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**Research Report**

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Short Video and Mental Health: Evidence from China Family Panel Survey 2020

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# Short Video and Mental Health: Evidence from China Family Panel Survey 2020

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## Abstract

The emergence of short video platforms has reshaped social media consumption globally. These platforms, driven by personalized content algorithms and incentivized creators, differ from traditional social media, potentially impacting mental health through immersive and sensationalized content consumption. In this paper, we use data from the China Family Panel Survey of 2020 (CFPS 2020) to empirically investigate the impact of short video viewing on viewers' mental health. Our finding shows that frequent viewing of short videos has a negative effect on viewers' mental health, as evidenced by their self-reported depression levels. This negative effect is significant for both the OLS and 2SLS regression. Furthermore, our analysis reveals that a more pessimistic outlook on major social issues, resulting from short video viewing, is a key factor driving this outcome. This suggests that the algorithm-based nature of these platforms can intensify viewers' concerns about social issues, thereby influencing their mental health. Finally, our heterogeneity analysis documents a significant urban-rural difference in the negative effect of short video viewing on mental health and underscores the importance of the identified channel.

Keywords: Short Video, Mental Health, CFPS

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# 1 Introduction

Since the launch of Douyin in China in 2016, short videos have taken the digital media landscape by storm, reshaping media consumption in China and beyond. Globally, platforms like Tiktok, Instagram Reel, and YouTube Shorts have amassed tens of billions of monthly active users (Statista, 2024). In China, platforms like Douyin and Kuaishou have become a central feature of daily life for a vast segment of the population, boasting over 873 million users who spend an average of 120 minutes daily watching short videos (China Netcasting Services Association, 2021). The burgeoning of short video platform has a profound impact on our society. These platforms influence not only how individuals gather information but also how they perceive and engage with societal issues, ultimately impacting their welfare. However, while the impact of traditional social media (e.g., Facebook) on various socioeconomic aspects has been extensively studied (Allcott et al., 2020; Bhandari and Bimo, 2022; Fusi and Feeney, 2018; Zhuravskaya et al., 2020), research on the distinct effects of short video viewing have been scarce.

Short videos represent a significant shift from traditional social media platforms. Traditional platforms such as Facebook primarily rely on a user's social network for content dissemination, where viewers' exposure to content is determined through connections with friends (Bhandari and Bimo, 2022). Short video platforms differ from their predecessors in two major aspects: (1) the platforms use sophisticated algorithms to curate a personalized stream of content based on individual interests; (2) content creators are rewarded benefits (e.g., extra traffic, monetary reward, commercial opportunities) for being viewed more (Ran et al., 2022). As a result, more sensationalized content tends to be more organically promoted on these platforms (Shadmy, 2022).

These departures from traditional social media platforms may have significant implications for mental health. The algorithm-based approach allows short-video platforms to deliver content that maximizes viewer engagement through rapid cycles of highly engaging content, leading to a deeply immersive and prolonged viewing experience (Bhandari and Bimo, 2022). This mode of highly immersive viewing, often coupled with sensational content, can amplify feelings of anxiety,

depression, and distorted perceptions of reality. Unlike traditional social media, where users have more control over their content consumption, the algorithmic nature of short videos can result in unmoderated and extensive content exposure, potentially exacerbating their negative effects on mental health. Therefore, this research aims to empirically investigate the impact of short video viewing on individuals' mental health. By doing so, we seek to shed light on the profound and widespread effects of this new media form on society and highlight its critical implications for welfare.

Our empirical analysis is based on the 2020 China Family Panel Studies dataset (CFPS 2020), which offers comprehensive data on Chinese households, including detailed reports on social media viewing frequency, outlook on social issues, and self-reported mental health states. Specifically, the self-reported ratings on a clinically validated depression scale (Center for Epidemiological Studies-Depression Scale; CESD score) are used as the measurement of mental health.

In our benchmark analysis, we investigated the relationship between short videos and mental health using Ordinary Least Squares (OLS) regression and show that daily viewing of short videos has a negative effect on viewers' mental health. Due to the presence of omitted variables, measurement errors, or reverse causality, the estimated effect of short videos on mental health may be biased due to endogeneity issues. To identify the causal impact between short video viewing and mental health, we adopt the two-stage least squares (2SLS) specification and use the self-reported surfing time spent via mobile devices as the instrumental variable (IV) for short video viewing frequency. The estimation results show a significantly negative impact of short video viewing on mental health. Our results remain robust even after controlling for viewers' interpersonal relationships, a factor identified in previous research as a key mechanism in the negative impact of traditional social media on mental health.

We then explore why short video viewing negatively impacts mental health. As discussed earlier, the algorithm-driven approach of short video platforms, which often prioritizes sensational and emotionally charged content, can significantly shape viewers' perceptions of societal issues. With an increasing number of people turning to short video platforms as a primary source of news ([Shearer et al., 2024](#)),

the exposure to content related to major societal issues is likely to capture the attention of most viewers. This constant exposure to alarming content may lead viewers to perceive these issues as more severe, thereby exacerbating feelings of anxiety and depression.

To test this hypothesis, we regress viewers' perceptions of the severity of major social issues on whether they watch short videos daily. The regression results (using both OLS and IV) show that watching short videos does lead to a more negative perception of important social issues like housing and education. Mediation analysis further reveals that once these channels are controlled for, the estimated coefficient of short video viewing on mental health decreases. These findings suggest that short video viewing can alter individuals' perceptions of social issues, which in turn affects their mental health. In other words, the algorithm-based nature of short video platforms, where content is tailored to user behavior, may amplify concerns about social issues, leading to increased anxiety and depression. This mechanism is crucial in explaining how short video viewing contributes to a rise in depressive symptoms.

Furthermore, our heterogeneity analysis reveals a significant urban-rural difference, such that the negative effect of short video viewing on mental health is only significant in urban areas and not in rural areas. Moreover, economic conditions will affect the relationship: For urban residents, higher income will reduce depression levels, mitigating the negative effects of short video viewing. Regression analysis of short video viewing on social issues outlook, utilizing urban and rural sub-samples, indicates that short video viewing has a negative impact on individuals' outlook on social issues in urban areas but not in rural areas. This finding provides further evidence supporting our earlier channel analyses, since these social issues are more severe in urban areas, especially for low-income households.

Finally, we conducted a comparative analysis by examining the impact of WeChat Moments posting on mental health. Surprisingly, Moments posting frequency has no effect on depression. This finding suggests that short videos differ significantly from traditional social media platforms like WeChat, not only in their effects on mental health but also in the mechanisms through which they influence viewers' well-being. The unique algorithm-driven approach and the emphasis on



sensational content on short video platforms are perhaps the primary factors contributing to these differences.

