Social Media and Well-Being: Impact of TikTok on Screentime and Sleep Patterns

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Abstract

In this paper, we investigate the behavioral changes associated with TikTok adoption, focusing on its impact on screen time, nighttime phone usage, sleep patterns, and substitution across other apps. We employ a Difference-in-Differences (DiD) framework leveraging a high-frequency app usage dataset from nearly 7,000 TikTok adopters. Our findings reveal a significant increase in overall screen time—averaging 221 minutes per week for heavy TikTok users and 43 minutes for medium users—following TikTok adoption, alongside notable declines in usage of other social media and gaming apps, suggesting a strong substitution effect. The screen time effects are highest during late night hours. We also observe shifts in sleep patterns, including delayed bedtimes and a moderate reduction in sleep duration, among high-intensity users. We observe no effects for low-intensity users, who engage minimally with TikTok post-adoption. These results underscore the potential impacts of heavy usage of short-form video platforms on well-being. As a side result, our analysis provides clear evidence of substitutability between TikTok and traditional social media platforms, which has immediate implications for ongoing antitrust proceedings.

Keywords: Social media, Digital Well-being, Screentime, Sleep, Short-form Video, TikTok, Substitution

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1 Introduction

‘ Social media platforms have become an immensely popular means of entertainment and information. A 2024 Pew research study found that over 83% of Americans use at least one social media site. The widespread use of social media has raised concerns among healthcare professionals, educators, parents, and policymakers about its addictive nature and downstream effects on well-being. The U.S. Surgeon General recently called for warning labels on social media platforms to remind users of their adverse impacts (Murthy, 2024). Despite the slew of accusations against social media platforms by lawmakers across the country, causal evidence linking social media usage to objective indicators of well-being remains elusive.

The best known causal link between social media usage and well-being is documented by Braghieri et al. (2022), who use the staggered roll out of Facebook and survey data from 2009 to demonstrate a decline in mental health due to Facebook usage. However, since 2009, the social media landscape has evolved significantly with the rise of numerous platforms, each offering unique features. For instance, short-form video platforms like TikTok have seen a meteoric rise since their launch in 2016, becoming cultural sensations around the world. TikTok now has over 1 billion monthly active users globally and 120 million in the U.S alone. The same Pew research study found that nearly 1 in 3 Americans use TikTok in 2024, with usage particularly high among young Americans aged 18-29. Concerns about the negative effects of social media use have become particularly pronounced for TikTok, which consistently tops global app download and usage charts (AppAnnie, 2021) .

Despite TikTok's widespread adoption and increasing concerns about its potential negative effects, no studies to date have provided a comprehensive, detailed analysis of the behavioral changes—both online and offline—that occur following its use. In this paper, we examine the causal impact of TikTok adoption on several objective factors that influence wellness, such as total screen time, nighttime phone usage and sleep patterns and propose recommendations for platform designers to implement behavioral nudges that could help mitigate any negative effects. We also analyze how TikTok usage leads to a redistribution of users' time spent on other apps.

The consequences of TikTok adoption are unclear ex ante. Social media platforms have existed

for a couple of decades, and TikTok could be just another new platform in this space. If so, we might expect users to simply reallocate their time from other social media platforms, leading to minimal overall behavioral changes following TikTok adoption. However, TikTok is fundamentally different from conventional social media platforms in several ways.

Unlike traditional platforms, which are often built around a user's existing social network, TikTok's primary content delivery mechanism is its "For You" feed, which curates videos using a highly personalized and sophisticated algorithm. This algorithm prioritizes engagement metrics such as watch time and interactions over a user's social connections, making content discovery less about who you know and more about what holds your attention. This creates a lean-back consumption experience, where users are continuously served new content without needing to actively search or follow other users. As a result, TikTok is more immersive and can quickly move users from passive viewing to prolonged engagement.

Further, TikTok's focus on short-form videos significantly differs from conventional platforms that emphasize longer posts, static images, or text. The short duration of TikTok content makes each video extremely easy to consume, with users able to watch a video in a matter of seconds. As a result, the marginal cost of watching another video could be minimal, which may encourage users to keep consuming content without feeling an immediate need to stop. Over time, this minimal cost may lead users into an "infinite scrolling trap", where they lose track of time and engage with the platform longer than intended (Rixen et al., 2023; Cho et al., 2021). These factors suggest that TikTok may be uniquely positioned to create more intense and sustained engagement.

One of the difficulties in studying the impact of social media use, especially TikTok, on user behavior is the lack of reliable data. Much of the existing research in this area is based on self-reported data or experiments conducted in lab settings. Self-reported measures of screen time, sleep patterns, and well-being are prone to recall bias and inaccurate reporting. Prior work has shown that users tend to underestimate or overestimate their screen time or sleep, and subjective assessments of well-being can be influenced by factors such as mood, memory, or social desirability bias. Although technology companies meticulously track user interactions within their platforms, this data is generally limited to each company's app. As a result, it becomes difficult to measure how

time spent on TikTok affects the usage of other apps, complicating the assessment of substitution effects across platforms.

In this paper, we address these challenges in three ways. First, we leverage detailed smartphone touch stream panel data from close to 7,000 TikTok adopters. This data captures every interaction that the panelists have with their phones over many months, offering a rare glimpse into when, and for how long people engage with different apps including TikTok and other social media platforms. Specifically, we can determine the exact number of times any app on the users' phone is accessed, the duration of each session, the time of day these interactions occur and periods of non-usage (screen-off time). This granular data allows us to pinpoint the time of TikTok adoption, track our outcomes of interest at the individual level and observe substitution patterns across the full spectrum of apps. Second, our data span TikTok's explosive growth in the US from 2019 to 2021, enabling us to observe a large number of users during the period surrounding their adoption of TikTok. Third, we break away from the conventional focus on subjective self-reported well-being measures by focusing on objective factors that directly impact well-being. The well-established clinical relationship between screen time, night-time phone usage, sleep, and well-being forms the basis of our analysis (Baglioni et al., 2016). For example, Twenge and Campbell (2018) found that high screen time is associated with lower psychological well-being, lower self-control, and more distractability. Scott et al. (2021) conducted a meta-analysis of 65 randomized trials with more than 8,600 participants, concluding that sleep is strongly tied to mental health. Our mobile phone data enables us to estimate total screen time and infer daily sleep patterns, including bedtime and wake-up times, by analyzing screen-off periods. This approach provides a rare opportunity to examine the impact of TikTok adoption on screen time and sleep in real-world settings for a large number of users.

Our empirical strategy leverages the staggered adoption of TikTok at the individual level within a Difference-in-Differences (DiD) framework. A key challenge in this analysis is that the decision to adopt TikTok is not exogenous. Users self-select into adoption, which may result in systematic differences between TikTok adopters and non-adopters that are difficult to control for. To mitigate this concern, we focus on comparing outcomes between early adopters and late adopters, excluding

those who never adopted TikTok during the study period. This approach aligns with a body of prior research that examines the effects of staggered, endogenous interventions (Deshpande and Li, 2019; Gu and Kannan, 2021; Bapna et al., 2018; Petrova et al., 2021). While these studies typically only observe the binary adoption decision, our data provides the exact amount of time users spend on TikTok after adoption. This enables us to compare early adopters with those late adopters who eventually exhibit similar TikTok usage intensity, allowing us to control for unobserved factors that could simultaneously influence the extent of TikTok usage and our outcomes of interest. Additionally, we match early adopters to late adopters (among those having similar usage intensity) based on pre-adoption characteristics. A more detailed discussion of endogeneity concerns is provided in section 5.1.

Our results show that adoption of TikTok led to an average increase of 221 minutes per week in overall screen time for the heaviest users, and 43 minutes per week for the medium users during the six week period post TikTok adoption. In contrast, we observe no effects for low-intensity users, who engage minimally with TikTok post-adoption. Importantly, the rise in screen time among heavy and medium users is entirely attributable to TikTok itself. We observe a notable decline in non-TikTok screen time, indicating that TikTok had a strong substitution effect on other apps. The most substantial declines in usage post-adoption are observed in social media and gaming apps. This finding suggests that TikTok is, in fact, replacing other forms of screen time that are also considered unproductive and potentially harmful to well-being. However, the time gained from the reduced use of these apps is more than offset by the additional time spent on TikTok, resulting in a net increase in overall screen time. These substitutability results also have immediate policy implications. The Federal Trade Commission does not consider TikTok to be a direct competitor to Facebook, primarily due to the differences in product offerings. This distinction affects how the FTC defines the social media market, which is crucial in evaluating monopolistic behavior and antitrust actions (Aridor, 2022a). However, we provide clear evidence that TikTok's adoption led to large declines in the usage of traditional social media platforms, especially Facebook and Instagram, supporting Facebook's claim that TikTok is a direct competitor[1].

[1] https://www.bloomberg.com/news/articles/2022-02-04/meta-user-slowdown-bolsters-blame-it-on-tiktok-antitrust-de

Our analysis reveals that the impact on screen time is especially pronounced during nighttime hours, which is concerning given that late-night smartphone use has been linked to various forms of mental health disorders (Baglioni et al., 2016; Woods and Scott, 2016). Although we cannot directly measure sleep quality, the detailed nature of our data allows us to infer sleep duration, bedtime, and wake-up time. We identify continuous periods of screen-off time, assuming that the longest uninterrupted sequence within a 24-hour period corresponds to an individual's primary sleep session. For the heaviest users, each minute spent on TikTok led to a 0.07 minute decline in sleep. We observe an average delay in bedtime of 85 minutes per week. Wake-up time similarly shifted later by about 49 minutes, resulting in a moderate net reduction in sleep duration of 36 minutes per week on average.

Finally, we find that among the heaviest users, the overall number of "pick-ups"— the number of times the phone screen is actively turned on—declines sharply after TikTok adoption, despite a significant increase in overall screen time. This suggests an intruiging underlying mechanism: while users may activate their phones less frequently, they engage with TikTok for longer periods during each session. In other words, despite TikTok's reputation for "short-form" videos, users tend to be engaged for longer durations than the length of individual videos might suggest. We confirm this through a descriptive comparison of session durations across various social media apps in section 11.

It is important to contextualize these findings within broader TikTok usage in the U.S. The effects manifest primarily among heavy users of TikTok who have over 30 minutes of TikTok usage per day, comprising about 10% of our overall sample. According to industry estimates, there are around 120.5 Million TikTok users in the United States, and 10% of all users is a significant number[2]. While casual users may not experience significant adverse effects based on the measures we track, our findings suggest that heavy users are at risk of spending more time on their smartphones, particularly at night, leading to a measurable decline in sleep. This is especially concerning given TikTok's popularity among young Americans, with 62% of those aged 18-29[3] and 63% of teens

[2] https://www.statista.com/statistics/1299807/number-of-monthly-unique-tiktok-users/
[3] https://www.pewresearch.org/internet/2024/01/31/americans-social-media-use/

aged 13-17 using the platform, 17% of whom report being on TikTok "constantly"[4].

The rest of this paper is organized as follow. We review the relevant literature in section 2. Section 3 discusses the motivation behind the key outcome variables in our analysis. Section 4 describes the data and section 5 describes the empirical analysis and results. Section 6 concludes with a discussion on the implications of our findings.

2 Literature

2.1 Societal Impact of Digital Platforms

There is a rich body of work in the IS literature studying digital platforms and the increase in efficiency afforded by these platforms due to their ability to facilitate better matching and increasing price transparency (Brynjolfsson and Smith, 2000; Parker and Van Alstyne, 2005; Brynjolfsson et al., 2003). Most of the work in the platforms area were focused on studying the larger economic impact of e-commerce platforms, online reviews, etc. However, in the last two decades, there has been an increased interest in understanding the societal impact of platforms. Scholars in this area have studied the impact of technology adoption and platform proliferation on a variety of offline and societal outcomes. For example, Chan and Ghose (2014); Greenwood and Agarwal (2016) study the relationship between STDs and the adoption of matching platforms. Chan et al. (2016) show how adoption of broadband internet leads to an increase in hate crimes. Similarly, Chan et al. (2019) and Liu and Bharadwaj (2020) leverage the roll-out of Craigslist to study the impact of technology adoption on prostitution and drug abuse, respectively. Studies also find positive downstream effects due to the adoption of specific platforms – for example, Cheng et al. (2022) show how Pokémon Go reduce depression and Pamuru et al. (2021) show the impact of Pokémon Go on local businesses.

In addition, studies that analyze the downstream and unexpected outcomes of the sharing economy find a range of interesting societal outcomes due to technology adoption. For example, Greenwood and Wattal (2017) show how the entry of Uber leads to a reduction in alcohol-related motor vehicle fatalities. However, studies in this literature also document the negative downstream

[4] https://www.pewresearch.org/internet/2023/12/11/teens-social-media-and-technology-2023/

impacts of sharing economy platforms, such as an increase in noise complaints due to the increase in Airbnbs (Ozer et al., 2024) and increase in congestion due to Uber (Agarwal et al., 2023).

While much of the existing literature focuses on the societal impacts of digital platforms through aggregate measures—such as crime rates, fatalities, noise complaints, or congestion—we contribute to this body of work by examining individual-level outcomes related to health and well-being following the adoption of a widely popular social media platform. By shifting the focus from societal aggregates to personal behaviors and experiences, we aim to provide a deeper understanding of how different types of users respond to the usage of these platforms.

2.2 Digital Consumption and Well-Being

The question of digital addiction and the impact of social media platforms has garnered significant attention from both policymakers and researchers (Aridor et al., Forthcoming). There are several bodies of literature in this area that attempt to answer some portion of this problem using either theoretical modeling, observational data, or experimental research spanning many different domains including medical and psychology, HCI, informatics and, economics. Various surveys and meta-analyses have explored the effects of social media on well-being, yielding mixed results—some finding negative impacts, others positive, and still others showing no significant effect (Huang, 2017; Dienlin and Johannes, 2020; Meier and Reinecke, 2021; Masur, 2021; Orben, 2020; Appel et al., 2020). The wide array of studies across different disciplines, combined with these inconclusive results, highlights both the profound influence of social media on users' lives globally and the challenges involved in establishing its causal effects on well-being.

Most of the policy debates around social media are on the negative effect of social media on mental health. Twenge and Campbell (2019) conduct a large scale survey of over 220,000 adolescents across two countries and find that heavy usage of social media is associated with 48% to 171% higher reports of being unhappy, depressed, and having suicidal thoughts. Similarly, other nationally representative survey-based studies (Twenge et al., 2018; Kelly et al., 2019; Boer et al., 2020) also find similar negative associations between mental health issues and usage of social media. Studies in the medical literature have documented similar correlations using self-reported

usage data and some decrease in mental health (Primack et al., 2017; Rosen et al., 2014; Robinson et al., 2019; Primack et al., 2018).

While much of the above literature focuses on the negative aspects of well-being, there are several aspects of social media that could lead to positive well-being. This is intuitive, since the positive health effects of social ties are well documented (Holt-Lunstad et al., 2010), and the increase in such connections in a digital setting is likely to improve and expand the nature of social ties (Rainie, 2012). Some studies in the literature find the positive impacts of social media on health outcomes. For example, Burke and Kraut (2016) contextualizes the type of communications that occur on these platforms – the goals, nature of communications such as targeted, stylized, or one-click responses, and the relationship between the communicators. The authors leverage a panel of 1910 Facebook users and find that targeted communications with intentional text lead to increased self-reported well-being. Further, a large-scale study comparing Facebook users to non-Facebook users finds that an increase in friendships is associated with lower mortality and the ability to maintain friendships (Hobbs et al., 2016).

The third set of papers in this literature find no effects of social media on well-being. In particular, Orben et al. (2019) use an eight-wave, nationally representative panel to study the links between social media use and well-being among adolescents and find that the effects on well-being are small and not economically significant. Przybylski and Weinstein (2017) collect data from a small panel of young users of social media to study the relationship between screen time and mental wellbeing. They find a quadratic relationship between screen time and mental well-being, with significant heterogeneity in usage patterns, suggesting that technology use is not inherently harmful and its impact varies across individuals. Downey and Gibbs (2020) leverage teacher and parents' evaluations of social skills to demonstrate that increased screen-time does not necessarily translate to decreased social skills. A meta-analysis of social media use among adolescents suggest that there is a small correlation between social media usage, but conclude that there is a lot of confounding factors and high heterogeneity in how social media affects mental health (Ivie et al., 2020). Similarly, Vuorre et al. (2021) examine nationally representative samples and do not find associations between social media and mental health.

