whether policies regulating website access cause shifts in internet behavior, hypothesizing that internet regulation limiting access would shift demand to unregulated alternatives. The original pre-registration focused on a confirmatory replication of the effects observed in Louisiana for 2022's HB142 (later enrolled as Act 440) when Utah passed a similar law. We planned to analyze daily-level relative search volume (RSV) data using a broader set of search terms including TikTok, jailbreak, Tor, and others. Our analytical strategy included multiverse analysis with permutation testing, and we designed placebo

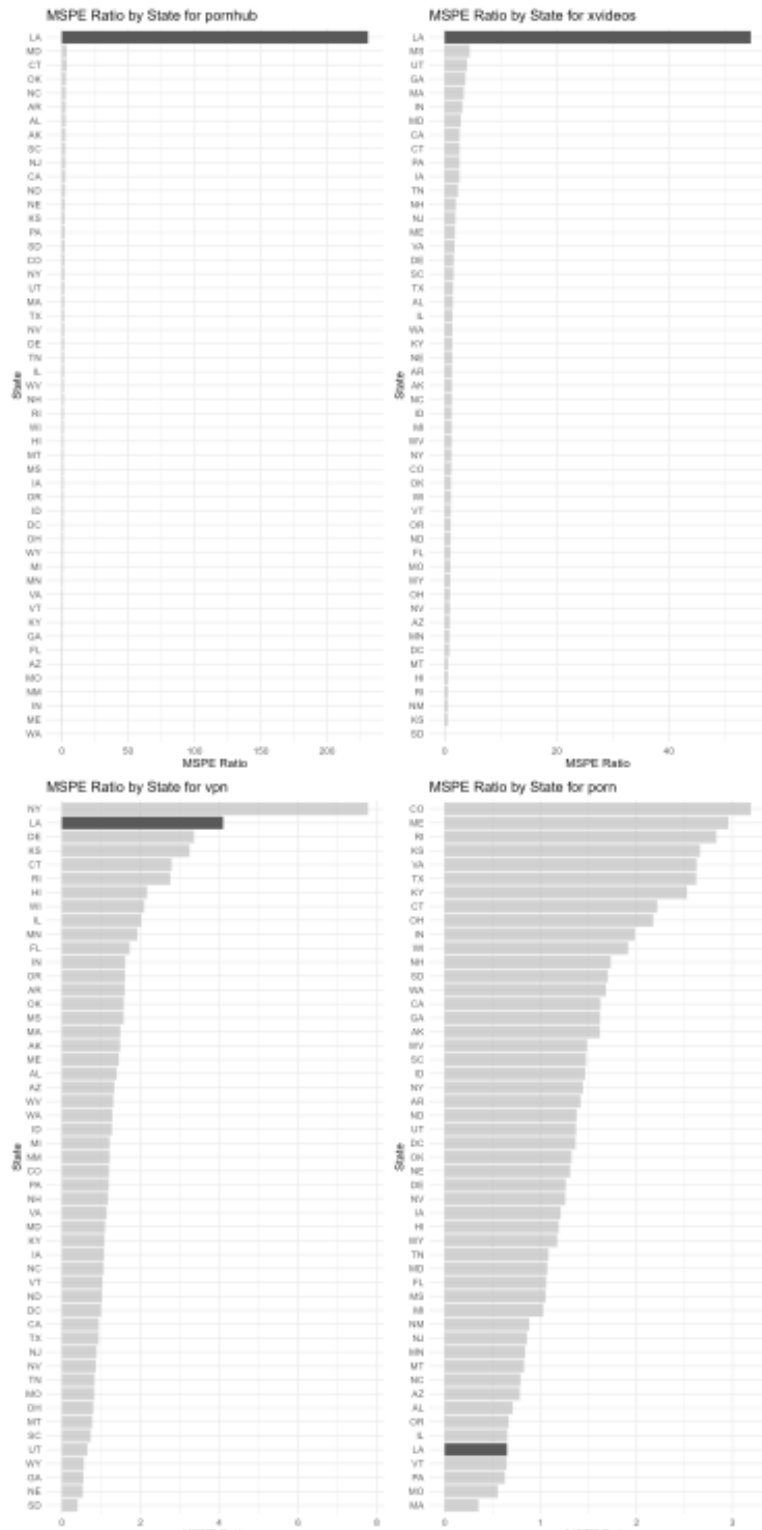

Figure 11: Permutation Test Results for Louisiana by Search Term

tests assuming staggered adoption would not be an issue, allowing us to exclude Louisiana from the analysis and focus on identifying the best-fitting pre-treatment models. Following (Lundberg, Johnson, and Stewart, 2021), we have maintained our target estimand as the average treatment effect of the policies on relative search volume in Google Trends on the treated states (ATT). The Github for the repo and analysis lives here. We modified it such that individuals who dropped off the paper would not have their identity readily retrievable.

C.1 Key Updates and Deviations

1. **July 1, 2023:**
    - Adjustments to the *timeframe* in response to the following considerations:
        - We limited the analysis of Google search trends to four key terms: *pornhub*, *xvideos*, *vpn*, and *porn*.
        - Six states that passed laws were identified for analysis, and we decided not to evaluate states beyond the pre-specified evaluation period.
2. **August 31, 2023:**
    - A change log was posted to document the removal of `scpi` from our multiverse of analytical tools.
    - A daily version of the multiverse was added to address issues with Google Trends data, which coarsens results to a weekly level. This adjustment aimed to improve precision in capturing treatment timing for all states within the revised time horizon.
3. **Current Version of the Paper**
    - In order to generate results prior to the FSC versus Paxton ruling being issued, we truncated data collection to 2024-10-31.
    - The pre-specified placebo analysis using the MSPE of control states was abandoned due to the complexity and unwieldy combinatorics.
    - The number of trends analyzed was significantly reduced to two points in time and estimators.
    - API throttling issues were encountered, which influenced data collection.
4. **Final Version of the Paper**
    - These results will be updated when a ruling comes down in *FSC versus Paxton*. More specifically, the update will reflect one of two outcomes:
    - In the event the lower court's ruling is upheld, we will run analyses once all states that have passed age verification laws have had them in effect for at least three months.
    - In the event of a reversal, we will run the analysis through the date the opinion was issued.

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