Our research makes several contributions to existing research. To the best of our knowledge, this research is the first to examine the effect of short video viewing on mental health using a nationally representative survey data. This research extends the existing body of knowledge by specifically isolating the impact of short video platforms from general social media influences. By focusing on short video viewing, the study not only addresses a significant gap in the digital media literature but also enhances our understanding of how this new form of digital media reshapes individuals' perception of societal problems and ultimately their well-being. The findings provide pivotal insights for policymakers, platform designers, and mental health professionals, offering evidence-based insights for mitigating the potential adverse effects of these platforms.

Moreover, our study reveals how algorithm-driven content delivery on short video platforms affects viewers' mental health through its impact on viewer's outlook on social issues. When viewers are more concerned about some issues, the algorithm-based content delivery of short video may lead to immersive and prolonged viewing experience on these issues and amplify feelings of anxiety, depression, and distorted perceptions of reality. In comparison to earlier studies on traditional social media, our findings identifies a unique channel through which new forms of social media like short video may affect viewers' mental health.

Additionally, utilizing data from the 2020 China Family Panel Studies, this research provides context-specific insights on the impact of short videos on mental health in China. While this study focuses on the Chinese context, the insights can have broader implications for understanding digital media's global impact on mental health. Given the universal popularity of short video platforms like TikTok and Instagram Reels, these findings may be applicable to other cultural settings, offering a foundation for comparative studies that how short video viewing impacts well-being across different populations.

Finally, the findings of this research carry important implications for policymakers and regulators. The demonstrated negative impact of short video viewing on mental health suggests a need for policies that enforce greater transparency

in content algorithms and provide users with more control over their content exposure. Regulators should consider implementing guidelines that encourage platforms to prioritize user well-being, such as integrating time limits, mental health warnings, or content moderation practices. By adopting these measures, stakeholders can help mitigate the mental health risks associated with short video platforms, ensuring that their rapid growth does not come at the expense of public well-being.

The remainder of the paper is organized as follows: Section 2 reviews past research on the impact of social media on mental health. In Section 3, we provide a detailed description of the data and definitions of the variables used in our analyses. Section 4 presents our empirical framework and discusses instrumental variable approaches. In Section 5, we discuss the main empirical results, including the positive association between social media watching and viewer's depression and the channel through which it may affect mental health. Finally, in Section 6, we summarize the main findings and discuss the broad societal implications of our findings.

## 2 Related Work

Despite the global popularity of short video platforms such as TikTok, empirical studies on their impact have been relatively scarce (Montag et al., 2021). While some research has examined the cognitive effects of short videos, such as impairing memory (Chioffi et al., 2023; Zheng, 2021) and decreasing work productivity (Trisha et al., 2023), the specific impact of short video viewing on mental health remains underexplored. Most existing studies in this area have relied on content analysis, which limits our understanding of the direct psychological effects of short video viewing (McCashin and Murphy, 2023).

In contrast, the impact of traditional social media platforms, such as Facebook, Twitter, and Instagram, on mental health has been extensively studied. Research consistently shows that social media can reduce the cost of connecting and enhance social connectedness and support, which are vital for mental well-being (Seabrook et al., 2016). However, negative impacts often outweigh the positives,

with numerous studies linking social media use to increased anxiety, depression, and loneliness (Vannucci et al., 2017). For example, Braghieri et al. (2022) conducted a quasi-experimental study that leveraged the staggered introduction of Facebook across U.S. colleges, revealing that Facebook's rollout negatively impacted student mental health and increased reports of academic impairments due to poor mental health. Similarly, in a large-scale experiment, Allcott et al. (2020) found that deactivating Facebook led to significant improvements in subjective well-being, reduced online activity, and increased offline interactions, including spending more time with family and friends.

Several mechanisms have been proposed to explain how traditional social media affects mental health. One primary mechanism by which social media impairs well-being is by reducing social interactions and harming interpersonal relationships, leading to increased feelings of loneliness and depression (Twenge et al., 2018). Another important mechanism is social comparison, where individuals measure their lives against the often idealized portrayals of others on social media. This can lead to feelings of inadequacy and lower self-esteem (Appel et al., 2016). Additionally, social media can create a sense of Fear of Missing Out (FoMO), causing individuals to feel they are not participating in enjoyable experiences that others are enjoying, leading to overall dissatisfaction with life (Przybylski et al., 2013).

While traditional social media platforms have been extensively studied, short video platforms like TikTok and Douyin present distinct differences in content delivery and user engagement strategies, hence warranting a closer examination of their potential impact on mental health. These platforms use sophisticated algorithms to maximize engagement by curating personalized streams of content based on individual user interests and behaviors (Bhandari and Bimo, 2022; Shadmy, 2022). Unlike traditional social media, which primarily relies on a user's social network for content dissemination, short video platforms create an "algorithmized self" where users engage with content that continuously adapts to their preferences. This can lead to a deeply immersive and prolonged exposure to the often sensationalized content (Bhandari and Bimo, 2022), potentially contributing to distinct mental health effects that warrant further investigation. Therefore, this

study aims to address these gaps by focusing on the impact of short video viewing on mental health, thereby shedding new light on our understanding of this new form of digital media.

## 3 Data and Variables

### 3.1 Data Source

In this study, we utilize data from the 2020 China Family Panel Studies (CFPS), a comprehensive and nationally representative survey initiated in 2010 by the Institute of Social Science Survey (ISSS) at Peking University. Conducted every two years, CFPS gathers extensive data from a large sample of households and individuals, providing detailed information on the social, economic, and demographic characteristics of Chinese families and households.

The CFPS 2020 dataset encompasses multiple modules that survey respondents on a wide range of information, including individuals' behaviors of social media usage, perceptions on social issues, and mental health states, making it ideal for addressing our research question. Specifically, the CFPS wave 2020 contains information on short video entertainment and the time spent on mobile devices, which enables us to investigate the impact of short videos on mental health, as we can assess the potential associations between individuals' viewing of short videos and their mental well-being.

### 3.2 Variables

#### 3.2.1 Main Dependent Variables: Mental Health

The dependent variable in this study is mental health, measured in the CFPS 2020 data using the CESD (Center for Epidemiological Studies Depression) scale, which was developed by [Radloff \(1977\)](#) and widely utilized by researchers. The CESD scale is a clinically validated self-report questionnaire that measures the presence and intensity of depressive symptoms. In the 2020 wave of CFPS data, as shown in Appendix Table [A1](#), the 8-item version of the CESD includes eight

questions: “I felt depressed”, “I felt that everything I did was an effort”, “My sleep was restless”, “I was happy”, “I felt lonely”, “I enjoyed life”, “I felt sad”, and “I could not get going”. These questions capture how individuals have felt during the past week.