The ambiguities in the findings of these studies demonstrate the challenges in studying this extremely important question, as tracking social media usage in a reliable manner is quite difficult. There have been several criticisms of studies performed with survey-based or self-reported data due to inaccuracies between actual usage and self-reported usage. For example, Scharkow (2016) compare self-reported technology usage data with actual usage from logs usage and find that the accuracy of self-reported data is quite low, with high incidence of over-reporting. Similarly, Junco (2013) compare the actual and reported usage of Facebook and find significant discrepancies. Wilcockson et al. (2018) suggest that analyzing actual smart-phone usage for even five days will reflect typical weekly usage and corroborate prior studies to show significant difference between actual usage and self-reported data. Ellis (2019) argue that most of the self-reported psychometric tools used in studies to measure smartphone usage are unreliable and vary widely from actual usage due to social-desirability and cognitive burden. In addition, they call on researchers to collect behavioral data from digital devices that reflect the real world. These studies are also largely correlational and struggle to establish causality due to omitted variable bias and reverse causality. For instance, users who are already experiencing mental health challenges may be more likely to engage in heavy social media use. Additionally, unobserved factors like socioeconomic status or offline social support networks might simultaneously influence both social media usage and mental health outcomes, leading to omitted variable bias.

Building on these concerns, several studies have employed randomized controlled trials (RCTs) and tracking software to more accurately capture digital activities and assess the causal impact of social media on various health and wellness measures. These studies often incentivize participants in the treatment group to limit their social media usage, measuring outcomes such as academic performance and self-reported well-being. For instance, Collis and Eggers (2022) track the daily digital activities of college students and find that those restricted from social media do not decrease their time, but instead instead substitute towards instant messaging. Allcott et al. (2022) conduct an RCT with tracking software among 2,000 American adults, providing evidence of habit formation and self-control issues, with many participants unaware of these problems. In another study, Mosquera et al. (2020) find that participants in the restricted Facebook usage group are more

likely to report improvements in well-being.

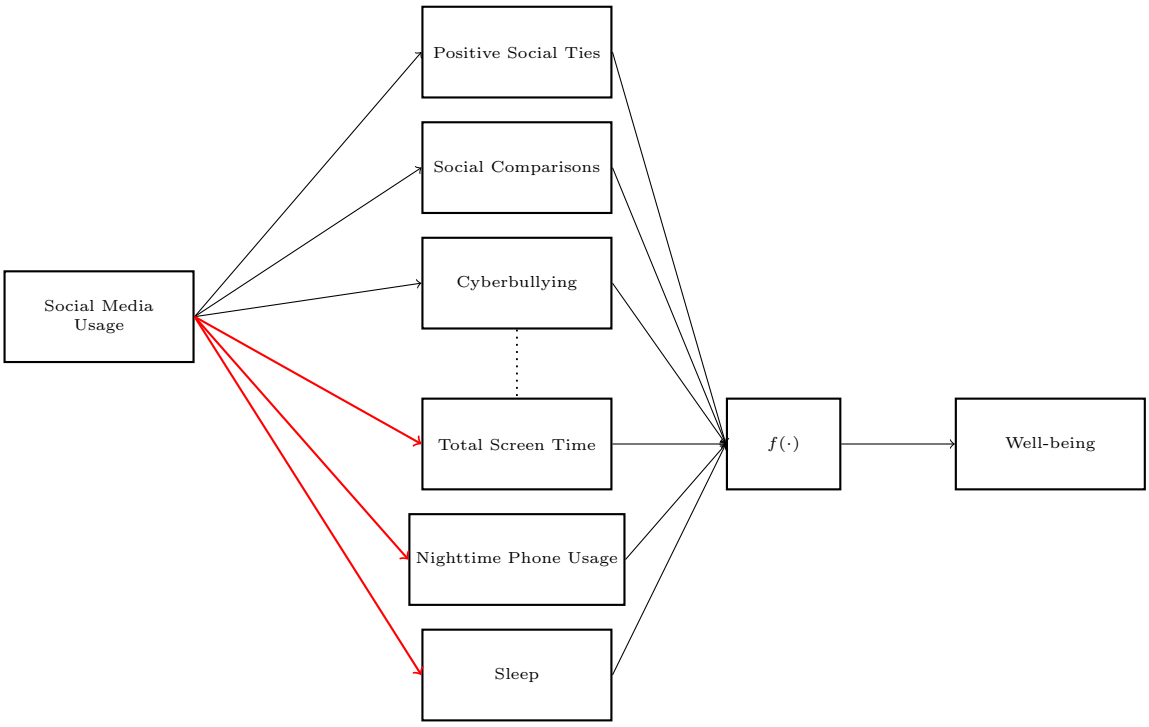
Other studies in social science literature has leveraged observational data and quasi-experimental techniques to examine this question. For example, Braghieri et al. (2022) use the staggered expansion of Facebook across universities in the U.S in mid-2000s and find that the introduction of Facebook led to poor mental health (self-reported). Belo et al. (2014) investigate the impact of providing broadband access to students and show that high levels of broadband lead to poorer academic performance, but schools that block access to YouTube do better.

Our study differs from this rich literature in several important ways, that makes our contribution salient in this field.

First, directly measuring the causal impact of social media on well-being is empirically challenging, as the relationship between social media and well-being is highly complex, shaped by a range of factors that can have both positive and negative influences (figure 1). Unlike prior observational studies that rely on self-reported outcomes, our analysis leverages objective data to capture more nuanced measures. Specifically, we leverage session-level "touch-stream" data to track sleep patterns, actual screen time, and nighttime usage—factors that are well-established as having a significant impact on mental health and well-being. This level of precision allows us to overcome many of the limitations inherent in self-reported surveys, offering a more reliable understanding of actual digital engagement. By using these precise behavioral indicators, we provide one of the most reliable and detailed causal evidence of some of the components of the multifaceted relationship between social media usage and well-being (red lines in figure 1).

Second, much of the existing literature, including Allcott et al. (2022), focuses on habit formation and self-control issues related to traditional social media apps such as Facebook, Instagram, Twitter, Snapchat, and YouTube (collectively, "FITSBY"), which are essentially built around social networks and communication. In fact, Collis and Eggers (2022) show that when social media usage is restricted, users substitute it with instant messaging, highlighting the central role of communication on these platforms. However, TikTok is an entirely different modality, requires very little input from the users and relies on personalized algorithm to prioritize content based on engagement metrics like watch time, rather than social connections (Verduyn et al., 2017). This creates a passive,

Figure 1: Social Media and Well-being



immersive experience where users are continuously fed new short videos that are easy to consume without needing to search or follow others. Given the growing popularity of the short-form video format, pioneered by TikTok and rapidly adopted by other platforms, studying TikTok's impact is especially important. Despite its global influence, TikTok remains highly understudied, making our contribution both timely and significant in understanding its effects.

Finally, our panel fortuitously covers the period of rapid Tiktok adoption in the United States, coinciding with its meteoric rise in popularity. The individual-level variation in the timing of TikTok adoption, combined with the granular nature of our data allows us to implement suitable controls and handle concerns related to omitted variable bias and reverse causality. Unlike lab-based studies, which often lack ecological validity, our observational data provide stronger external validity and a more accurate representation of real-world user behavior over time.

2.3 Substitutability Across Platforms

Our study also adds to the growing literature on substitutability across digital platforms (Agarwal et al., 2022; Aridor, 2022b) by showing that TikTok competes directly with a wide variety of platforms, including traditional social media, gaming and other video and entertainment apps. Current government regulations define platform markets narrowly based on product attributes, treating TikTok as distinct from traditional social media platforms, with the latter facing scrutiny for monopolistic practices. However, our findings demonstrate that TikTok serves as meaningful competition across multiple digital sectors, including social media platforms like Facebook and Instagram. This has important implications for competition law and policy, as it challenges the current narrow definitions regulators use to assess market competition. Furthermore, these insights are valuable for advertisers and platform managers, offering a clearer understanding of TikTok's competitive landscape (Arens and Hamilton, 2016). This knowledge can inform more effective strategies related to market positioning, user engagement, and advertising decisions.

3 Outcome Measures

In the previous section, we placed our research within the broader body of literature on this topic. In this section, we will explain the theoretical and practical basis for the outcome measures used in our analysis.

3.1 Screen Time

The relationship between screen time and well-being has become a significant area of concern for policymakers, as excessive screen use is increasingly being recognized as a public health issue. Prolonged screen time has been linked to a range of negative mental health outcomes, including increased levels of anxiety, depression, and loneliness, particularly among adolescents and young adults (Twenge et al., 2018; Twenge and Campbell, 2018; Babic et al., 2017; Page et al., 2010). Stiglic and Viner (2019) conduct a systematic review of this literature and find evidence for association between screen time and increased obesity.

In response to these concerns, several governments and health organizations have started to track screen time as a critical health outcome, with policy interventions aimed directly at regulating screen use. For instance, countries like China have implemented strict screen time limits to curb gaming addiction and improve mental health. Similarly, the American Academy of Pediatrics has issued guidelines recommending limits on daily screen time for children and adolescents (Hill et al., 2016). These policies reflect a growing recognition that screen time, regardless of content, can disrupt sleep patterns, increase sedentary behavior, and reduce face-to-face social interactions—all of which are critical for mental well-being (Appel et al., 2020). As a result, screen time itself has become a key metric to monitor and regulate, with almost all social media platforms introducing in-app tools to help users track and limit their usage (Kim, 2018).

Anecdotal evidence suggests that people often spend hours scrolling through TikTok's short videos. Despite this, it's unclear whether TikTok leads to a net increase in screen time. Users may simply be substituting time away from other apps, which could balance out their total screen usage. Whether TikTok usage results in increased screen time, therefore, remains an empirical question.

3.2 Nighttime Usage and Sleep

Nighttime screen usage has emerged as an important area of study due to its potential negative impact on sleep patterns and mental health (Lissak, 2018). The adverse effects of nighttime screen usage, particularly its disruption of circadian rhythms and the associated physiological impacts, have been studied extensively in the medical literature (Carter et al., 2016; Falbe et al., 2015; Figueiro and Overington, 2016; Cheung et al., 2017). Blue light emitted by screens interferes with the production of melatonin (Blask, 2009), the hormone that regulates sleep. Exposure to blue light in the evening suppresses melatonin levels, making it more difficult to fall asleep and reducing overall sleep quality (Chang et al., 2015). Sleep plays a crucial role in maintaining overall well-being, with far-reaching effects on mental health, cognitive performance, and physical health (Scott et al., 2021; Blask, 2009; Figueiro and Overington, 2016).

We expect that TikTok's effect on screen time will be most pronounced during nighttime hours due to its highly engaging content and the absence of external stopping signals. The reasons why

users break out of infinite loops have been of considerable interest to researchers in HCI. In a recent study of infinite scrolling, Rixen et al. (2023) record the activity usage of a small sample of users (N=46) on their smartphone, and qualitatively study the reasons why the users choose to break out of infinite scrolling sessions. Importantly, they find that TikTok usage contributes to the highest levels of infinite scrolling activity with significantly longer sessions than any other social media app and they attribute this to highly engaging and personalized video-based attributes[5]. Further, this study suggests that users tend to break out of infinite scrolling loop when there are other "real world" reasons such as work during the day.

TikTok's short-form videos, paired with its infinite scroll feature, are designed to keep users engaged, making it difficult to stop even when users intend to. Anecdotal evidence supports this, with many users reporting that they stay up much later than planned while scrolling through TikTok. With fewer distractions or responsibilities at night, users are more likely to lose track of time, allowing TikTok usage to infringe into their intended sleep period. Thus, we expect that high levels of TikTok usage likely leads to delays in bedtime. However, whether this delay results in a reduction of overall sleep duration remains unclear, ex-ante.

Policy responses to the issue of nighttime screen use are beginning to emerge. For instance, China has introduced nighttime curfews for social media platforms like Douyin, restricting access after 10 PM to help combat sleep deprivation and related mental health concerns. Public health experts emphasize the importance of limiting screen exposure before bedtime to promote better sleep hygiene. These policies underscore the growing recognition of nighttime screen usage as a significant outcome to track, distinct from overall screen time, due to its direct interference with sleep and its potential downstream effects on mental well-being.

[5]Infinite Scrolling is used interchangeably with that of swiping and does not just refer to physical act of scrolling

4 Data

4.1 Mobile Usage Data

The widespread adoption of smartphones has fundamentally transformed how people stay connected, offering unprecedented access to communication, entertainment, and information. Most users report never leaving home without their phones (Deutsche Telekom, 2012), using their phone the last thing before sleeping (Alshobaili and AlYousefi, 2019; Andrews et al., 2015) and checking them within the first 10 minutes of waking up[6]. The ubiquity of smartphones presents a unique opportunity to track and analyze societal outcomes that were previously difficult to measure.

This study is based on a comprehensive mobile usage dataset of approximately 250,000 Android users in the US, provided by a market intelligence firm. These users opted-in with consent in exchange for compensation and installed the firm's app on their phones, which tracked their app usage activity in real time. For each user we can observe a complete log of all the apps that they used, along with the exact opening and closing times down to the millisecond, for as long as they remain in the panel. Only apps that are in the foreground are captured. Each time a user opens an app, a timestamped entry is created, along with a unique identifier for the app and a unique app session ID (table 1). Since most smartphone functions (eg. making/receiving calls, browsing the internet, gaming) are driven by individual apps, this dataset provides an unprecedented view into the digital footprint of a large set of users in the US. The table below shows the format of the data.

The fact that these panelists have opted in to provide their data naturally raises concerns about selection bias and the generalizability of our findings. While we recognize that our dataset may not be perfectly representative of all users across the country, it should still reflect a significant portion of the population given the size of the data. It's also important to consider that even the most widely accepted metrics on the Android app market rely on opt-in data. Major providers such as App Annie, Sensor Tower, and Similarweb use similar individual-level data from opt-in users to estimate aggregate market numbers, including metrics like monthly active users and downloads.

[6] https://www.reviews.org/mobile/cell-phone-addiction/

Table 1: Format of App Usage Data

Panelist ID	App Identifier	Start Timestamp	End Timestamp
⋮	⋮	⋮	⋮
xyz	screen_off	2019-08-08T16:38:21.595	2019-08-08T16:45:27.594
xyz	com.google.android.launcher	2019-08-08T16:45:27.634	2019-08-08T16:46:29.452
xyz	com.zhiliaoapp.musically	2019-08-08T16:46:29.467	2019-08-08T16:52:35.056
xyz	com.google.android.launcher	2019-08-08T16:52:35.100	2019-08-08T16:53:42.327
xyz	com.google.android.youtube	2019-08-08T16:53:42.343	2019-08-08T16:55:45.356
xyz	screen_off	2019-08-08T16:55:45.376	2019-08-08T16:55:49.097
⋮	⋮	⋮	⋮

Note: The timestamps are in local time for the user. The app identifiers correspond to specific packages on the Android system. For instance, com.zhiliaoapp.musically is the identifier for TikTok. screen_off corresponds to periods when the user's screen was off. Launcher is an entry for a system app that corresponds to the main menu screen.

Moreover, numerous academic papers have been written utilizing these aggregate numbers (Garg and Telang, 2013; Karanam et al., 2023). The strength of our dataset lies in its granularity; while most analyses rely on aggregate data, we have access to the underlying individual-level data on which those aggregate metrics are based. This allows us to conduct a more detailed and precise analysis of TikTok adoption and usage behavior.

4.2 Estimating Screentime

One of the primary metrics in our analysis is total smartphone screentime, which we estimate at the panelist-week level by summing up the time spent by each panelist across all apps in a given week, excluding periods when the phone screen was turned off. The measure that we are truly interested in is the total time that users spend looking at their smartphone screens. Therefore, there is bound to be some measurement error since we are effectively measuring app foreground time, and a user may have an app open without looking at the screen. Accurately measuring screentime would ideally require eye-tracking technology, which is not feasible in this context. Even the built-in screen time trackers for iOS and Android rely on app foreground times, which are reliable proxies for active screen engagement.