For each question, individuals are required to select one of the following four options according to their status in the past week: “Never (less than one day),” “Sometimes (1-2 days),” “Often (3-4 days),” or “Most of the time (5-7 days).” As a result, the CESD score ranges from 0 to 24.<sup>1</sup> The CESD score is one of the most commonly used measures for depression screening. A higher CESD score indicates a higher level of depressive symptoms, or in other words, poorer mental health. In later analysis, we will call it CESD8 score.

### 3.2.2 Main Explanatory Variables: Short Video Viewing

The primary explanatory variable in this study is short video viewing. Ideally, having information on the specific daily duration of short video viewing would be beneficial. However, the CFPS 2020 dataset does not include questions on the daily duration of short video viewing.<sup>2</sup> Instead, Section U of the Individual Questionnaire in CFPS 2020 includes a specific question on short video viewing: “During the past week, did you watch short videos or online live streaming programs almost every day (including Volcano, Tiktok, Wesee, DouYu, etc.)?” The response options are YES/NO. We consider individuals to be daily short video viewers if they answer YES; otherwise, they are classified as non-daily viewers. Therefore, we define a binary variable to indicate whether an individual watches

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<sup>1</sup>The CFPS user manual indicates that the reported CESD score ranges from 8 to 32, with response options scored from 1 to 4. However, this differs from the commonly used scale in the literature, where response options are scored from 0 to 3 (Radloff, 1977), resulting in a total score range of 0 to 24. To maintain consistency with the literature, we have adjusted the CESD score to match the 0-24 range.

<sup>2</sup>In Section U of the Individual Questionnaire in CFPS 2020, two questions pertain to internet usage time. One inquires, “In general, how long do you access the internet using mobile devices every day?” while the other asks, “In general, how long do you access the internet using computers every day?” However, there is no specific question regarding the duration of short video viewing.

short video every day ( $short\ video_{ic}$ ) and use this as our explanatory variable to identify frequent short video viewers.

To address the endogeneity issue, we also construct an instrumental variable for short video viewing and use the 2SLS method. In section U of the CFPS survey, participants were asked about the time they spend accessing the internet via mobile devices every day. This variable will be denoted as  $Screen\ Time_{ic}$  and used as the instrumental variable for short video entertainment ( $short\ video_{ic}$ ).

### 3.2.3 Control Variables

Apart from daily short video viewing as the main explanatory variable, other personal characteristics may also influence an individual's mental health. In the regression analysis, we incorporate controls for these characteristics, encompassing variables such as age, gender, education attainment, income, hukou status (urban vs. rural) and the residential county.

Also, as discussed earlier, one major mechanism through which traditional social media like Facebook impairs well-being is by reducing social interactions and harming interpersonal relationships. Also, social comparison represents another important mechanism through which social media affects mental health. On social media platforms, individuals often seek validation and approval through likes, comments, and follower counts. The pursuit of popularity and social status in the digital realm can lead to feelings of inadequacy, anxiety, feelings of loneliness, and self-doubt if one's online presence does not garner the desired level of attention or validation.

To distinguish between short video platforms and traditional social media, we introduce a variable related to social interactions in the regression analysis. In the CFPS 2020, individuals were also asked the following question: "If 0 stands for the lowest, 10 stands for the highest, do you think you are popular?" We will label this variable as  $popularity$ , representing an individual's interpersonal relationship and acceptance within their social environment, and incorporate it as an additional control variable in our primary regression model to check the robustness of our benchmark results.

### 3.2.4 Other Dependent Variables: Perception of Social Issues

As discussed in the introduction, to explore the mechanism through which the short video viewing influences mental health, we examine how short video viewing affects viewers' perceptions of various social issues. In the CFPS 2020 survey, respondents were asked to evaluate the perceived severity of societal issues in China, including governmental corruption, environmental challenges, socioeconomic inequality, employment dynamics, educational access, healthcare services, housing, and social security. The specific survey questions are listed in Appendix Table A2. Respondents were asked to rate each question on a scale of 0 to 10 (with "0" representing "not severe" and "10" representing "extremely severe"). These ratings will be used as variables to assess viewers' perceptions of severity of various social issues in our channel and mediation analyses.

### 3.2.5 Other Explanatory Variables: Wechat Moments Posting

Finally, to distinguish the effect of short video viewing on mental health from that of traditional social media like WeChat, we conducted a comparative analysis to examine whether posting on WeChat Moments influences depression. In the CFPS 2020 survey, respondents were asked how frequently they shared posts about their life and work on WeChat Moments over the past year. They could choose from seven categories: "Almost every day," "3-4 times each week," "Once or twice each week," "2-3 times each month," "Once a month," "Once in a few months," or "Never." For our empirical analysis, we convert these categories into the frequency of posting on WeChat Moments per week. Specifically, the corresponding frequencies for the seven categories are 7, 3.5, 1.5, 0.625, 0.25, 0.05, and 0, respectively. We then use this variable as an explanatory factor in Section 5.4.

## 3.3 Summary Statistics

Table 1 presents a statistical summary of all variables used in this study. CESD8 is utilized to measure the mental health and is the key dependent variable in this study. The mean and standard deviation of CESD8 is 5.17 and 3.80,

respectively. In Figure 1, we present the distribution of CESD8. The red dash line indicate the mean. The key explanatory variable is the short video viewing, which is a dummy variable indicating whether respondents watch short videos every day. In the sample, 55% of individuals report daily short video viewing.

[Table 1 about here.]

[Figure 1 about here.]

The survey includes individuals aged 9 to 86 years old, with an average age of 35.8. Among them, 52% are male, and 57% have an urban hukou. The average annual income is 50198 Yuan. About half of the participants reported their income, while others may be unemployed or ineligible for employment (e.g., those under 15 years old).

In terms of their perceptions of the severity of major societal issues, participants rated them on a scale of 0 to 10, with average ratings generally falling between 6 and 7. Notably, perceptions about the severity of the inequality issue received an average rating slightly above 7.

Before conducting the regression analysis, we compared the background characteristics and social issue perceptions of two groups. In Appendix Table A3, we observed notable differences between individuals who watch short videos every day and those who do not. Those who watch short videos daily tend to have higher CESD8 scores, be older, male, have a rural hukou, and earn lower incomes. Furthermore, daily viewers of short videos also tend to perceive social issues as more severe.