It is also important to note that our pre- and post-adoption comparisons, coupled with the assumption that these errors remain fairly consistent over time, help mitigate concerns related to

measurement error. Nonetheless, we implement several adjustments to further reduce potential inaccuracies. First, we exclude time spent on dialer apps, which correspond to phone calls and should not be included towards screen time. Next, we exclude time spent on map and navigation apps, such as Google Maps and Waze, since these are typically used passively, with the user not actively staring at the screen[7]. Additionally, we identify and exclude apps related to home screen personalization, which allow users to display time, weather and other information as screensavers when the phone is not in use instead of turning the screen off. Since these activities do not reflect active screen engagement, they are excluded from our screen time measure. These adjustments help ensure that our screen time estimates more accurately reflect the time users spend actively engaging with their smartphones. Further details on how we identified apps in these categories are provided in section 4.5.

4.3 Inferring Sleep Duration, Bedtime and Wake-up time

Historically, sleep studies have relied on self-reported data sources like time-use diaries and surveys (Jin and Ziebarth, 2020; Barnes and Wagner, 2009). Despite their widespread use, these methods are plagued by significant limitations. Research has consistently shown that self-reported behavior often fails to align with actual behavior due to factors such as recall bias. Although laboratory experiments employing fitness trackers and other monitoring tools yield precise sleep measurements, they tend to be invasive and their findings are often limited by small sample sizes and controlled environments that don't easily translate to everyday situations. Our approach introduces a significant innovation by leveraging technology-driven behavioral big data from smartphone usage to examine sleep patterns at scale in a non-invasive manner, offering a more accurate insight into real-world behavior.

Our app usage data allows us to identify all instances when a user's smartphone screen is turned off. We assume that the longest uninterrupted screen-off sequence within a 24-hour period corresponds to an individual's primary sleep session. Since most people interact with their smartphones just before sleeping (Alshobaili and AlYousefi, 2019; Andrews et al., 2015), often use them as alarms

[7]Our results are unchanged if we include these apps in the measurement of screentime

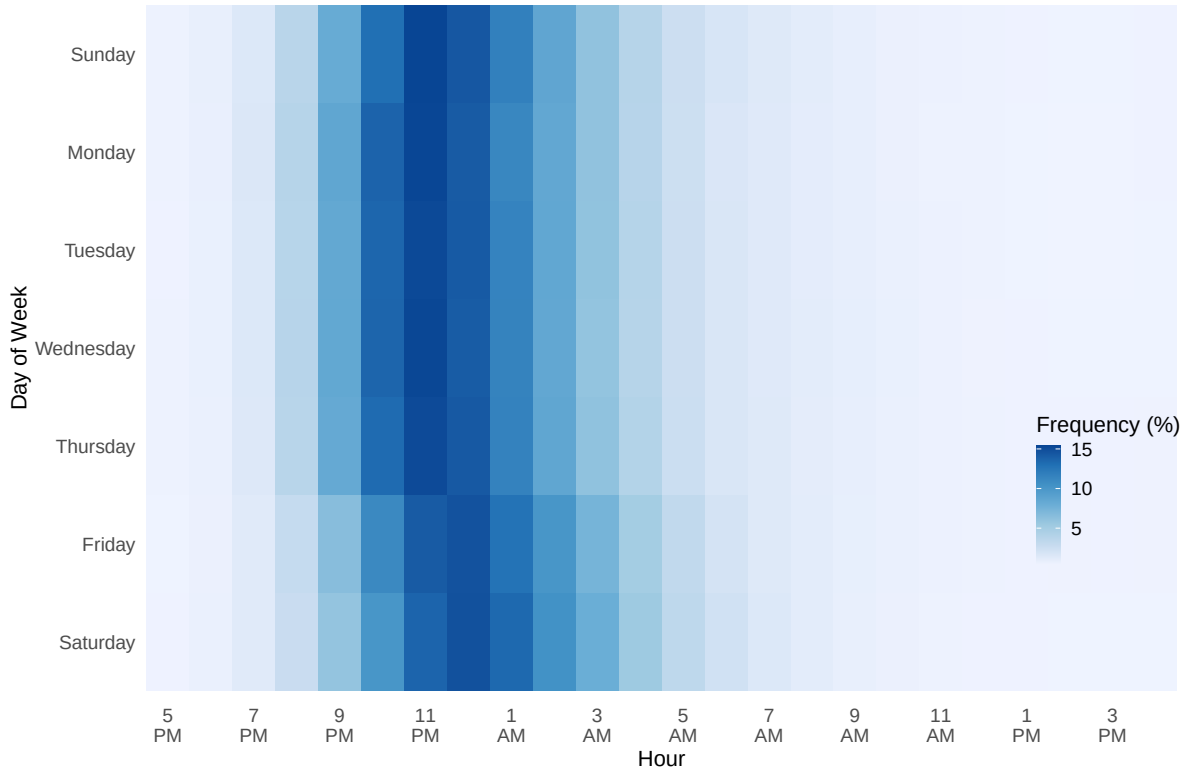
and check them just after waking up (IDC, 2015), the timing of the longest screen-off period should closely align with users' natural sleep cycles, making it a reliable indicator of their primary sleep sessions. We define the length of the longest screen-off period as the sleep duration, with the start time marking bedtime and the end time indicating wake-up time. As with screentime, some amount of measurement error is inevitable in this analysis. However, our estimates should remain unbiased as long as the error is not correlated with time. 1% of the panelist-week observations had a mean sleep duration of less than 3 hours, and 1% had a mean sleep of over 11 hours. We exclude these panelists since their sleep patterns are likely significantly mismeasured. To account for edge cases and exceptions, we conducted data cleaning procedures which are outlined in the appendix (A1.1).

We conducted multiple checks to assess the validity of this measure. Figure 2 below shows the distribution of bedtimes and wake-up times in the data for each day of week. The trends in Figure 2 appear reasonable, as the majority of users go to sleep between 10 PM and 1 AM, and wake up between 5 AM and 10 AM on weekdays. On weekends, this trend is shifted rightwards by approximately an hour. This pattern aligns with typical sleep schedules, providing confidence in the accuracy and validity of the sleep measures.

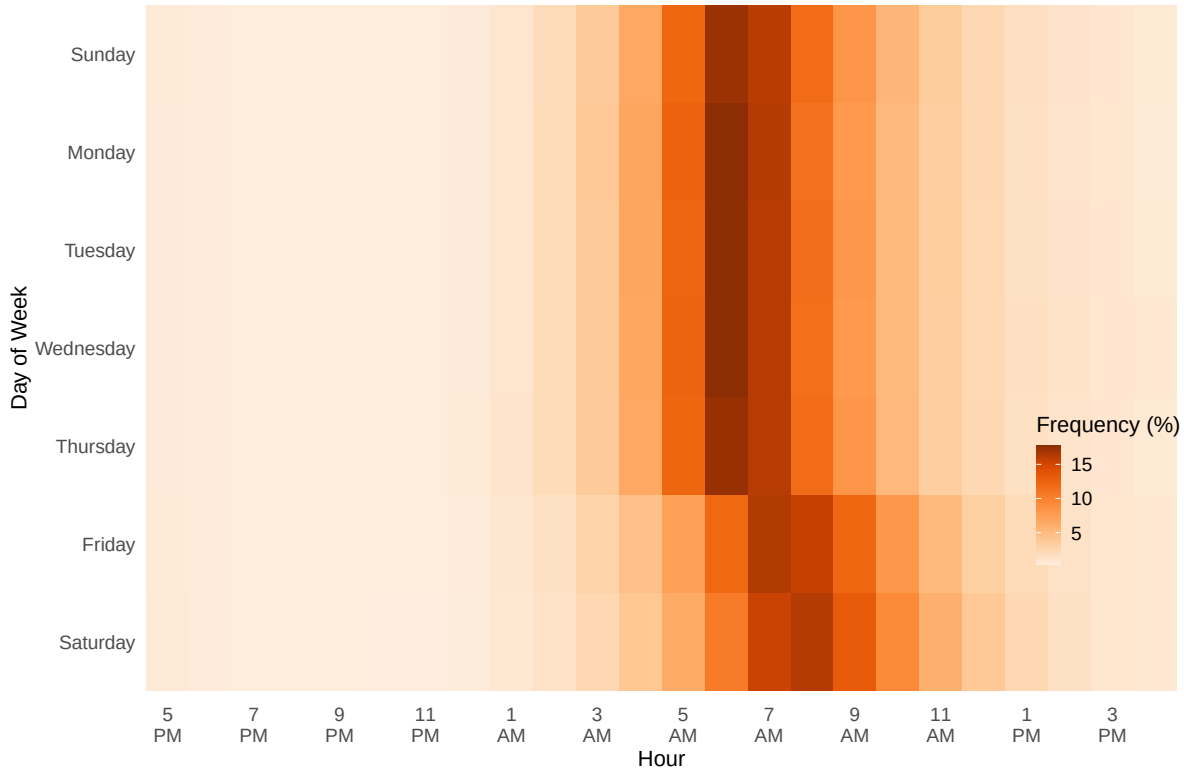
To further assess the sanity of these measures, we examine their trends over time. Figures A1, A2, A3 in the appendix shows that all three measures reflect expected variations, such as later bedtimes and wake-up times on holidays, as well as shifts corresponding to the daylight savings time transitions. These trends further validate the reliability of the inferred sleep measures.

To standardize bedtime and wake-up time for regression analysis, we apply the following adjustment. Bedtime for a given night's sleep is measured as the number of minutes past 5 PM on that date[8]. For example, an 11 PM bedtime would be recorded as 360 minutes, while 1 AM would be 480 minutes. This method allows us to use a linear scale (e.g., 1 AM is two hours later than 11 PM) and facilitates consistent comparisons of bedtimes across different days. Wake-up time is calculated in a similar manner, as the number of minutes past 5 PM on the same date. As shown in table 2, for each date, the wake up time assigned is the wake-up time corresponding to that night's sleep, which falls on the next morning.

[8]The choice of 5 PM is arbitrary, just to have a reference point, and has no bearing on the results.



((a)) Sleep Time Distribution by DOW



((b)) Wake Time Distribution by DOW

Figure 2: Distribution of Bedtime and Wake-up Time

Note: Figure 1a shows the distribution of bedtimes for each day of the week. Each hour bucket includes all observations falling in the full hour. For instance, 11 PM includes all bedtimes between 11 PM and 11 59 PM. Figure 1b similarly shows the distribution of wake-up times for each day of the week. Friday refers to the wake up time corresponding to Friday nights' sleep, which should correspond to Saturday morning.

Table 2: Bedtime and Wake-up Time Standardization Illustration

Example	Date	Bedtime	Bedtime Standardized (Mins past 5 PM)	Wake-up Time	Wake-up Time Standardized (Mins past 5 PM)
1	2021-10-05	2021-10-05 23:00:00	360 minutes	2021-10-06 07:00:00	840 minutes
2	2021-10-05	2021-10-06 01:00:00	480 minutes	2021-10-06 09:00:00	960 minutes

4.4 Estimating Number of Pickups

To estimate the number of pickups, we count the instances when a user transitions from 'screen_off' to any app during the day, excluding dialer apps and home screen personalization apps. This variable is helpful in understanding how TikTok contributes to increased screen time, particularly among heavy users. Specifically, we can explore whether users are picking up their phones more frequently throughout the day or whether they are engaging in longer sessions during each interaction.

4.5 App Categorization

Our app usage data gave us a list of all android apps used by all the users (over 500,000 unique apps). We identified the categories of these apps using Google' Gemini 1.5 Pro. Because of API limits, we only categorized the top 5,000 apps in our data, and clubbed all the others into a separate cateogory ('outside top 5K'). The top 5,000 apps in the data account of 97 percent of all the app usage in terms of duration. Based on a random sample of 200 apps, the LLM based classification was 100% accurate, which is unsurprising, since the LLM model was likely trained on Google's own play store data, and the function of most apps can be inferred from the title.

Table A3 in the appendix provides the list of app categories along with the top apps in each category.

5 Empirical Analysis

5.1 Identification challenges

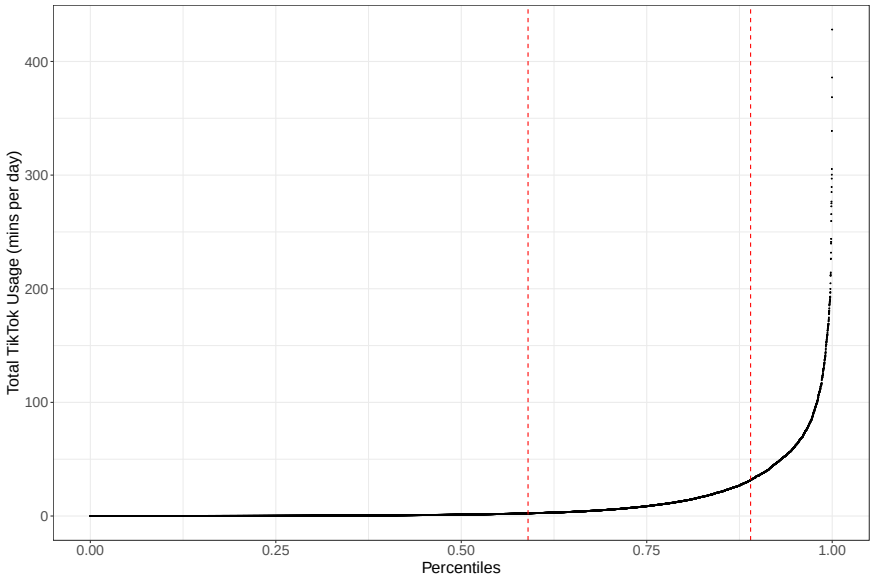
There are several challenges in identifying the causal impact of TikTok adoption on wellness measures. There are three key dimensions of endogeneity that we need to address to establish a causal relationship.

1. Selection into adoption: Individuals who choose to adopt TikTok may systematically differ from those who do not. For instance, adopters might have a higher propensity for spending extended periods on their phones or follow routines that accommodate later bedtimes. As a result, directly comparing the outcomes of adopters and non-adopters may lead to biased conclusions. This should be less of a concern for our analysis, as we are conducting a DID comparison that inherently focuses on changes over time. Nonetheless, to reduce any heterogeneity between treated and control users, we exclude non-adopters and just use late adopters as controls for early adopters. This approach is consistent with prior research on similar endogenous interventions (Deshpande and Li, 2019; Bapna et al., 2018; Gu and Kannan, 2021; Petrova et al., 2021). To further minimize observable differences between early and late adopters, we employ a matched sample in our analysis. Early users are matched with late users based on their levels and trends in key outcome variables prior to the early users' adoption week. The matching procedure is described in section 5.3.

2. Usage Intensity Post-Adoption: Our dataset captures not only TikTok adoption, but also the extent of usage after adoption. As expected, there is significant variation in TikTok usage among different individuals. Since usage intensity is self-selected, directly comparing light and heavy users could introduce bias due to omitted variables. To address this, we segment all adopters into three groups ('Low', 'Medium', and 'High') based on the intensity of usage in the six weeks following adoption (Figure 3). As expected, there is a long tail of users who barely use the platform even after adopting it. Users with less than 2.5 minutes of average daily use (corresponding to the 60th percentile) were classified in the 'Low' group. Those between 2.5 and 30 minutes of average daily usage (90th percentile) were classified in the 'Medium' group. All others were classified as 'High' TikTok users. For each adopter, we pick control users only from those late adopters who fall in the same TikTok usage group after their eventual adoption. This ensures that we are comparing users with comparable tendencies for TikTok engagement, allowing us to control for unobserved factors that simultaneously affect usage intensity and our outcomes of interest.