## 4 Methodology

### 4.1 Baseline Regression

We use OLS method to examine the relationship between short video and mental health. Considering individual  $i$  in county  $c$ , the regression equation is as follows:

$$Y_{ic} = \alpha + \beta \text{short video}_{ic} + \gamma X_{ic} + \delta_c + \epsilon_{ic}. \quad (1)$$



where the  $Y_{ic}$  represents the mental health of individual  $i$  in county  $c$ , captured by the self-reported CESD8 score discussed in Section 3.2.1.  $short\ video_{ic}$  is a dummy variable indicating whether individual  $i$  in county  $c$  watches the short videos every day.  $short\ video_{ic}$  equals to one if the individual watches the short videos almost every day, and zero otherwise. To address potential endogeneity issues from omitted variables, we control for other factors that may be simultaneously correlated with short video viewing or mental health. These factors are captured by  $X_{ic}$ , which encompasses individual characteristics like gender, age, education, income and hukou status (urban or rural), as well as  $\delta_c$ , which refers to the county fixed effects.  $\epsilon_{ic}$  is the error term.

## 4.2 Instrumental Variable Method

We also use the Instrumental Variables (IV) method to identify the causal link between watching short videos and mental health. The presence of omitted variables, measurement errors, or reverse causality can lead to endogeneity issues. Firstly, despite controlling for individual characteristics  $X_{ic}$  and county fixed effects  $\delta_c$ , some other unobserved relevant variables may still introduce bias to our estimates. Secondly, potential measurement errors in assessing mental health could add complexity to the analysis. Moreover, reverse causality is possible, as individuals with depressive symptoms may be more inclined to develop an addiction to short videos. Hence, we employ the IV approach to address potential biases in our analysis.

As discussed in Section 3.2.2, we will use the daily surfing time spent on mobile devices ( $Screen\ Time_{ic}$ ) as the instrumental variable for short video viewing ( $short\ video_{ic}$ ). Since the internet surfing time spent via mobile devices is likely to influence the duration and frequency of watching short videos, we believe this instrument variables is positively correlated with short video viewing and therefore satisfies the relevance condition. This is also confirmed by the first stage regression results in Tables 3 and 6.

The first stage of 2SLS regression is:

$$short\ video_{ic} = \alpha + \beta Screen\ Time_{ic} + \gamma X_{ic} + \delta_c + \epsilon_{ic}, \quad (2)$$

where  $Screen\ Time_{ic}$  is the self-reported internet surfing time spent via mobile devices. From the first stage, we can get the predicted  $\widehat{short\ video}_{ic}$ . The second stage of IV replaces the  $short\ video_{ic}$  in Eq. 1 by the predicted value, i.e.,

$$Y_{ic} = \alpha + \beta \widehat{short\ video}_{ic} + \gamma X_{ic} + \delta_c + \epsilon_{ic}. \quad (3)$$

### 4.3 Channel and Mediation Analysis

To understand the mechanism underlying the negative impact of short video viewing on mental health, we investigate how short video viewing influences people's perceptions of severity of various social issues. This includes examining their perceptions of societal issues such as government corruption, environmental concerns, income inequality, employment challenges, educational issues, healthcare services, housing problems, and social security. We denote these intermediary variables as  $PerSocial_{ic}$  and analyze the association between short video viewing and these perceptions using the following equation:

$$PerSocial_{ic} = \alpha + \beta short\ video_{ic} + \gamma X_{ic} + \delta_c + \epsilon_{ic}. \quad (4)$$

When conducting the mediation analysis, we will add viewers' perceptions of social issues to the right-hand side of Eq. 1 and check if the inclusion of viewer's perceptions of major social issues will reduce the coefficient on  $short\ video_{ic}$ .

## 5 Empirical Results

### 5.1 Baseline Results

#### 5.1.1 OLS Regression

We first examine the relationship between short video viewing and depression using OLS regression. The regression results, based on Eq. 1, are presented in Table 2. In column (1), the measure of depression, CESD8, is regressed solely on short video viewing. The coefficient is positive and significant, indicating a positive link between frequent short video viewing and depression. In column (2), personal control variables and county fixed effects are included in the regression.

The results remain consistent with those in column (1). Quantitatively, holding other factors constant, daily short video viewers are expected to experience a 0.336 increase in their CESD8 score.

The estimates for the other control variables also provide interesting insights. Age demonstrates an inverted U-shaped relationship with depression, initially rising with age, peaking around 34.25 years, and then declining. The coefficient for gender suggests that females are more prone to depression than males. In column (3), we include personal income in the regression<sup>3</sup>. The significantly negative coefficient for income suggests that depression levels decrease as personal income increases. Given this finding, we further explore the impact of regional economic development on the outcome. To do so, we substitute county fixed effects with county GDP and GDP per capita in columns (4) and (5)<sup>4</sup> to investigate how county-level income factors impact viewers' depression. Our analysis reveals that neither of these regional income factors has a significant effect on individual viewer's mental health. Meanwhile, even after accounting for regional economic development, as demonstrated in column (5), the regression coefficient for the personal income factor remains significantly negative.

[Table 2 about here.]

### 5.1.2 IV Regressions

As discussed in Section 4.2, we use the IV method to identify the causal relationship between short video viewing and depression, addressing potential endogeneity problem. Internet surfing time spent on mobile devices ( $Screen\ Time_{ic}$ ) is used as an IV for short video viewing, and the results are presented in Table 3.

The first-stage regression follows Eq. 2. As shown in the bottom panel of Table 3, coefficients on the screen time variable are all positive and significant, suggesting that the screen time is positive correlated with the dummy variable for frequent short video viewing. Moreover, the  $p$  value of the Kleibergen-Paap

<sup>3</sup>The sample size decreased because some interviewees did not report their income.

<sup>4</sup>The sample size decreased because we do not have residence information for some interviewees.

$F$ -statistic is smaller than 0.01, thereby rejecting the null hypothesis that the screen time is a weak instrument. These first-stage results suggest that the instrument variable satisfies the relevance condition.

Based on Eq. 3, the second-stage regression results, presented in the top panel of Table 3, suggested that the IV regression results are consistent with our OLS benchmark findings. In columns (2)-(5), we gradually introduce the same control variables as in the OLS regression. It is evident from all columns that the daily viewing of short videos has a notably negative impact on viewers' mental well-being.

[Table 3 about here.]

### 5.1.3 Robustness

Existing research on the influence of traditional social media platforms on mental health has highlighted the detrimental impact of social media on interpersonal relationships and social interactions. Conceivably, individuals addicted to short videos may distance themselves from real-world social engagements, potentially resulting in depression stemming from a lack of social connections. Meanwhile, social comparison on social media platforms represents another important channel through which traditional social media may affect individuals' mental well-being.