3. Timing of Adoption: Even after accounting for the decision to adopt and the level of usage, the timing of TikTok adoption may still be correlated with factors that independently influence outcomes such as screen time and sleep. For example, macro-level events such as university holidays

Figure 3: TikTok Usage Distribution



Note: This figure shows the distribution of average daily TikTok usage (total usage minutes/42) for all the adopters in the six weeks post adoption. The vertical lines denote the 60th and 90th percentiles of the distribution.

or the onset of a pandemic could trigger TikTok adoption and also lead to increased screen time, which would have happened regardless of TikTok adoption. Similarly, individual-level events like job loss, illness, or significant lifestyle changes could also lead to TikTok adoption and alter screen time and sleep patterns simultaneously, making it difficult to isolate the effects of TikTok adoption. We address this concern in four different ways.

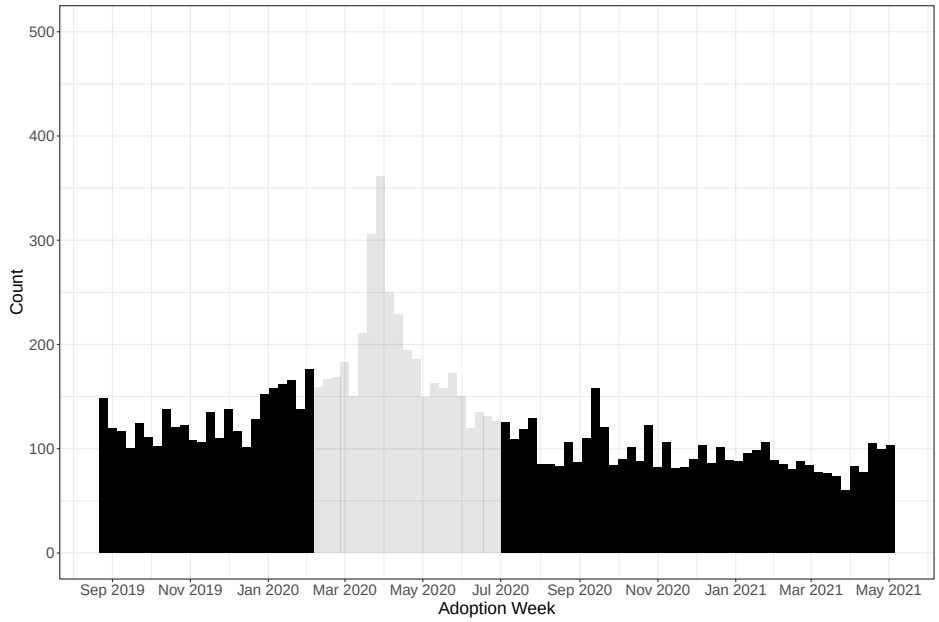
First, if macro-level events were the primary drivers of TikTok adoption, we would expect to see noticeable clustering around specific dates in the adoption timeline. However, as shown in Figure 4, this is not the case. Apart from a spike coinciding with the onset of the Covid-19 pandemic, the adoption pattern remains relatively stable over time. To minimize the confounding influence of this anomaly, we exclude the data from the Covid period (mid-February to June 2020) from all subsequent analyses[9].

Second, if individual-level events were driving both TikTok adoption and increased screen time simultaneously—such as individuals experiencing more free time due to job loss or illness—we

[9]Those who adopt TikTok during the Covid period will still serve as control users for those who adopt earlier. But they will not appear as treated users in the panel.

would expect to see a significant increase in non-TikTok screen time as well, given their higher time availability. However, our data does not support this (Figure 7). Instead, we observe that the entire increase in screen time is driven by TikTok usage, while non-TikTok screen time actually declines after TikTok adoption. This suggests that TikTok adoption is a key factor driving the shift in screen time, rather than general increases in device usage across all apps resulting from a greater availability of free time.

Figure 4: Distribution of TikTok Adoption Dates



Note: This figure shows the total number of TikTok adopters on each week in our data. For each of these adopters, we have unbroken data from 3 weeks prior and 6 weeks post TikTok adoption. The period in gray corresponds to the onset of the COVID pandemic, and has been excluded from the analysis.

Third, to ensure that the observed effects are truly a result of TikTok adoption and not due to pre-existing trends, we estimate dynamic lead and lag models. These models allow us to check whether changes in screen time and sleep patterns began before TikTok adoption. The results show no significant effects or trends in the periods leading up to adoption, confirming that the changes only emerge after users adopt TikTok. This helps us rule out the possibility of reverse causality, where pre-existing shifts in screen time or sleep might have driven TikTok adoption, rather than the other way around.

Fourth, we extend our panel to examine long-run effects up to 4 months post-TikTok adoption. We find that the increase in screen time, delay in bedtime, and moderate reduction in sleep duration persist at least up to 4 months, suggesting that these effects are not short-term responses but reflect more stable behavioral changes.

5.2 Stacked Panel

Our dataset covers the period from July 2019 to June 2021; however, most panelists are only observed for a portion of this time frame, as they join the panel at different points and can opt out at any time. Restricting the analysis to users with uninterrupted data from 2019 to 2021 would significantly reduce the sample size, limiting the feasibility of a meaningful analysis. To address this, we adopt a stacked panel approach (Baker et al., 2022; Cengiz et al., 2019; Deshpande and Li, 2019), focusing on users we observe consistently for a sufficiently long period around their TikTok adoption, as described below.

Our Difference-in-Differences (DiD) analysis is designed to compare early TikTok adopters (treated group) with late TikTok adopters (control group) within a window of three weeks before to six weeks after the treated group's adoption. Thus, we exclude individuals who never adopted TikTok. Among those who did adopt TikTok, we retain only those for whom we have continuous app usage data without any breaks during the window of -3 to 5 weeks (including week 0) relative to adoption and exclude all others. Additionally, we remove data from the second week of February 2020 to June 2020 due to significant disruptions caused by the onset of the COVID-19 pandemic. This filtering process results in a dataset comprising 7,790 TikTok adopters[10].

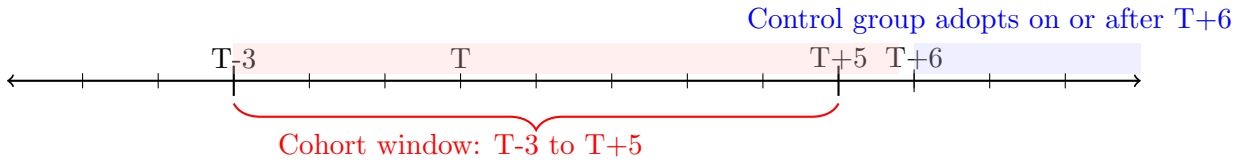
For each week in our dataset, we identify the panelists who adopted TikTok during that week (cohort) and designate them as the treated group for that cohort. We then identify those who adopted TikTok more than five weeks after the focal week and for whom we have complete data in the same -3 to +5 week window relative to the treated group's adoption week. These users form the control group for the TikTok adopters in that cohort. The lag ensures that the control group's

[10] Although we started with a dataset of 250,000 users, many users are observed only for a few days. Among them, not everyone uses TikTok. Even among the TikTok users, we only keep those who adopt TikTok during the data period and for whom we have unbroken data from -3 to 5 weeks.

observations are not influenced by their eventual TikTok adoption. For those who adopted on or after 9th May 2021, we do not have any control users because of right-censoring. These users are thus dropped, leaving us with 7,281 TikTok adopters.

For the treated and control users, we form a balanced panel at the panelist-week level going from -3 to 5 weeks relative to the focal week. We replicate this step for all the weeks in the data, and stack together the different balanced panels from the individual cohorts. By design, the treated users from a given focal week are not used as controls for subsequent weeks, which makes us immune to the common pitfalls associated with two way fixed effects DID estimators where already treated units act as controls for subsequently treated units (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021). All the outcome variables were initially computed at the panelist-date level, but are aggregated at the panelist-week level (by taking sums) since that is the level of our panel.

Figure 5: Timeline of cohorts and control groups based on TikTok adoption



5.3 Propensity Score Matching

To make the treated and control group users more comparable, we match the users based on levels and trends in the main outcome variables, prior to the treated group's adoption. We use k2k matching, giving us up to one control user for each treated user.

For each cohort and TikTok usage group combination, we run a logistic regression and identify matched users using nearest neighbour matching with a caliper of 0.05. We match users based on (i) total screen time, total bedtime (standardized) and total wake-up time (standardized) in week -1 (the week prior to adoption) and (ii) changes in each of these variables between weeks -1 and -3. This process gives us 6,544 matched users (4,248 low, 1,750 medium and 546 high users) out of a total of 7,281 TikTok adopters. Our final dataset is a subset of the original stacked panel containing only the matched pairs of users. There is no significant difference between the treated

and control users from the matched sample in the key outcome variables prior to the treatment group's adoption. More details are provided in appendix section A1.2.

Summary statistics from the final matched panel is provided in the table below.

Table 3: Summary Statistics for Sleep and Screen Time Data

Variable	N	Median	Mean	Min	Max
Screen Time (mins)	117,792	2099.7	2244.3	118.1	6987.6
Sleep Duration (mins)	117,792	2,868	2,861	1,260	4,260
Bed Time (mins relative to 5 PM)	117,792	3,290	3,438	517	9,298
Wake-up Time (mins relative to 5 pm)	117,792	6,163	6,299	2,645	12,657
# Pickups	117,792	267	304.2	11	5,135

Note: Summary statistics from the matched stacked panel which is at the user-week-cohort level. The median or mean daily values can be computed by dividing the median or mean columns by 7.

5.4 Regression Estimates

In our main specification, we compare outcomes for TikTok adopters relative to a matched sample of control users who adopt TikTok later and exhibit similar usage intensity. To operationalize this, we estimate the following regressions using the matched sample separately for each TikTok usage group-

$$y_{itc} = \sum_{\substack{r=-3 \\ r\neq -1}}^{5} \beta_r \cdot \mathbb{1}(rel_week_r) + \gamma_{ic} + \delta_{tc} + \epsilon_{itc} \tag{1}$$

$$y_{itc} = \beta \cdot (after_adoption)_{itc} + \gamma_{ic} + \delta_{tc} + \epsilon_{itc} \tag{2}$$

In these equations, i, t, c refer to panelist, week and cohort respectively. y refers to the outcome variable of interest (screen time, bedtime etc). $\mathbb{1}(\text{rel_week}_r)$ is a series of dummy variables from -3 to +5 which are set to one when week t is r weeks from the adoption week for that cohort. In equation (1), control users are assigned an arbitrary value for all rel_weeks (99), causing their rel_week coefficients to drop out (as intended) due to collinearity. Week -1 is the week prior to adoption and is used as the reference group. γ_{ic} refers to cohort-panelist fixed effects and δ_{ic} refers

to cohort-week fixed effects. When using stacked panels, it is essential to have cohort specific unit and time fixed effects, without which the estimates are not accurate (Baker et al., 2022). $after_adoption$ is a dummy variable that is set to 1 for treated group observations on or after the adoption week. $\hat{\beta}$ from equation (2) gives the overall DID estimate for that usage-group. $\hat{\beta}_r$'s from equation (1) provide the event study estimates. As noted in Baker et al. (2022), stacked regressions estimate the 2x2 DiDs from each of the cohorts, then apply variance weighting to combine the treatment effects across cohorts efficiently. In all our estimates, standard errors are clustered at the cohort level to account for the structure of the panel (Deshpande and Li, 2019).

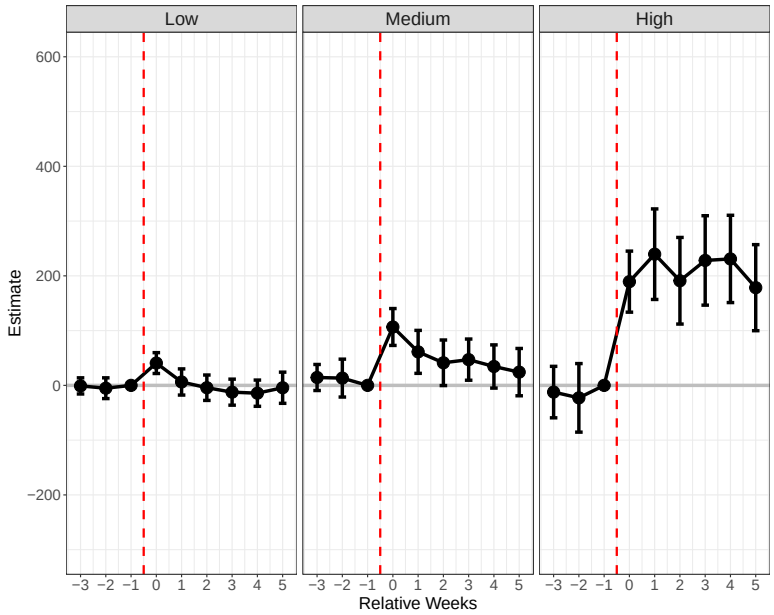
5.4.1 Screen Time

Figure 6 presents the results of estimating equation (1) separately for each TikTok usage group with the total screen time as the dependent variable. There is a sharp increase in screen time after TikTok adoption, especially among the medium and high users. While the effect dampens over time for the medium users, high users see a consistently large effect up to six weeks following TikTok adoption. The point estimate for the high users is 221.25 minutes, corresponding to an average daily screen time increase of roughly 32 minutes (Figure 7). For the medium users, we see an average increase in screen time of 43 minutes per week. Importantly, figure 6 also shows that the adopters were not on a differential trend relative to the control group prior to TikTok adoption.

A potential concern with this screen time analysis is the possible tautological relationship between high TikTok usage and increased total screen time, as time spent on TikTok directly contributes to overall screen time. However, it's important to note that total screen time includes both TikTok screen time and non-TikTok screen time. While TikTok screen time will mechanically increase post-adoption, the net effect on total screen time depends on how TikTok adoption influences non-TikTok screen time.

To examine this, we split total screen time into two variables, TikTok screen time and non-TikTok screen time. Figure 7 shows the overall DID effects ($\hat{\beta}$) for total screen time as well as the two components discussed above. For TikTok screen time, this reduces to just a pre-post comparison, since TikTok screen time is zero for the control group throughout.

Figure 6: Screen Time Effects by TikTok Usage Group

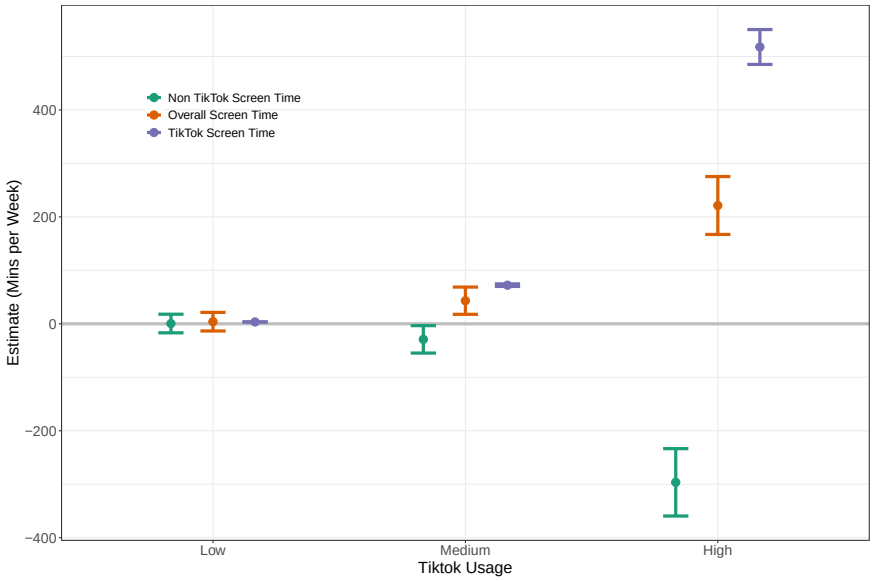


Note: This figure shows the coefficients (β_r) from equation (1), estimated separately for each TikTok usage group (Low, Medium and High). DV is total screen time (minutes per user per week). Relative week 0 corresponds to the adoption week. Bars correspond to 95% CIs with SE clustered at the cohort level.