Therefore, to check whether our baseline results remain robust after controlling for factors emphasized in previous studies on other social media, we add a control variable, *popularity*, indicating viewers' social interactions, to our benchmark regression Eq. 1. The results are presented in Table 4. The coefficients for short video viewing remain consistently positive across all columns, indicating that the influence of watching short videos on depression remains robust even after accounting for viewers' social connections. Furthermore, the negative coefficient for popularity suggests that higher levels of popularity are associated with lower levels of depression, which aligns with common intuition.

[Table 4 about here.]

## 5.2 Mechanism and Mediation Analysis

### 5.2.1 Mechanism: Perception of Social Issues

Next, we delve into the reasons behind the negative impact of short video viewing on mental health. As discussed in the Introduction, the “algorithmized self” feature of short video platforms, driven by algorithm-based content curation, can amplify viewers’ anxieties by continuously exposing them to sensationalized or negative content.

Research indicates that 40% of TikTok users turn to the platform for news (Shearer et al., 2024). This suggests that a significant portion of short video viewers are regularly exposed to content about current events and societal issues. Short video platforms often emphasize sensational and alarming content related to topics like employment dynamics, educational access, healthcare services. This constant exposure can skew viewers’ perceptions, leading to a more negative and intensified view of these social issues, which may, in turn, heighten anxiety and concern, ultimately contributing to a decline in mental health. Therefore, we examine whether short video viewing will lead to a more pessimistic outlook on important social issues measured in Section 3.2.4.

We test this hypothesis in two steps. First, based on Eq. 4, we regress viewers’ perceived severity of eight major social issues,  $PerSocial_{ic}$ , on short video viewing. The results are presented in Table 5. In columns (1) to (3) and (8), the coefficients for short video are significant and positive, suggesting that increased frequency of watching short videos is associated with heightened perceptions of the severity of corruption, environmental issues, inequality, and social security.

[Table 5 about here.]

The OLS estimation results may be biased due to the reverse causality issue, since perceived severity of social issues may lead to increased short video viewing. To address potential endogeneity concerns, we employ the IV method to establish the causal relationship between short video viewing and viewers’ perception for major social issues. As in earlier analysis, screen time is used as the IV, and the regression results are outlined in Table 6.

As shown in the bottom panel of Table 6, the first-stage results demonstrate that our IV satisfies the relevance condition, making it suitable for our analysis. Both the Kleibergen-Paap  $F$ -statistic and the  $p$  value show that our proposed instrumental variable is positively correlated with the short video viewing. The second-stage results show that, in addition to the significant coefficients for the four social issues in the OLS estimation, the coefficients for the other four social issues (unemployment, education, healthcare, and housing) are also significant. In other words, the effect of short video viewing for all eight aspects of social issues are significant and positive, suggesting that frequent short video viewing significantly worsens viewers' perceptions of the severity of various social issues.

[Table 6 about here.]

### 5.2.2 Mediation Analysis

The second step in testing our assumption involves conducting a mediation analysis by sequentially incorporating the perceptions of each social issue into the right-hand side of Eq. 1. The regression results are presented in Table 7. Across all columns, the coefficients for the specific social issues are positive and significant, confirming their mediating role in elevating levels of depression. Moreover, the coefficients for short video viewing in all columns remain significant, but with a smaller magnitudes than those in Table 2, indicating a partial mediation effect. These findings suggest that viewers' more pessimistic outlook on major social issues is a key mechanism through which short video viewing affects viewers' mental health. It also highlights that the importance of "algorithmized self" feature of short video platform. Through an algorithm-based approach, short video viewing can amplify viewers' apprehension about social issues and influence their mental health.

[Table 7 about here.]

Meanwhile, the findings from Table 4 indicate that while social connections (as captured by the variable *popularity*) is a critical mechanism through which traditional social media influence mental health, it is not a important factor in

the impact of short video viewing on mental health. When *popularity* is introduced on the right-hand side of Eq. 1, the coefficients for short video viewing remain significant. However, in comparison to those in Table 2, the magnitudes do not decrease, suggesting that the inclusion of popularity does not alter the effect of short videos on depression. This outcome implies that social connection is not the primary driver of the negative impact of short video viewing on mental health.

### 5.3 Heterogeneity Analysis: Urban-Rural Comparison

A notable feature of the Chinese economy is the significant economic and social disparities between urban and rural areas. Therefore, we examine the impact of these gaps on our research findings through a heterogeneity analysis. To do this, we divide our sample into urban and rural groups based on interviewees' hukou status.

We first run the baseline regression on the two subsamples and report the results in Table 8. The first two columns present the results for the urban subsample. Like the baseline results in Table 2, we found that short video viewing is positively and significantly associated with higher depression levels among urban residents. Meanwhile, the negative coefficient for income suggests that depression levels decrease with higher income for urban residents. In contrast, the coefficients for short video viewing are insignificant in columns (3) and (4), indicating that short video viewing has no effect on depression levels for rural residents.

[Table 8 about here.]

Next, we explore why the negative impact of short video viewing on mental health is more significant in urban areas. To investigate if this is related to social issues, we run regressions on the two subsamples using Eq. 4. The results for the urban subsample are presented in Table 9. In all columns, the coefficients for short video viewing are positive and significant, suggesting that urban residents' perceptions of the severity of all eight major social issues increases with daily short video viewing.

[Table 9 about here.]

Conversely, the regression results in Table 10 reveal that short video viewing does not have a significant impact on viewers' perceived severity of any of the eight social issues in rural areas. The results from these two tables suggest that while short video viewing adversely affects individuals' perceptions of social issues in urban areas, it does not have the same effect in rural areas. Therefore, short video viewing only contributes to higher depression levels among urban residents. This comparison offers further evidence for findings in the mechanism analyses, since these social issues are more pronounced in urban areas, especially for low-income households.

[Table 10 about here.]

#### 5.4 Comparative Analysis

Finally, to better understand the differences in mental health effects between traditional social media and short video platforms, we conducted a comparative analysis by examining the impact of posting on WeChat Moments. While both activities involve online social interactions, short video viewing uniquely involves passive consumption of algorithmically tailored content. Thus, the comparison with WeChat allows us to explore how the algorithm-driven approach and sensational content of short videos specifically affect viewers' mental health.

We regress depression levels on WeChat Moments posting frequency based on Eq. 1 and present the results in Table 11. Surprisingly, as shown in column (1), the coefficient for WeChat Moments is insignificant, indicating that Moments posting frequency has no effect on depression. This finding suggests that short video viewing differs significantly from traditional social media platforms like WeChat, not only in their effects on mental health but also in the mechanisms through which they influence viewers' well-being. Due to data limitations, we are unable to conduct further tests on other forms of traditional social media and their various impacts on depression. However, it is highly likely that the unique algorithm-driven approach and the emphasis on sensational content on short video platforms are the key factors contributing to the differences between short video and traditional social media.



[Table 11 about here.]

## 6 Conclusion

Using the CFPS 2020 dataset, this paper empirically explores the effects of watching short videos on viewers' mental health. Both the OLS and the 2SLS regressions suggest that daily viewing of short videos will increase viewers' self-reported depression level.

To understand why watching short video negatively affects mental health, we explore the relationship between short video and viewer's perceptions of the severity of major social issues. The results indicate that short video viewing leads to a more pessimistic outlook on significant social issues such as housing and education. Mediation analysis further reveals that this pessimistic outlook on social issues, resulting from short video viewing, is a key channel through which short video viewing increases viewers' depression. This suggests that short videos can alter viewers' perceptions of social issues and, in turn, impact mental health. This finding is further supported by our heterogeneity analysis, which reveals a significant urban-rural difference in the negative effect of short video viewing on mental health, with a particularly strong impact among higher-income urban residents.

By focusing on the impact of short video platforms, our research provides new insights into how this distinct form of social media influences mental health. Moreover, our study reveals how algorithm-driven content delivery on short video platforms affects mental health by shaping viewer's perceptions of social issues. Compared to mechanisms identified in previous literature on social media and mental health, this represents a unique mechanism through which short videos may affect viewers' well-being.

The findings from this paper enhance our understanding of the broader social implications of short video platforms and provide a foundation for developing targeted interventions to mitigate their potential negative effects on mental health. Policymakers should consider implementing regulations or guidelines to monitor and regulate algorithm-driven content on short video platforms, particularly algo-

rithms that prioritize engagement by amplifying content that can increase anxiety, depression, and distorted perceptions of reality. Additionally, promoting digital literacy and encouraging responsible usage of these platforms are crucial steps in helping users navigate and mitigate the negative impacts of short video consumption. By fostering a more informed and cautious approach to these platforms, we can better protect mental health in an increasingly digital society.

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## References

- Allcott, H., Braghieri, L., Eichmeyer, S., and Gentzkow, M. (2020). The welfare effects of social media. *American Economic Review*, 110(3):629–676.
- Appel, H., Gerlach, A. L., and Crusius, J. (2016). The interplay between facebook use, social comparison, envy, and depression. *Current Opinion in Psychology*, 9:44–49.
- Bhandari, A. and Bimo, S. (2022). Why’s everyone on tiktok now? the algorithmized self and the future of self-making on social media. *Social Media+ Society*, 8(1):20563051221086241.
- Braghieri, L., Levy, R., and Makarin, A. (2022). Social media and mental health. *American Economic Review*, 112(11):3660–3693.
- China Netcasting Services Association (2021). 2021 china online audio-visual development research report. Technical report, China Netcasting Services Association, Available at <http://www.cnsa.cn/attach/0/2112271351275360.pdf>.
- Chiossi, F., Haliburton, L., Ou, C., Butz, A. M., and Schmidt, A. (2023). Short-form videos degrade our capacity to retain intentions: Effect of context switching on prospective memory. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pages 1–15.
- Fusi, F. and Feeney, M. K. (2018). Social media in the workplace: information exchange, productivity, or waste? *The American Review of Public Administration*, 48(5):395–412.
- McCashin, D. and Murphy, C. M. (2023). Using tiktok for public and youth mental health—a systematic review and content analysis. *Clinical Child Psychology and Psychiatry*, 28(1):279–306.
- Montag, C., Yang, H., and Elhai, J. D. (2021). On the psychology of tiktok use: A first glimpse from empirical findings. *Frontiers in public health*, 9:641673.

- Przybylski, A. K., Murayama, K., DeHaan, C. R., and Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior*, 29(4):1841–1848.
- Radloff, L. S. (1977). The ces-d scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement*, 1(3):385–401.
- Ran, D., Zheng, W., Li, Y., Bian, K., Zhang, J., and Deng, X. (2022). Revenue and user traffic maximization in mobile short-video advertising. In *AAMAS'22: Proceedings of the 21st International Conference on Autonomous Agents and Multiagent Systems*, pages 1092–1100. Association for Computing Machinery.
- Seabrook, E. M., Kern, M. L., and Rickard, N. S. (2016). Social networking sites, depression, and anxiety: a systematic review. *JMIR Mental Health*, 3(4):e5842.
- Shadmy, T. (2022). Content traffic regulation: A democratic framework for addressing misinformation. *Jurimetrics: The Journal of Law, Science, and Technology*, 63:1.
- Shearer, E., Naseer, S., Liedke, J., and Matsa, K. E. (2024). TikTok users' experiences with news. <https://www.pewresearch.org/journalism/2024/06/12/tiktok-users-experiences-with-news/>.
- Statista (2024). Most popular short video platform and features worldwide 1st quarter 2024, average video views. Available at <https://www.statista.com/statistics/1466343/short-video-platform/>.
- Trisha, A. S., Rofi, I. B., Eshita, M. M., Biswas, J., and Ahmed, M. S. (2023). Content, consumption, and productivity: An empirical analysis of compact streaming and reel content's effects on the productivity of today's emerging generation. In *2023 15th International Conference on Software, Knowledge, Information Management and Applications (SKIMA)*, pages 181–186. IEEE.
- Twenge, J. M., Martin, G. N., and Campbell, W. K. (2018). Decreases in psychological well-being among american adolescents after 2012 and links to screen time during the rise of smartphone technology. *Emotion*, 18(6):765.