Figure 7 reveals several interesting insights. Non-TikTok screen time did not go up for any of the groups. This helps mitigate concerns that TikTok adoption was simply a consequence of external events leading to more free time and higher screen usage across all app categories. In fact, for the medium and high usage groups, non-TikTok screen time actually declined, indicating that TikTok had a strong substitution effect on other apps. However, the time spent on TikTok more than offsets this decline, resulting in a net increase in screen time for the medium and high usage groups. Figure 7 also highlights that the increase in total screen time was not an obvious consequence of TikTok usage, but instead depended on how TikTok altered usage patterns of other apps. The extent of substitution and the net effect on screen time was hard to anticipate, making this an interesting empirical finding. These results are shown in tabular form in table 4.

We examine substitution effects in more detail in Figure 8. For each user-week, we compute screen time spent on each of the app categories that we identified earlier and estimate equation (2) separately for each of these categories. The overall DiD estimates for the high TikTok usage group

Figure 7: Screentime Effects Decomposition



Note: This figure shows the estimates of β from equation (2) estimated separately for each TikTok usage group for three different DVs (i) Total screen time (ii) non-TikTok screen time (iii) TikTok screen time. Bars show 95% CIs. SE are clustered at the cohort level.

Table 4: Average Treatment Effects

Variable	Screen Time	Non-TikTok Screen Time	TikTok Screen Time	Sleep Duration	Bedtime	Wake-up Time
			High			
after_adoption	221.245***	-296.441***	517.686***	-35.491^	84.636**	49.309^
	(27.106)	(31.555)	(16.336)	(18.490)	(25.767)	(28.015)
N	9,828	9,828	9,828	9,828	9,828	9,828
R2	0.818	0.811	0.665	0.715	0.738	0.685
R2 Adj.	0.78	0.772	0.596	0.656	0.684	0.619
			Medium			
after_adoption	43.232**	-29.062*	72.294**	-10.829	23.359	12.671
	(12.761)	(12.848)	(1.194)	(9.334)	(14.584)	(11.761)
N	31,500	31,500	31,500	31,500	31,500	31,500
R2	0.828	0.83	0.405	0.698	0.724	0.666
R2 Adj.	0.803	0.804	0.316	0.653	0.682	0.616
			Low			
after_adoption	4.005	0.545	3.459***	1.221	3.784	5.069
	(8.707)	(8.722)	(0.075)	(6.633)	(11.066)	(9.901)
N	76,464	76,464	76,464	76,464	76,464	76,464
R2	0.84	0.84	0.264	0.722	0.739	0.697
R2 Adj.	0.818	0.818	0.165	0.685	0.704	0.656

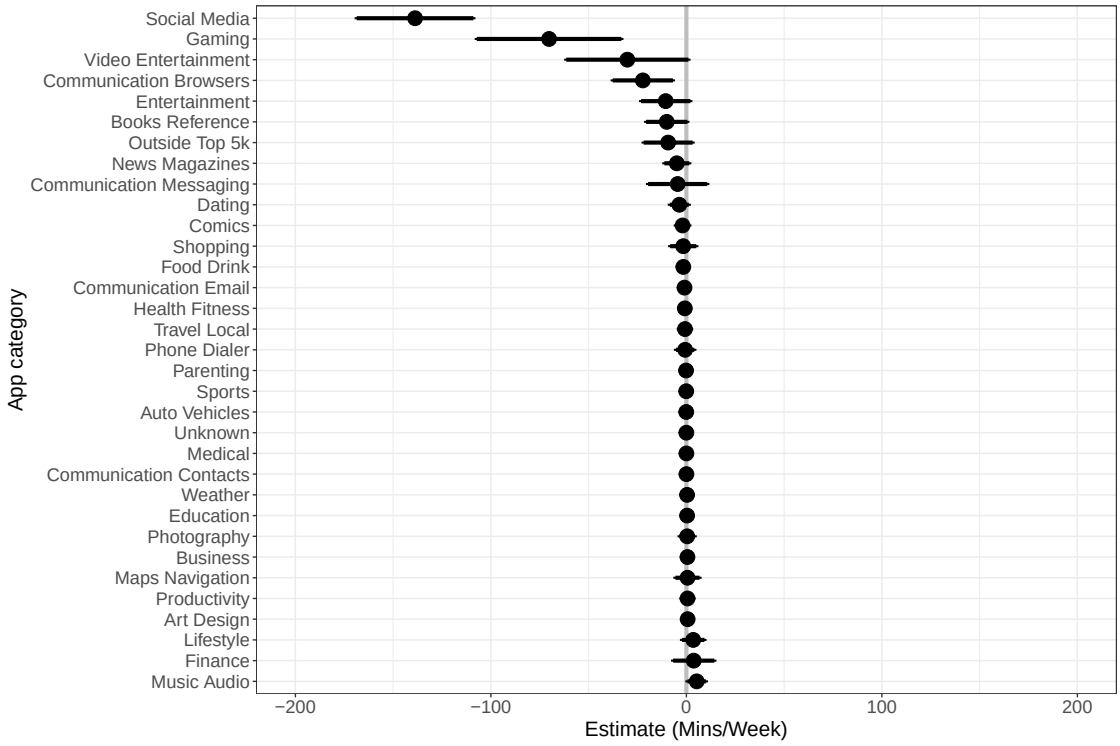
^$p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: High, Medium, and Low refer to the extent of TikTok use post-adoption. All regressions are based on a PSM_matched sample, and SEs are clustered at the cohort level. Cohort-panelist and cohort-week fixed effects are included in all regressions. For each cohort, observations from -3 to +5 weeks (include week 0) are included.

are plotted in figure 8.

Figure 8 shows that social media and gaming apps saw the largest decline among the high TikTok users, followed by video entertainment apps (eg. Netflix), browsers and general entertainment apps which saw much smaller declines. We find virtually no complementary effects on any of the app categories. This further reinforces that TikTok adoption was not driven by unobserved events causing a general increase in phone usage or social media activity. Similar plots for the medium and low TikTok usage groups are shown in figures A4 and A5 in the appendix. The effects are muted for these groups across all app categories.

Figure 8: Non-TikTok Screen Time Effects by App Category - High TikTok Usage Group



Note: This figure shows the estimates of β from equation 2 for the high usage group, separately estimated for each category. DV is total screen time in the respective category. Bars represent 95% CI. SE are clustered at the cohort level. TikTok usage is not included in any of these categories.

These findings carry interesting implications worth discussing. Our results demonstrate how users reallocate time post-TikTok adoption. There is a net increase in overall screen time that goes beyond the substitution of other leisure apps, such as gaming or traditional social media.

This increase in screen time is not merely a reallocation of time within the digital sphere but reflects a shift from other facets of life. The "displacement hypothesis" offers a useful framework to understand the broader implications of our findings (Neuman, 1988; Przybylski and Weinstein, 2017)). This hypothesis posts that the deleterious impact of increased screen time stems not just from the time spent online, but from displacement of time from other forms of salubrious use such as socialization, physical activities, and entertainment. While we do not directly observe physical activities in our study, we will demonstrate how among heavy TikTok users, the displacement also comes from sleep and potentially from time that would otherwise be spent on family interactions and restful leisure time, since these tend to occur during nighttime hours.

Our findings on increased screen time among medium and heavy users are somewhat concerning because of differences in the nature of engagement between TikTok and traditional social media. The experience on platforms like Facebook and Instagram depend a lot on the user's participation and the strength of their network. Further, the act of engaging with peers could provide tremendous positive surplus (Valkenburg and Peter, 2009). On the other hand, TikTok offers entirely passive engagement with almost no scope of connection with other users on the platform. While users can comment on the posts of the creators, the platform works by delivering highly engaging content that viewers swipe through as they spend time on the platform. Therefore, the large net increase in screen time after TikTok adoption comes via passive engagement which might counteract the benefits obtained from peer connections. This is consistent with findings from prior work which finds that passive social media engagement tends to have a stronger negative effect on overall well-being (Verduyn et al., 2017).

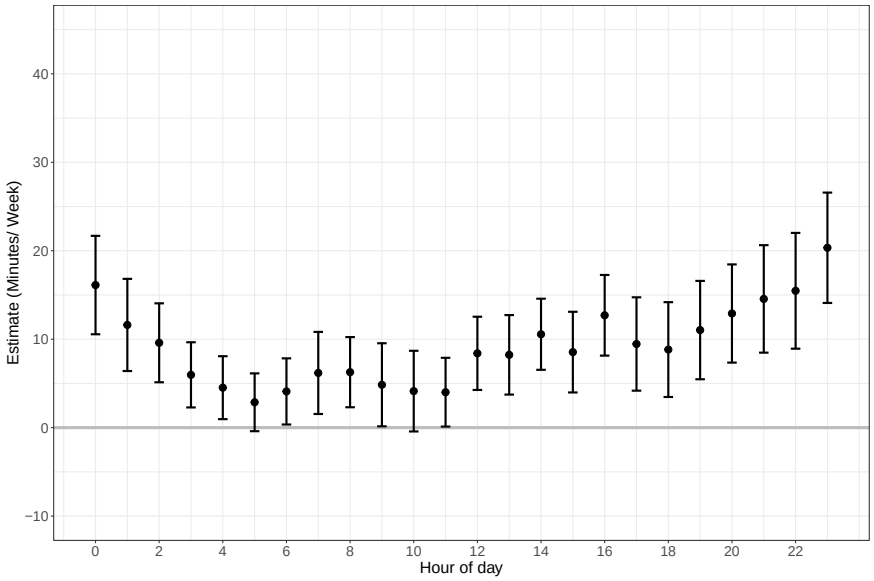
5.4.2 Nighttime Usage

The analysis thus far shows that TikTok led to a significant increase in screen time, especially in the high usage group. Next, we examine how these effects were distributed across time of day. As discussed earlier, we expect TikTok usage to be higher during the night. We confirm this through a descriptive analysis of usage of various app categories by time of day (figure A6). TikTok usage tends to be disproportionately high during night hours, possibly because of its passive nature of

engagement that makes it hard to end a session in the absence of external cues.

To estimate effects on total screen time by hour, we estimate equation (2) separately for each usage group as before. Instead of total screen time as the dependent variable, we use 24 different variables, each corresponding to screen time for the respective hour of the day. For instance, screen time for hour 1 will include total screen time between 1:00 AM and 1:59 AM for a user in the respective week. Results are shown in figure 9.

Figure 9: Screen Time Effects by Hour of Day - Highest TikTok Usage Group



Note: This figure shows the estimates of β from equation 2 for the highest usage group, separately estimated for each hour of the day. DV is total screen time in the respective hour. Bars represent 95% CI. SE are clustered at the cohort level.

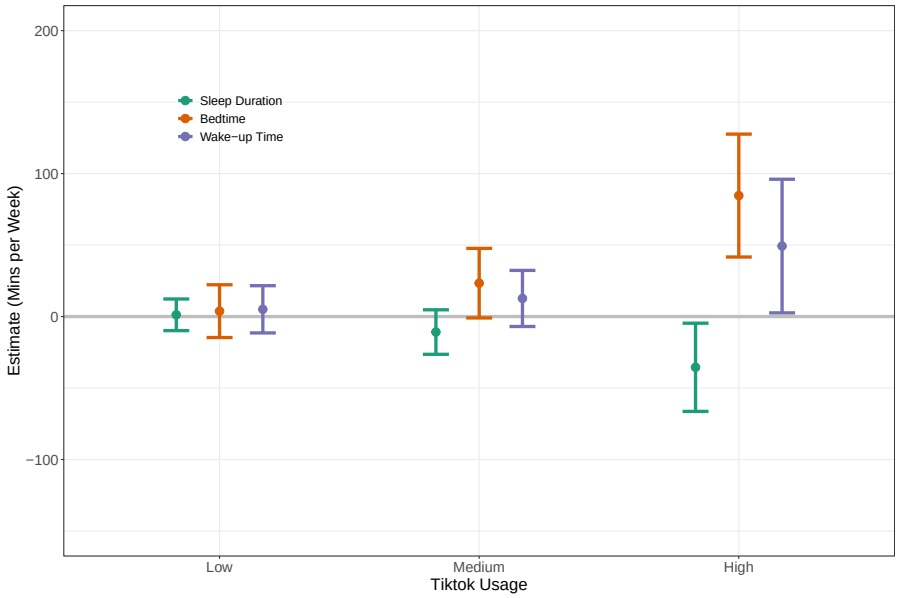
For the highest TikTok usage group, we find that total screen time increased almost throughout the day, but the maximum increase happens during nighttimes, between 9 PM and 1 AM. An increase in late night usage suggests that TikTok might be infringing into family time and sleep hours more than other social media apps. Similar estimates for the medium and low usage groups are shown in figure A7 in the appendix.

5.4.3 Sleep

Table 4 and figure 10 show the overall DID effects ($\hat{\beta}$) for total sleep duration as well as bedtime and wake-up time.

The strongest effects are seen in bedtime, which shifts by about 84 minutes per week, or 12 minutes everyday, for the highest usage group. We also see a moderate shift in wake-up time, leading to a moderate net reduction in sleep duration (about 35 minutes weekly) in the highest usage category. The sleep duration result for the highest usage group is marginally significant ($p = 0.059$). Medium users also experience a moderate shift in bedtime, but the effect is not statistically significant.

Figure 10: Sleep Effects Decomposition (90 percent CIs)



Note: This figure shows the estimates of β from equation (2) estimated separately for each TikTok usage group for three different DVs (i) Total sleep duration (ii) Total bedtime (standardized) (iii) Total wake-up time (standardized). Bars show 90% CIs. SE are clustered at the cohort level.

The estimates from equation (2) provide the net effect of TikTok adoption on sleep patterns. However, using a binary adoption variable limits our ability to capture the weekly variations in TikTok usage intensity that occur after adoption. To establish a stronger connection between actual TikTok usage and sleep patterns, we substitute the binary adoption dummy in equation (2) with

Table 5: Sleep Effects with Continuous TikTok Usage Intensity

Sleep Duration	Low	Medium	High
tiktok_mins	-0.157	-0.162***	-0.073***
	(0.228)	(0.034)	(0.016)
N	76,464	31,500	9,828
R2	0.722	0.699	0.716
R2 Adj.	0.685	0.653	0.657

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: High, Medium, and Low refer to the extent of TikTok use post-adoption. All regressions are based on a PSM_matched sample, and SEs are clustered at the cohort level. tiktok_mins refers to the total time spent on TikTok by a panelist in that week. Cohort-panelist and cohort-week fixed effects are included in all regressions. For each cohort, observations from -3 to +5 weeks (include week 0) are included.

a continuous measure of total TikTok usage (in minutes per week). This intensity measure will be zero by definition for both the control group users and for the treated group users during the pre-adoption period. The results of the regression estimates using the continuous intensity measure are presented in table 5.

For the high usage group, each additional minute of TikTok use leads to a decline of 0.073 minutes of sleep per week. This intensive margin number is higher for the medium TikTok users (0.162), but the overall sleep effects (extensive margin) are greater for the high users due to their significantly high TikTok usage (518 minutes per week as compared to 72 minutes for the medium users). The intensive margin of TikTok's effect on sleep is lower for the high usage group compared to the medium group because the high usage group has high TikTok usage during day times as well, which doesn't affect sleep. As confirmed in table A4 in the appendix, TikTok's effect on sleep comes mainly through the usage that happens during night and early morning hours. For the average user in the high group, TikTok usage led to a decrease of 36 minutes of sleep per week (518 * 0.07, as confirmed in table 4). However, for users in the far right of the usage distribution, this number is higher. The top 20 percentile users in the high usage category spent an average of 1,099 minutes per week on TikTok, leading to a net reduction in sleep of 80 minutes per week.

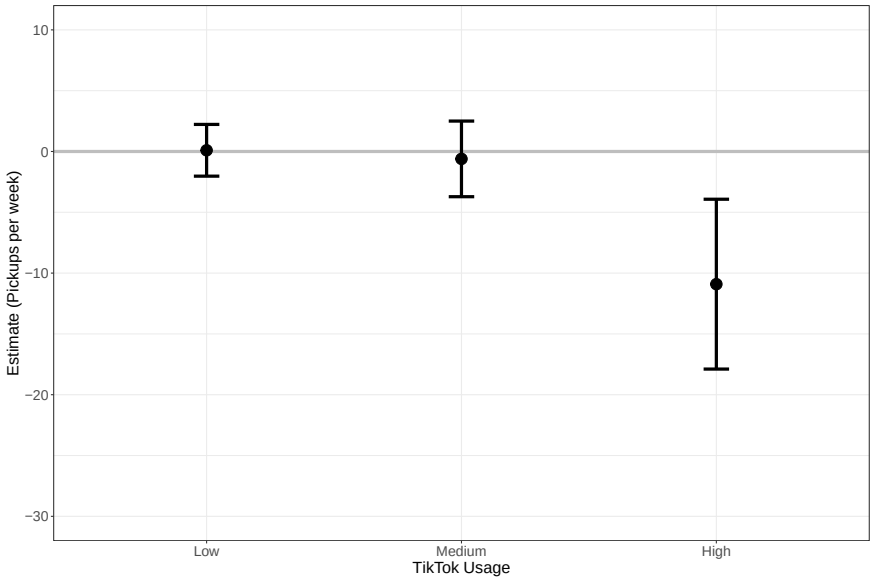
These results align with the displacement hypothesis, which posits that time spent on digital

activities, such as TikTok, displaces time that would have been spent on other activities, like sleep. While we are unable to comment on TikTok's effect on other forms of offline activity, finding measure effects on sleep is a significant contribution given the difficulty in finding granular sleep measures, and the well known link between sleep and mental well-being.

5.4.4 Pick-ups

Total screen time is determined by the number of phone pick-ups and the time spent per phone session. We examine whether the shift from traditional social media and gaming apps to TikTok led to an increase in the frequency of phone pick-ups, or the time per phone session or both. This analysis will provide suggestive evidence on the mechanism through which TikTok increases screen time. Do people spend longer time per TikTok session, or do they check TikTok more frequently? To examine this, we estimate equation (2) using the weekly total number of phone pick-ups as the DV and present the results in figure 11.

Figure 11: Effect on Phone Pickups



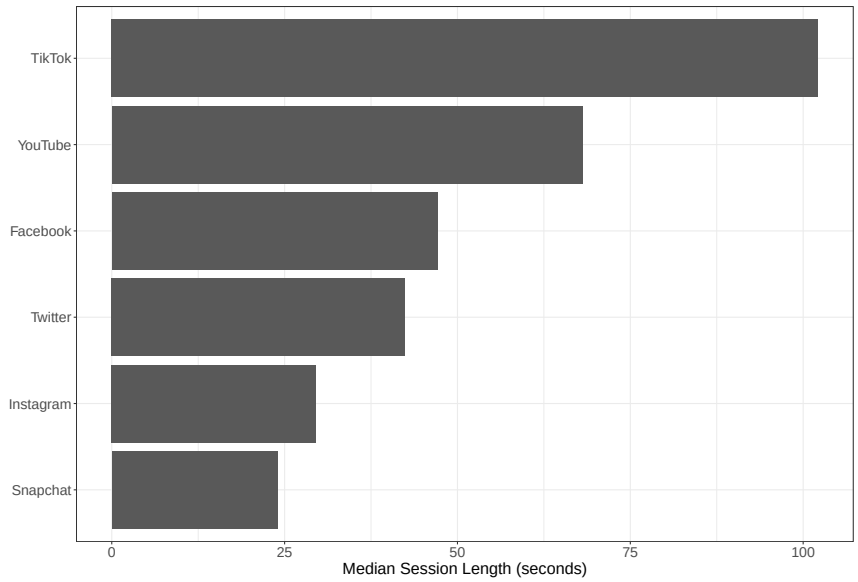
Note: This figure shows the estimates of β from equation (2) estimated separately for each TikTok usage group, with total phone pick-ups in a week as the DV. Bars show 95% CIs. SE are clustered at the cohort level.

Somewhat surprisingly, we find that the number of pick-ups decreases marginally for the high

usage group after TikTok adoption, despite a significant increase in overall screen time. Earlier, we showed that usage of other social media apps usage declined significantly. This suggests that users might be substituting the shorter, high-frequency interactions typical of other social media apps with longer, more immersive interactions on TikTok.

To further examine the difference in the nature of engagement between TikTok and other social media platforms, we carried out some descriptive analysis. For the top social media platforms in our data (Facebook, Youtube, Instagram, Snatpchat, Twitter and TikTok)[11], we plot the median session length in figure 12[12]. We find that TikTok sessions tend to be longer compared to other social media platforms. The median session length on TikTok is about 102 seconds, which is more than twice that of Facebook and almost four times that of Instagram. TikTok sessions are also significantly longer than YouTube. The full distribution of session lengths is plotted in figure A8 in the appendix. TikTok sessions tend to be significantly longer than other platforms throughout the distribution, except at the highest percentiles where Youtube sessions tend to be slightly longer.

Figure 12: Median Session Length by App



Note: This figure shows the median session length (in seconds) for the top social media platforms in the data. All users are included, not just the set of TikTok adopters.

[11] We are using the word social media loosely. Apps like Youtube are actually categorized in the 'Video and Entertainment' category in our data.

[12] For this analysis, we consider all the users in the data (and not just the set of TikTok adopters).

5.4.5 Long Term Effects

Since our data is derived from an opt-in consumer panel, users are free to join and leave the panel at any time, making it difficult to get consistent data from a single user for a large time window. Thus, all the results thus far were based on a sample of users who provided unbroken data from 3 weeks prior to 6 weeks post the relevant cohort week. To examine long-term effects, we expand the post window to 16 weeks. In the process, we lose users who we don't observe completely for longer time frame. Additionally, we drop all treatment-control pairs (since this was a matched sample) where the control user adopted TikTok before the end of the 16 week period. This leaves us with only 683 TikTok adopters along with the same number of matched control users (469 low, 164 medium and 50 high). We replicate the original analysis with this sample, the results of which are reported in table A5 in the appendix. Table A5 indicates that the main effects sustain even up to 4 months post TikTok adoption despite the small sample size. The bedtime delay increases even more in the long term, at about 151 minutes per week relative 84 minutes in the short run, leading to a larger effect on sleep duration (decrease of 135 minutes per week). Results with continuous TikTok usage intensity are shown in table A6. The high levels of TikTok do not just persist, but also moderately increase as TikTok screen time went up by 538 minutes per week in the long run, relative to 518 minutes in the shorter 6 week window. The net screen time effect dampens slightly—from 221 minutes per week in the short run to about 189 minutes per week in the long run, due to the fact that non-TikTok screen time declined even further in the long run. These results suggest that TikTok adoption led to significant behavioral changes that lasted over four months.

6 Discussion and Conclusions

The usage of social media is pervasive in our lives. Social media platforms like TikTok have become a global phenomenon with over 1.5 Billion monthly users and constitute a significant portion of leisure time for billions of people worldwide.

Social media confers tremendous positive surplus, and this has been demonstrated by several studies in the economics literature (Allcott et al., 2020). However, other studies also show that

prolonged social media usage can be addictive due to habit formation and self-control issues (Allcott et al., 2022). The growing popularity of social media platforms has attracted significant scrutiny regarding their potential effects on well-being. Yet, providing causal evidence on this topic has been notoriously hard. As noted in a recent New York Times article, "..it's unclear if time on social media is the problem, or if it's time away from other things like exercising or sleeping."[13]. Our results contribute to this important debate. We show that in the absence of TikTok, users would likely would have spent a large amount of time that they devoted to TikTok on other social media and gaming apps. Despite the substitution, TikTok still led to a significant increase in screen time, especially among high-intensity users. We also find evidence that TikTok usage led to persistent delay in bedtimes, along with a measurable reduction in sleep duration.

Healthcare professionals, policymakers, and parents have been concerned about the negative impact of social media on well-being, and the impact on well-being continues to be hotly debated even if the evidence is mixed. Immersive content and passive engagement with engaging content are prone to lead users into a loop that is difficult to break, especially when there are no real-world interruptions. Our results suggest that this might indeed be the case because TikTok usage peaks late at night, and the time per session is significantly longer.

We place our results in the context of how drug researchers view substance dependence among substance users (Kleiman et al., 2011), especially since social media usage in general, and TikTok usage, in particular, are often compared with smoking and alcohol. There is a substantial heterogeneity in problematic usage among the users of nicotine, alcohol, cocaine usage, with about 15.6% of nicotine and about 11% of alcohol and 14.8% of cocaine users transitioning to a dependent stage a full decade after usage (Lopez-Quintero et al., 2011). Kleiman et al. (2011) argue that only a minority of the already small number of people who use addictive substances tend to abuse substances, but when they do, the results are quite serious for self and others. Our results align with this thinking, where most of the detrimental effects on well-being as measured by nighttime usage or sleep are pronounced among the top ten percentile users of TikTok, while we don't observe such dramatic changes in the rest of the users.

[13]https://www.nytimes.com/2023/06/17/upshot/social-media-teen-mental-health.html

It is important to note that our study does not find overtly strong negative impacts of TikTok usage on casual or average users, but the potential negative effects through increase in screen time and changes in sleep patterns are mostly observed in heavy users. This is an important point to make given that the conversations around social media, tend to be overtly sensational, negative, and largely one-sided. As Kleiman et al. (2011) note in their book on drugs and drug policy, people tend to fall into and out of bad habits, even with the usage of highly addictive drugs, mostly on their own, and problematic usage is mostly on a very small percentage of users. They discuss the important role of encouragement from community, friends and family in behavioral modification.

We argue that these principles can essentially be applied to social media usage as well. In fact, carefully designed platform features can address some of the issues with TikTok usage. For platforms like Snapchat and Facebook, which involve more frequent, shorter sessions, limiting the number of daily sessions may better at addressing the fragmented and repeated checking behavior that leads to frequent phone use. For TikTok, implementing session-length limits, limiting nighttime usage, or providing behavioral nudges, like reminders after a certain period of use could help users moderate their time more effectively[14]. Even though we do not study minors in our study, most social media platforms, including TikTok, have introduced several comprehensive parental control features, including those with session-length limits and nighttime usage, sleep reminders, which could aid better supervision from parents instead of an outright ban[15]. It is also important to note that availability of self-control and commitment features for adults and parents to reduce social media usage does not automatically imply actual usage. In fact, Allcott et al. (2022) find that participants in their experiment perceived issues with self-control problems and were quite willing to pay for self-control/commitment-based tools such as those limiting screentime, even if only a small minority (5%) reported using these devices. Creating more awareness among users about these features, or auto-enabling some of the reminders among high users would be a step in the right direction to curb problematic usage[16].

Our work is not without limitations. Firstly, while we aim to contribute to the discussion on

[14] https://support.tiktok.com/en/account-and-privacy/account-information/screen-time
[15] https://techcrunch.com/2024/07/06/how-to-set-up-parental-controls-on-facebook-snapchat-tiktok-and-more-popular
[16] https://techcrunch.com/2023/01/06/tiktok-testing-sleep-reminders-feature-nudge-you-when-bedtime/

social media and well-being, we cannot measure TikTok's net effect on wellness. The relationship between social media and well-being is highly complex, shaped by a range of factors that can have both positive and negative influences. For instance, increased screen time, disrupted sleep patterns, unfavorable social comparisons, and exposure to cyberbullying are all likely to negatively impact well-being. Conversely, the social connections and peer support through community building and best practices, particularly for those who live in environments that are unwelcoming, social media could be tremendously beneficial[17]. Further, entertainment and informational value offered by social media could lead to positive effects. This is especially true since a majority of Americans get their news from social media platforms, even if they don't seek out these platforms for news[18]. Our work does not attempt to assess the net balance of these effects, because we do not observe what people do within any of the apps in our data, but rather focuses on some of the components of this multifaceted relationship. Second, we do not assess the impact of other social media platforms. Given the varying nature of user engagement across different platforms, understanding the broader effects of social media on well-being will likely require platform-specific studies to capture the nuances of each. Third, our results are based on a self-selected panel, which will limit the generalizability of the results. Further, most of the effects come from the top 10 percent of users. However, this is not a small number given that TikTok has over 120 Million monthly active users in the US. Finally, while our data allows us to infer sleep patters, our visibility is only limited to patterns of phone usage. How TikTok affected other kinds of offline behaviour and screen time are interesting questions that we leave for future research. Given these limitations, our paper still addresses an important public policy issue.

Our results also serve as evidence that traditional social media platforms such as Facebook and Instagram and even gaming platforms can be treated as 'relevant competition' for TikTok. This finding has significant implications for global discussions on competition policy. Competition authorities, including the FTC, tend to take a very narrow definition of social media markets and generally exclude platforms like TikTok. As a result, Facebook and Instagram are classified as monopolies due to the restrictive market definition. However, our findings do not support this

[17] https://www.nytimes.com/2023/05/24/upshot/social-media-lgbtq-benefits.html

[18] https://www.pewresearch.org/journalism/2024/06/12/how-americans-get-news-on-tiktok-x-facebook-and-instagram/

view, demonstrating that TikTok competes directly with these established platforms. This insight is especially relevant in cases like Facebook vs. FTC, where Facebook has cited TikTok's rapid growth as primary proof that it is not a monopoly. Much of the evidence supporting this argument has been correlational, assuming that Facebook's declining traffic and TikTok's rise must indicate direct competition[19]. Our study strengthens this argument with causal analysis of individual level data and contributes to the emerging literature on platform substitution, which suggests that platforms with diverse features and functions are part of a broader "market for attention."

As social media continues to grow, questions about its effects on well-being will only get louder. Policymakers and platform operators are grappling with understanding the causal impact of social media on well-being, and our study provides critical evidence in this direction.

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Online Appendix

A1.1 Sleep Measure Edge Cases and Exceptions

A1.1.1 Singleton App Entries

Our sleep measures are derived from the longest unbroken screen off entry for any day. However, there are some edge cases where some apps may come to the foreground even though the user did not engage with their phone. For instance, if a user gets a message or a call that they miss. Or if any other app sends a notification that causes the phone screen to turn on. Or the phone alarm rings and then turns off. In all these cases, we will see entries of the following form:

Table A1: Singleton App Entries

Panelist ID	**App Identifier**	**Start Timestamp**	**End Timestamp**
⋮	⋮	⋮	⋮
xyz	screen_off	2019-08-08T22:52:35.100	2019-08-08T03:53:42.327
xyz	any other app	2019-08-08T03:53:42.343	2019-08-08T03:53:45.356
xyz	screen_off	2019-08-08T03:53:45.376	2019-08-08T06:55:49.097
⋮	⋮	⋮	⋮

A singleton app entry sandwiched between two screen off sessions generally happens only when the user did not actively engage with the phone. If the user engages with the phone, she would have to unlock her phone (which would trigger a system app entry), then open any app and then turn their screen off. This would lead to an entry for a system app (eg. Android launcher) before the main app in the app data.

Singleton entries like this can cause the sleep variables to be mismeasured. To account for such cases, we ignore singleton app entries that occur in between successive screen off entries and assume that the screen off entries before and after the singleton entries were part of an unbroken screen off period. In table A1 above, the longest unbroken screen off period will be taken from 10:52 PM on 8th August up to 6:55 AM on 9th August. The sleep duration, bedtime and wake-up times will be inferred accordingly. This doesn't account for cases where a user wakes up in the middle of the night, engages actively with the phone and then sleeps again.

A1.1.2 Longest Session Doesn't Correspond to Screen Off

In our data, the median daily screen time is under 5 hours (table 1), suggesting that users have their screens turned off most of the time. The sleep variable was constructed under the assumption that the longest unbroken session in any day should correspond to a screen off period. Therefore, we restricted our search for sleep sessions to the longest unbroken screen off period.

We find that, for 95 percent of user date combinations in the data, the longest session in the data indeed corresponds to a screen off period. For the remaining 5 percent, the longest unbroken session is for other apps where the screen was kept on for longer than the longest screen-off session. These sessions generally correspond to lengths of more than 5-6 hours. Examples of these apps include Youtube, games such as Merge Dragons[20] or sleep apps such as Calm[21].