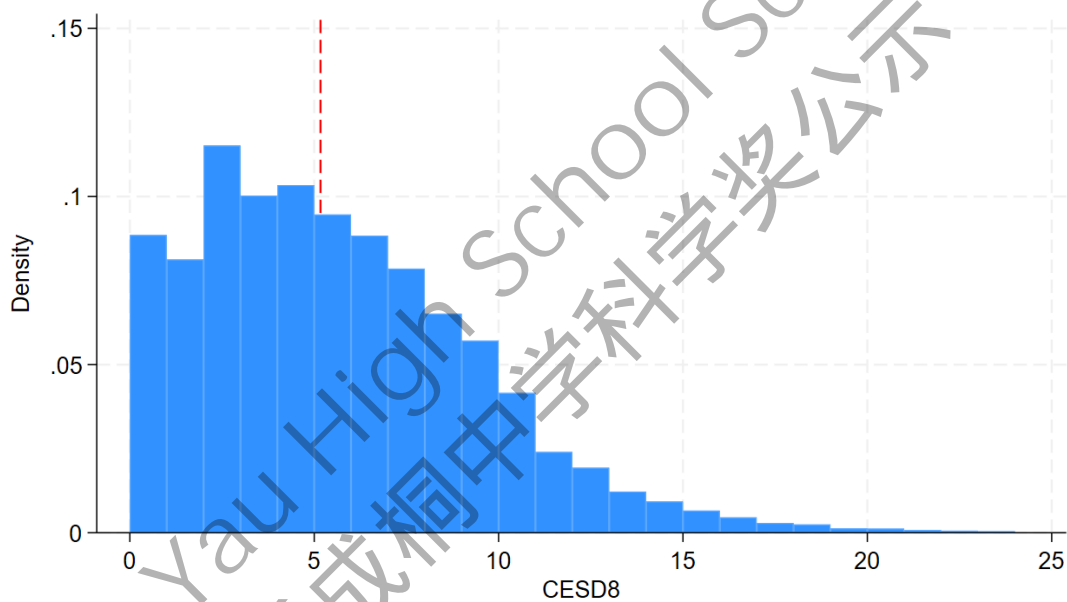
Vannucci, A., Flannery, K. M., and Ohannessian, C. M. (2017). Social media use and anxiety in emerging adults. *Journal of Affective Disorders*, 207:163–166.

Zheng, M. (2021). Influence of short video watching behaviors on visual short-term memory. In *2021 4th International Conference on Humanities Education and Social Sciences (ICHESS 2021)*, pages 1855–1859. Atlantis Press.

Zhuravskaya, E., Petrova, M., and Enikolopov, R. (2020). Political effects of the internet and social media. *Annual Review of Economics*, 12(1):415–438.

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Figure 1: Distribution of CESD8



Source: China Family Panel Study 2020

Note: The red dash line indicates the mean of the CESD8.

Table 1: Descriptive Statistics

	N	Mean	Std.Dev.	Min.	Max.
CESD8	16227	5.17	3.80	0.00	24.00
Short Video	16227	0.55	0.50	0.00	1.00
Screen Time	16162	2.95	2.81	0.00	24.00
WeChat Moments	15554	0.80	1.63	0.00	7.00
Age	16227	35.80	15.05	9.00	86.00
Age sq.	16227	1508.45	1186.44	81.00	7396.00
Gender	16227	0.52	0.50	0.00	1.00
Urban	15245	0.57	0.50	0.00	1.00
Income	8239	50198.90	48460.84	0.00	1000000.00
Popularity	16223	7.00	1.76	0.00	10.00
Corruption Issue	14527	6.29	2.62	0.00	10.00
Environment Issue	14728	6.76	2.56	0.00	10.00
Inequality Issue	14699	7.03	2.27	0.00	10.00
Unemployment Issue	14661	6.53	2.26	0.00	10.00
Education Issue	14695	6.53	2.62	0.00	10.00
Healthcare Issue	14711	6.51	2.58	0.00	10.00
Housing Issue	14684	6.41	2.56	0.00	10.00
Social Security Issue	14680	6.02	2.56	0.00	10.00
GDP	10403	419.64	842.21	11.08	5871.06
GDP Per Capita	7837	5.44	4.50	1.02	23.92

Table 2: Short Video Daily Viewing and Depression

	Dependent variable: CESD8				
	(1)	(2)	(3)	(4)	(5)
Short Video	0.440*** (0.060)	0.336*** (0.064)	0.374*** (0.091)	0.360*** (0.088)	0.601*** (0.127)
Age		0.137*** (0.010)	0.051* (0.027)	0.136*** (0.015)	0.028 (0.037)
Age sq.		-0.002*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001 (0.000)
Gender		-0.425*** (0.062)	-0.271*** (0.091)	-0.291*** (0.086)	-0.187 (0.130)
Urban		-0.062 (0.078)	0.023 (0.116)	-0.129 (0.093)	0.022 (0.139)
Income (ln)			-0.077*** (0.029)		-0.078** (0.039)
GDP				-0.000 (0.000)	-0.000 (0.000)
GDP Per Capita				-0.029 (0.018)	-0.011 (0.023)
Education level	NO	YES	YES	YES	YES
County FE	NO	YES	YES	NO	NO
Num. obs.	16227	15235	7605	7649	3440
R <sup>2</sup>	0.003	0.110	0.142	0.029	0.037

Notes: \*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ . Dependent variables in all columns are CESD8. Standard errors clustered at the person level are reported in the parenthesis.



Table 3: Short Video Daily Viewing and Depression (IV)

	Second stage, dependent variable: CESD8			
	(1)	(2)	(3)	(4)
Short Video	3.581*** (0.488)	3.245*** (0.815)	3.384*** (0.774)	2.278** (1.123)
Age	0.064*** (0.016)	0.054* (0.028)	0.060** (0.027)	0.012 (0.037)
Age sq.	-0.001*** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.000 (0.000)
Gender	-0.494*** (0.073)	-0.360*** (0.096)	-0.338*** (0.097)	-0.247* (0.129)
Urban	-0.007 (0.130)	0.005 (0.139)	-0.073 (0.168)	0.055 (0.168)
Income (ln)		-0.086*** (0.031)		-0.081** (0.035)
GDP			-0.000 (0.000)	-0.000 (0.000)
GDP Per Capita			-0.018 (0.032)	-0.005 (0.023)
First stage, dependent variable: Short Video				
	(1)	(2)	(3)	(4)
Screen Time	0.031*** (0.002)	0.025*** (0.002)	0.033*** (0.002)	0.028*** (0.004)
Controls	YES	YES	YES	YES
Education level	YES	YES	YES	YES
County FE	YES	YES	NO	NO
Num. obs.	15178	7578	7622	3428
R <sup>2</sup>	0.129	0.150	0.064	0.047
KP F statistic	133.820	30.216	61.783	13.216
KP F p-value	0.000	0.000	0.000	0.000

Notes: \*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ . Standard errors clustered at the person level are reported in the parenthesis.