Given the distribution of session length for some of the most popular apps in the data (figure A8) it is extremely unlikely that users were continuously using these apps for so long without any interruption. Even going to the home screen once and coming back would count as an interruption that would reset the session length. Therefore, these likely correspond to cases where users kept the app turned on the whole night (for instance, a gaming app to accumulate rewards, or a sleep app featuring screensavers and background sounds).

In these cases, we consider the longest unbroken session for that day to correspond to the user's primary sleep, irrespective of the app. This is a small adjustment which improves the sanity of the measures, without affecting the results.

[20] https://play.google.com/store/apps/details?id=com.gramgames.mergedragons&hl=en_US
[21] https://play.google.com/store/apps/details?id=com.calm.android&hl=en_US

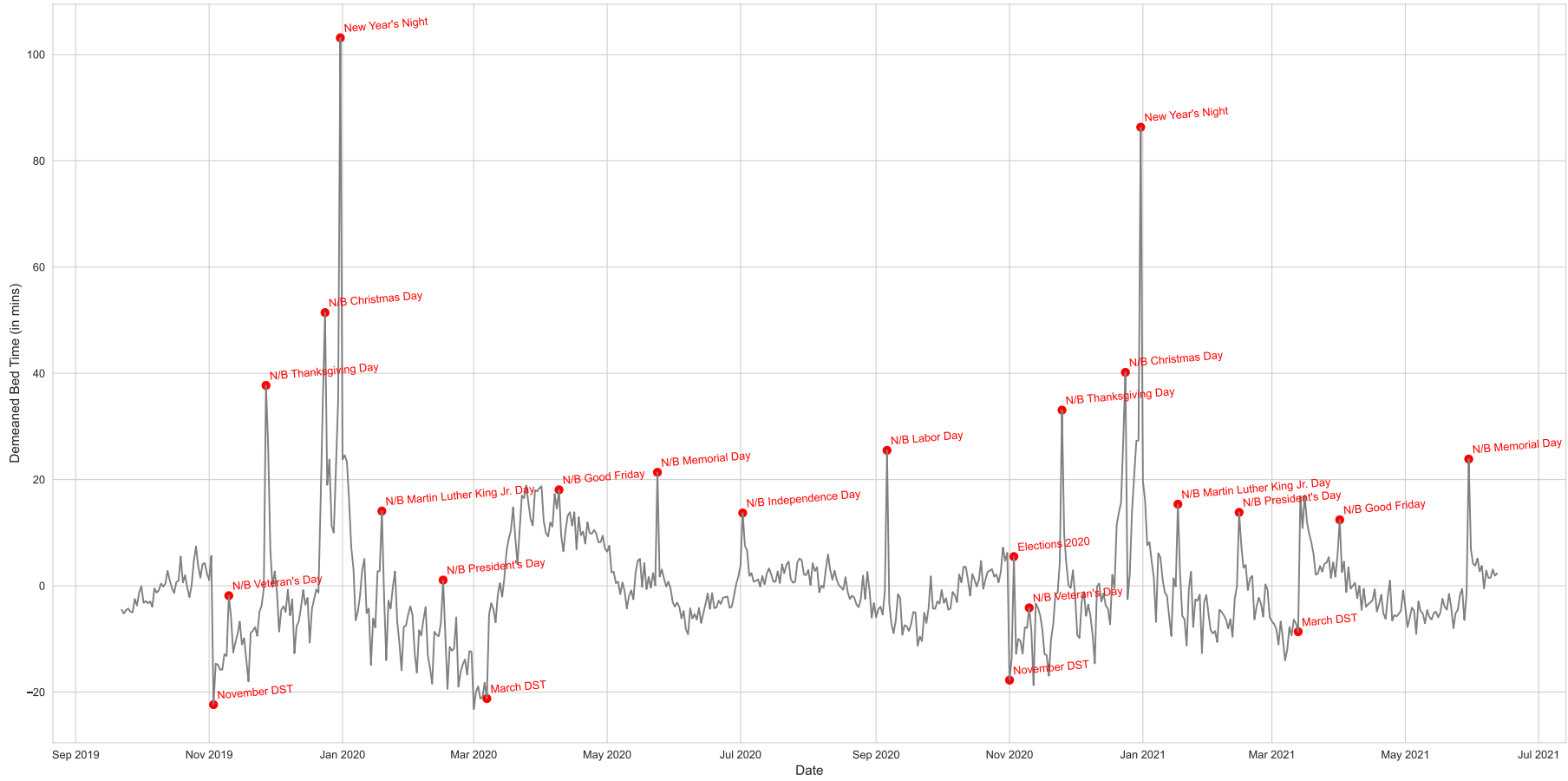
A1.2 Propensity Score Matching

Table A2: Pre-treatment Balance Check Before and After Matching

TikTok Usage	Variable	Before matching			After matching		
		Treated Mean	Control Mean	t-stat	Treated Mean	Control Mean	t-stat
		(1)	(2)	(3)	(4)	(5)	(6)
High	**Screen time**	2369.112	2186.476	8.0627	2310.950	2270.425	1.2275
	Sleep Duration	2881.050	2894.775	-0.96191	2892.344	2908.630	-0.76071
	Bedtime	3496.712	3314.537	7.9384	3363.741	3363.611	0.0039276
	Wake-up time	6377.866	6208.636	7.6973	6255.857	6272.003	-0.51965
Medium	**Screen time**	2249.405	2128.296	8.7623	2191.891	2189.854	0.10762
	Sleep Duration	2881.632	2847.169	4.006	2883.159	2890.390	-0.59623
	Bedtime	3490.409	3393.980	6.7352	3461.493	3446.284	0.75558
	Wake-up time	6371.913	6240.426	9.736	6344.486	6336.444	0.42401
Low	**Screen time**	2254.721	2182.841	7.4859	2233.095	2223.681	0.73701
	Sleep Duration	2853.173	2856.459	-0.54793	2862.685	2858.284	0.54251
	Bedtime	3480.097	3411.377	6.9708	3444.229	3438.615	0.42585
	Wake-up time	6333.158	6267.193	7.0593	6306.719	6296.680	0.80039

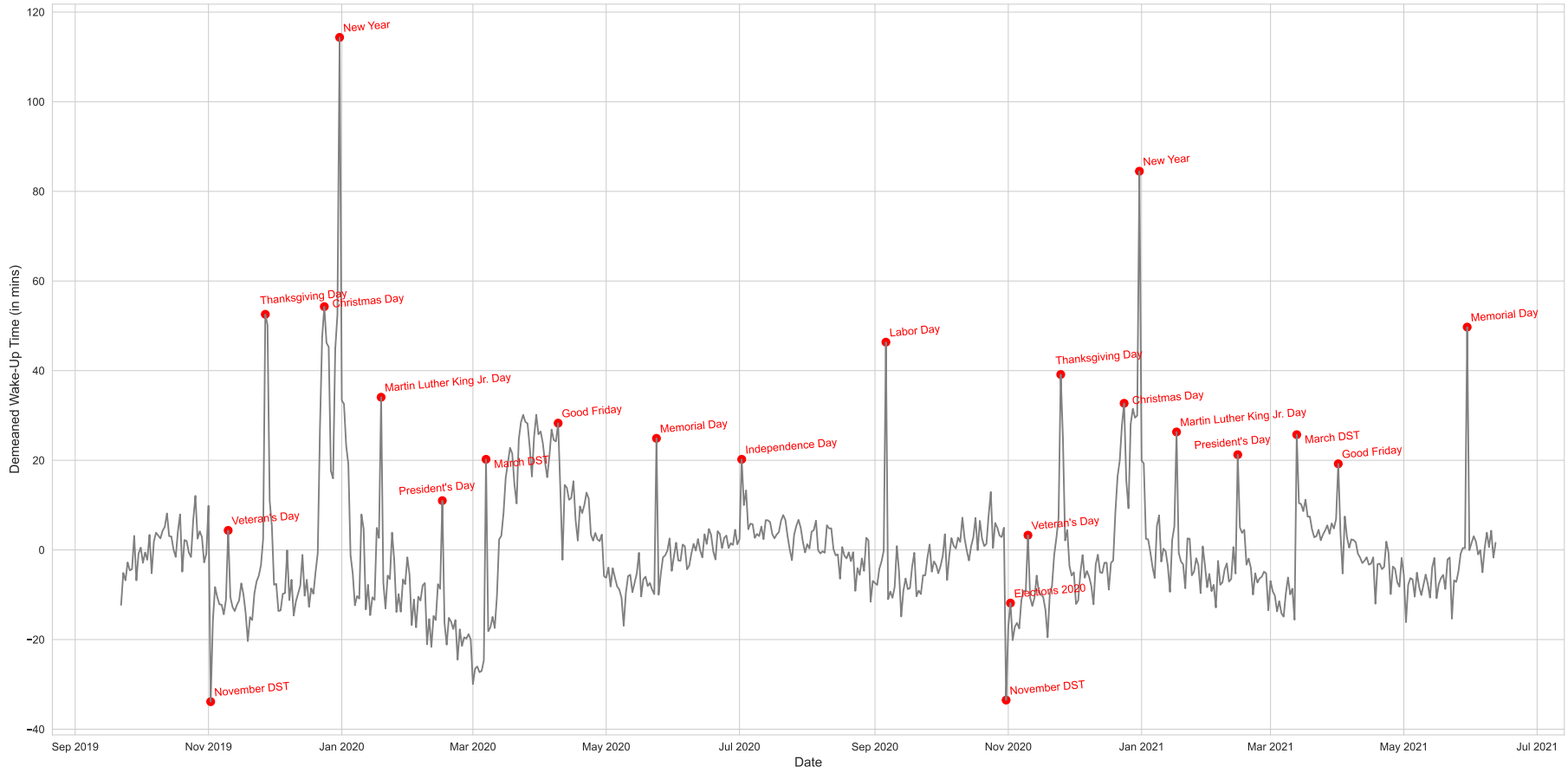
To account for differences between the treated and control users, we match them based on the levels and trends of key outcome variables prior to the treatment group's adoption. We match users based on 1) total screen time, total bedtime and total wake up time in week -1 (the week prior to the treatment group's adoption) and 2) changes in each of these variables between week -1 and -3. The changes help account for the concern that treatment group users may already be on a differential trend (eg. increasing screen time, decreasing sleep) prior to TikTok adoption. We use logistic regression to estimate the probability of being treated, and identify matched users using nearest neighbour matching and a caliper of 0.05 (using R's Matchit function). We were able to find matched users for 6,544 out of 7,281 TikTok users. Control users were chosen among the later adopters who ended having falling in the same TikTok usage intensity group. The table above shows that the matched treated and control users have similar values of the key outcome variables prior to the treatment group's adoption. The means were computed using data from weeks -3 to -1.

Figure A1: Bedtime Trends



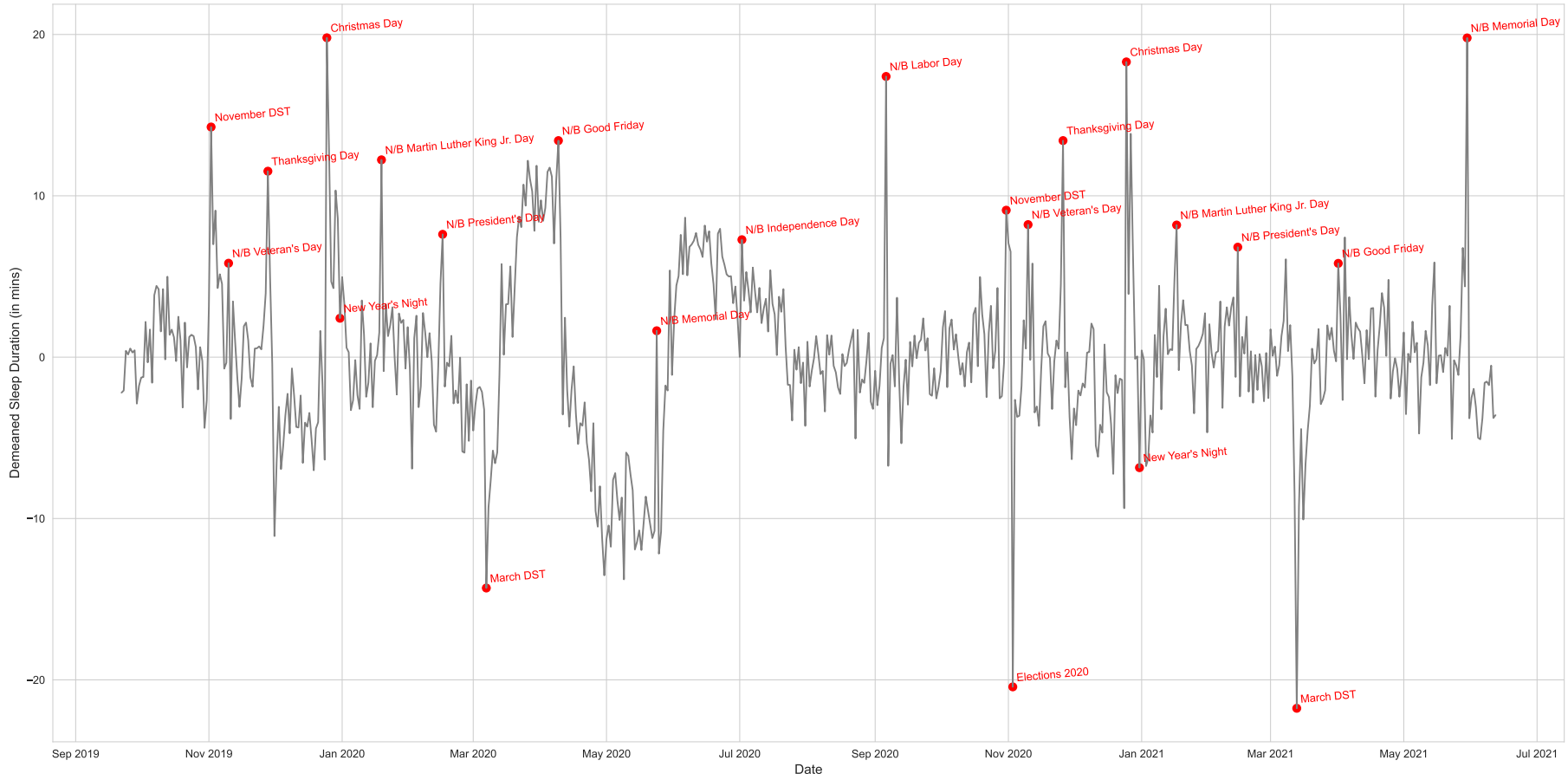
Note: This figure shows the median bedtime among all users for each date. For each date, day of week (DOW) effects have been eliminated by substracting the mean of median bedtimes for the same DOW from the previous week and the week before. N/B refers to night before. Bedtimes were generally late on the night before the holidays, and not the holidays themselves.

Figure A2: Wake-up Time Trends



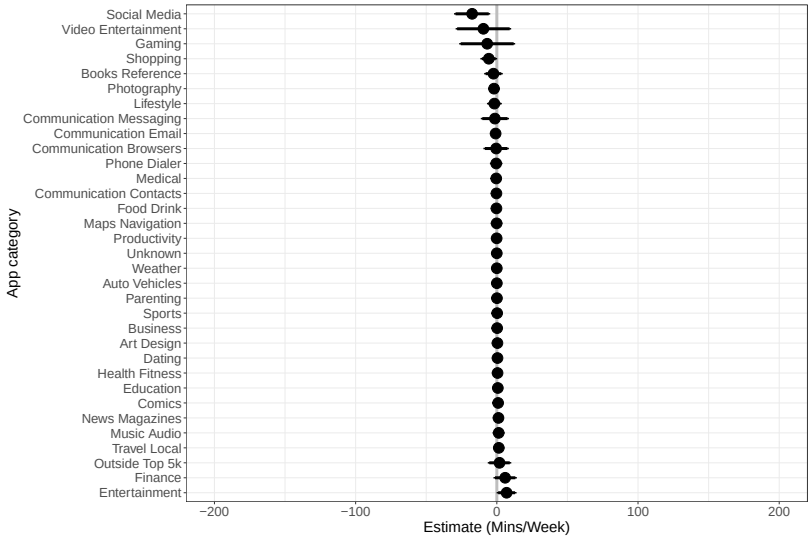
Note: This figure shows the median wake-up time among all users for each date. For each date, day of week (DOW) effects have been eliminated by substracting the mean of median wake-up times for the same DOW from the previous week and the week before.

Figure A3: Sleep Duration Trends



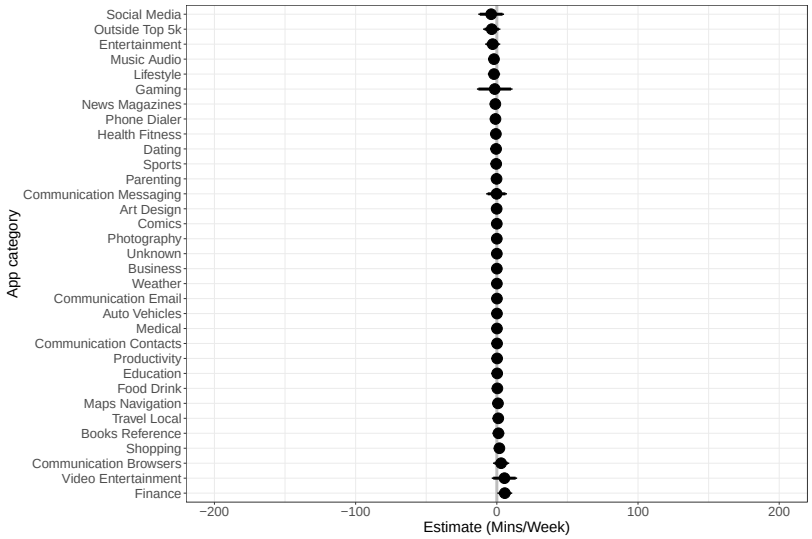
Note: This figure shows the median sleep duration among all users for each date. For each date, day of week (DOW) effects have been eliminated by substracting the mean of median sleep durations for the same DOW from the previous week and the week before.

Figure A4: Screen Time Effects by App Category - Medium TikTok Usage Group



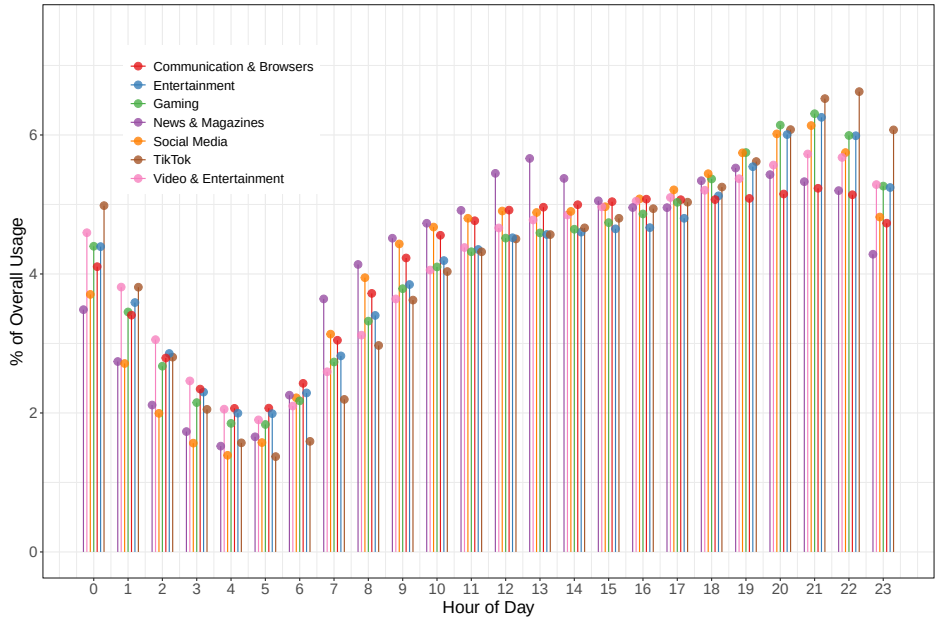
Note: This figure shows the estimates of β from equation 2 for the medium usage group, separately estimated for each category. DV is total screen time in the respective category. Bars represent 95% CI. SE are clustered at the cohort level. TikTok usage is not included in any of these categories.

Figure A5: Screen Time Effects by App Category - Low TikTok Usage Group



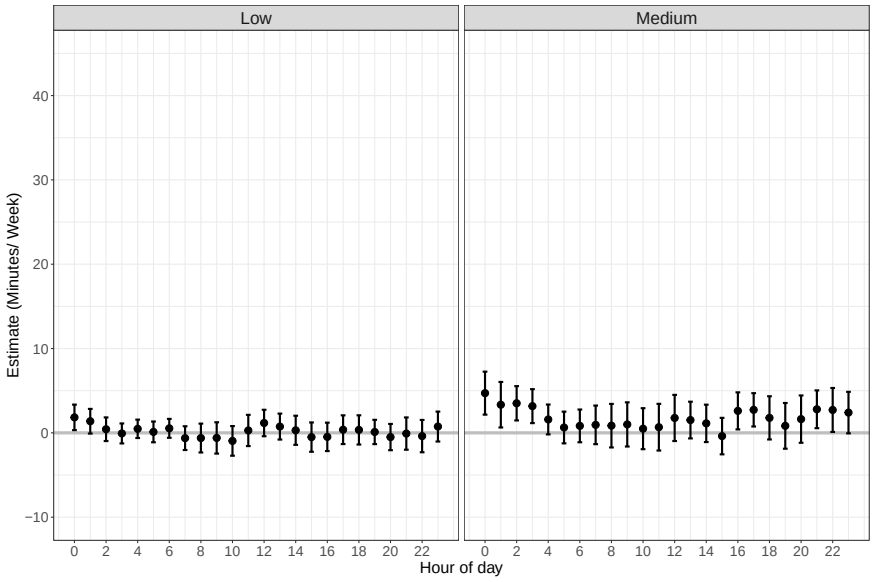
Note: This figure shows the estimates of β from equation 2 for the low usage group, separately estimated for each category. DV is total screen time in the respective category. Bars represent 95% CI. SE are clustered at the cohort level. TikTok usage is not included in any of these categories.

Figure A6: Distribution of Usage by Hour of Day across Top App Categories



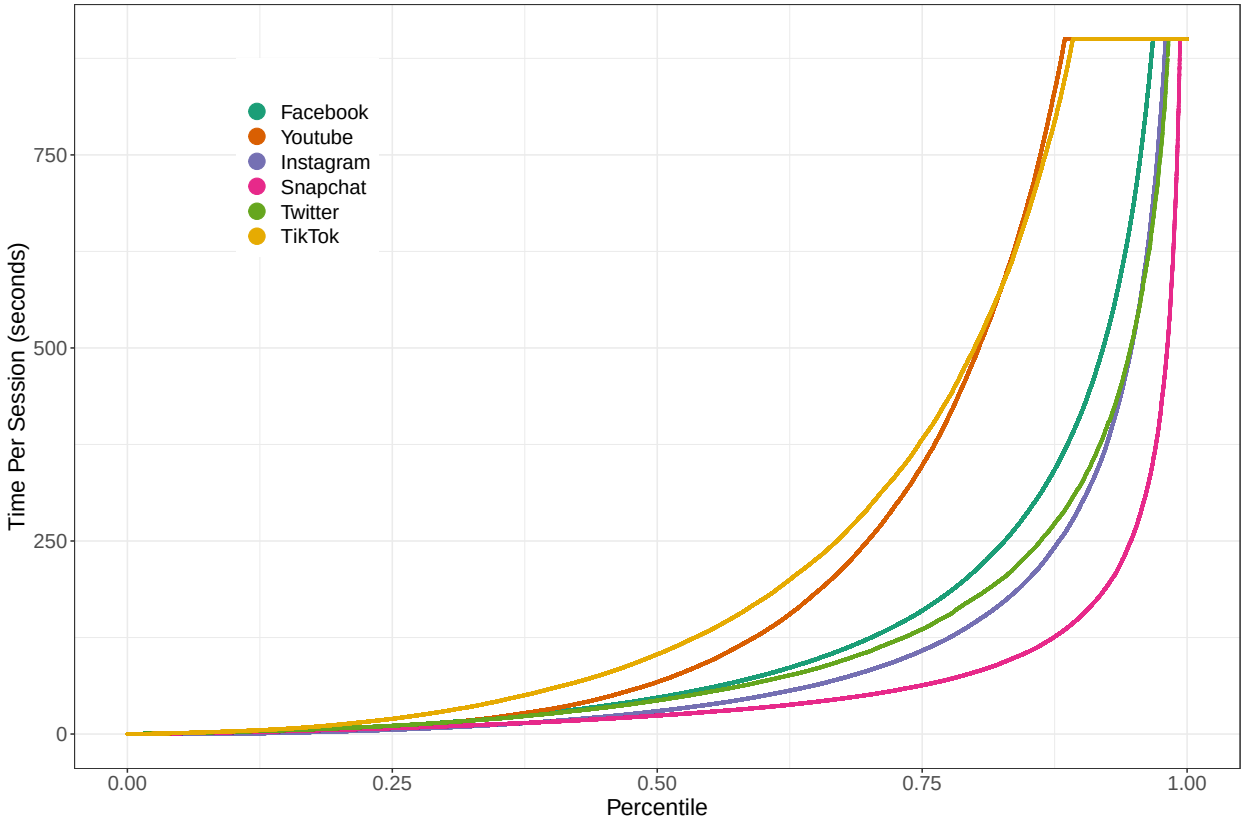
Note: This figure shows the percentage of all usage for a given app category that happens in a specific hour of day. For any category, the numbers across the hours add up to 100 percent.

Figure A7: Screen Time Effects by Hour - Medium and Low TikTok Usage Group



Note: This figure shows the estimates of β from equation 2 for the medium and low usage groups, separately estimated for each hour. DV is total screen time in the respective hour. Bars represent 95% CI. SE are clustered at the cohort level. TikTok usage is not included in any of these categories.

Figure A8: Session Length Distribution



Note: This figure shows the distribution of the length of the individual sessions for the top social media apps. Percentiles are shown on the x axis, and the session lengths are on the y axis (in seconds). Duration values are capped at 900 seconds to preserve the scale.

Table A3: App Categories and Their Corresponding Top 3 Apps

Category	**App Names**
Art & Design	IBISPaint X, SketchBook, DeviantArt
Auto & Vehicles	DigiHUD Speedometer, CarGurus, myChevrolet
Books & Reference	Amazon Kindle, Wattpad, Bible
Business	Microsoft Outlook, Zoom, Indeed Job Search
Comics	Line Webtoon, Tachiyomi, Manga Rock
Communication & Browsers	Google Chrome, Samsung Internet Browser, Firefox
Communication & Contacts	Contacts, Samsung Contacts, CallApp
Communication & Email	Gmail, Yahoo Mail, Samsung Email
Communication & Messaging	Facebook Messenger, Samsung Messages, Discord
Dating	POF Dating, Tinder, SKOUT
Education	Duolingo, ClassDojo, Canvas Student
Entertainment	Mistplay, Pixel Art, Lucky Money
Finance	XYO Network, Samsung Pay, Cash App
Food & Drink	DoorDash, Uber Eats, McDonald's
Gaming	Pokemon GO, Roblox, Coin Master
Health & Fitness	Fitbit, Step Counter, Cashwalk
Lifestyle	Swagbucks, Slidejoy, Lucky Day
Maps & Navigation	Google Maps, Waze, CoPilot GPS
Medical	MyChart, Medisafe, MyTherapy Medicine Reminder
Music & Audio	Spotify, YouTube Music, Pandora
News & Magazines	Reddit, News Break, SmartNews
Parenting	Owlet Care, Miku Baby Monitor, Nanit
Personalization	Basic Daydreams, Photo Table, Night Clock
Phone & Dialer	Samsung Dialer, Phone (Android default), One Plus Dialer
Photography	Google Photos, Samsung Gallery, Samsung Camera
Productivity	Google Drive, Samsung Calendar, Samsung Notes
Shopping	Amazon, Walmart, Wish: Shop and Save
Social Media	Facebook, Instagram, Snapchat
Sports	ESPN, Sportly, NFL
Travel & Local	Uber Driver, DoorDash Driver, Lyft Driver
Video & Entertainment	YouTube, Netflix, Hulu
Weather	1Weather, NOAA Weather Radar, The Weather Channel

Table A4: Sleep Effects with Continuous TikTok Usage Intensity

sleep duration	**Coefficient (Std. Error)**
tiktok_mins_0	-0.422*** (0.107)
tiktok_mins_1	-0.385*** (0.107)
tiktok_mins_2	-0.786*** (0.124)
tiktok_mins_3	-0.419* (0.167)
tiktok_mins_4	-0.770*** (0.184)
tiktok_mins_5	-0.696*** (0.146)
tiktok_mins_6	-0.844*** (0.159)
tiktok_mins_7	-0.574*** (0.113)
tiktok_mins_8	-0.300** (0.107)
tiktok_mins_9	-0.177 (0.104)
tiktok_mins_10	-0.274*** (0.091)
tiktok_mins_11	-0.161 (0.095)
tiktok_mins_12	-0.181 (0.109)
tiktok_mins_13	0.111 (0.108)
tiktok_mins_14	0.179 (0.096)
tiktok_mins_15	0.020 (0.113)
tiktok_mins_16	-0.028 (0.089)
tiktok_mins_17	0.023 (0.105)
tiktok_mins_18	-0.0001 (0.102)
tiktok_mins_19	0.023 (0.089)
tiktok_mins_20	0.077 (0.083)
tiktok_mins_21	-0.233** (0.072)
tiktok_mins_22	-0.267** (0.107)
tiktok_mins_23	-0.619*** (0.110)
N	9,828
R2	0.754
R2 Adj.	0.701

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Results for the high usage group only. All regressions are based on a PSM_matched sample, and SEs are clustered at the cohort level. tiktok_mins refers to the total time spent on TikTok by a panelist in that week. The suffix refers to the specific hour of day. Cohort-panelist and cohort-week fixed effects are included in all regressions. For each cohort, observations from -3 to +5 weeks (include week 0) are included.

Table A5: Long Term Treatment Effects

Variable	Screen Time	non-TikTok Screen Time	TikTok Screen Time	Sleep Duration	Bedtime	Wake-up Time
			High			
after_adoption	188.588*	-349.703***	538.292***	-134.496^	150.987*	17.626
	(82.348)	(82.758)	(48.620)	(67.322)	(70.039)	(64.362)
N	1,900	1,900	1,900	1,900	1,900	1,900
R2	0.826	0.815	0.779	0.727	0.791	0.771
R2 Adj.	0.731	0.715	0.659	0.578	0.678	0.646
			Medium			
after_adoption	69.493	-11.747	81.240***	-30.359	37.863	7.645
	(42.454)	(42.476)	(7.398)	(30.819)	(39.382)	(40.293)
N	6,232	6,232	6,232	6,232	6,232	6,232
R2	0.787	0.787	0.494	0.649	0.711	0.656
R2 Adj.	0.740	0.741	0.383	0.571	0.647	0.580
			Low			
after_adoption	-38.933^	-52.575*	13.642***	-12.644	17.844	5.392
	(21.320)	(21.990)	(2.510)	(21.716)	(24.455)	(28.281)
N	17,822	17,822	17,822	17,822	17,822	17,822
R2	0.809	0.808	0.280	0.683	0.713	0.680
R2 Adj.	0.787	0.787	0.200	0.648	0.681	0.644

^$p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: SEs are clustered at the cohort level. Cohort-panelist and cohort-week fixed effects are included in all regressions. For each cohort, observations from -3 to +15 weeks (include week 0) are included.

Table A6: Sleep Effects with Continuous TikTok Usage Intensity — Long Term

sleep duration	Low	Medium	High
tiktok_mins	-0.007	-0.064	-0.174***
	(0.028)	(0.070)	(0.042)
N	17,822	6,232	1,900
R2	0.683	0.649	0.729
R2 Adj.	0.648	0.571	0.582

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: SEs are clustered at the cohort level. Cohort-panelist and cohort-week fixed effects are included in all regressions. For each cohort, observations from -3 to +15 weeks (include week 0) are included.