Table 4: Short Video Daily Viewing, Popularity, and Depression

	Dependent variable: CESD8			
	(1)	(2)	(3)	(4)
Short Video	0.358*** (0.063)	0.400*** (0.090)	0.400*** (0.086)	0.605*** (0.126)
Popularity	-0.356*** (0.019)	-0.350*** (0.028)	-0.376*** (0.026)	-0.304*** (0.039)
Age	0.134*** (0.010)	0.054** (0.027)	0.134*** (0.014)	0.027 (0.037)
Age sq.	-0.002*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001 (0.000)
Gender	-0.397*** (0.061)	-0.267*** (0.090)	-0.261*** (0.085)	-0.181 (0.129)
Urban	-0.096 (0.078)	0.016 (0.115)	-0.202** (0.092)	0.004 (0.138)
Income (ln)		-0.065** (0.029)		-0.067* (0.039)
GDP			-0.000 (0.000)	-0.000 (0.000)
GDP Per Capita			-0.036** (0.017)	-0.017 (0.023)
Education level	YES	YES	YES	YES
County FE	YES	YES	NO	NO
Num. obs.	15231	7604	7646	3439
R <sup>2</sup>	0.135	0.164	0.060	0.055

Notes: \*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ . Standard errors clustered at the person level are reported in the parenthesis.

Table 5: Short Video Daily Viewing and Perceptions of Social Issues

	Corruption	Environment	Inequality	Unemployment	Education	Healthcare	Housing	Social Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short Video	0.1907*** (0.0480)	0.1389*** (0.0463)	0.1394*** (0.0415)	0.0528 (0.0411)	0.0783 (0.0476)	0.0761 (0.0468)	0.0675 (0.0463)	0.1118** (0.0465)
Age	0.1009*** (0.0092)	0.0382*** (0.0088)	0.0519*** (0.0080)	0.0152* (0.0078)	0.0826*** (0.0092)	0.0952*** (0.0091)	0.0538*** (0.0088)	0.1045*** (0.0090)
Age sq.	-0.0010*** (0.0001)	-0.0007*** (0.0001)	-0.0006*** (0.0001)	-0.0003*** (0.0001)	-0.0010*** (0.0001)	-0.0011*** (0.0001)	-0.0008*** (0.0001)	-0.0013*** (0.0001)
Gender	-0.0466 (0.0463)	0.0201 (0.0445)	0.2561*** (0.0401)	-0.1957*** (0.0398)	-0.2594*** (0.0461)	-0.2083*** (0.0455)	-0.0392 (0.0449)	-0.3300*** (0.0450)
Urban	0.0136 (0.0599)	0.0841 (0.0577)	0.0083 (0.0513)	0.1141** (0.0508)	-0.0138 (0.0597)	-0.0313 (0.0590)	0.0371 (0.0579)	-0.0505 (0.0575)
Education level	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Num. obs.	13583	13766	13737	13702	13735	13752	13725	13722
R <sup>2</sup>	0.0840	0.0980	0.0781	0.0785	0.0825	0.0801	0.0929	0.0865

Notes: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . Standard errors clustered at the person level are reported in the parenthesis.

Table 6: Short Video Daily Viewing and Perceptions of Social Issues (IV)

	Second stage, dependent variables:							
	Corruption	Environment	Inequality	Unemployment	Education	Healthcare	Housing	Social Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short Video	1.314*** (0.343)	1.224*** (0.314)	1.564*** (0.290)	1.250*** (0.286)	0.639* (0.327)	0.656** (0.327)	0.709** (0.318)	0.744** (0.313)
Age	0.090*** (0.010)	0.029*** (0.010)	0.039*** (0.009)	0.004 (0.008)	0.078*** (0.010)	0.090*** (0.010)	0.048*** (0.009)	0.099*** (0.010)
Age sq.	-0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.083* (0.048)	-0.016 (0.046)	0.207*** (0.043)	-0.235*** (0.042)	-0.279*** (0.047)	-0.226*** (0.047)	-0.061 (0.046)	-0.349*** (0.046)
Urban	0.029 (0.061)	0.101* (0.059)	0.028 (0.054)	0.125** (0.053)	-0.010 (0.060)	-0.026 (0.059)	0.043 (0.059)	-0.047 (0.058)
First stage, dependent variable: Short Video								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Screen Time	0.027*** (0.002)	0.028*** (0.002)	0.028*** (0.002)	0.027*** (0.002)	0.028*** (0.002)	0.028*** (0.002)	0.028*** (0.002)	0.028*** (0.002)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Education level	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Num. obs.	13542	13720	13692	13657	13690	13706	13681	13677
R <sup>2</sup>	0.114	0.115	0.115	0.114	0.114	0.115	0.115	0.115
KP F statistic	69.227	70.746	70.666	69.697	69.290	70.860	70.512	70.991
KP F p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: \*\*\*p < 0.01; \*\*p < 0.05; \*p < 0.1. Standard errors clustered at the person level are reported in the parenthesis.

Table 7: Short Video Daily Viewing, Perceptions of Social Issues, and Depression

	Dependent variable: CESD8							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short Video	0.258*** (0.067)	0.273*** (0.067)	0.244*** (0.067)	0.268*** (0.067)	0.264*** (0.067)	0.266*** (0.067)	0.276*** (0.067)	0.267*** (0.067)
Corruption Issue	0.132*** (0.013)							
Environment Issue		0.026* (0.013)						
Inequality Issue			0.120*** (0.015)					
Unemployment Issue				0.097*** (0.016)				
Education Issue					0.103*** (0.013)			
Healthcare Issue						0.110*** (0.013)		
Housing Issue							0.125*** (0.014)	
Social Security Issue								0.117*** (0.013)
Age	0.081*** (0.013)	0.094*** (0.013)	0.088*** (0.013)	0.094*** (0.013)	0.086*** (0.013)	0.084*** (0.013)	0.089*** (0.013)	0.082*** (0.013)
Age sq.	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.385*** (0.066)	-0.394*** (0.066)	-0.419*** (0.065)	-0.374*** (0.066)	-0.359*** (0.066)	-0.372*** (0.066)	-0.392*** (0.065)	-0.350*** (0.066)
Urban	-0.042 (0.084)	-0.042 (0.084)	-0.055 (0.084)	-0.059 (0.084)	-0.043 (0.084)	-0.041 (0.084)	-0.054 (0.084)	-0.036 (0.084)
Education level	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Num. obs.	13583	13766	13737	13702	13735	13752	13725	13722
R <sup>2</sup>	0.122	0.113	0.117	0.116	0.118	0.118	0.119	0.119

Notes: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . Standard errors clustered at the county level are reported in the parenthesis.

Table 8: Short Video Daily Viewing and Depression by Urban/Rural

	Urban		Rural	
	(1)	(2)	(3)	(4)
Short Video	0.555*** (0.084)	0.471*** (0.118)	0.084 (0.099)	0.200 (0.151)
Age	0.122*** (0.014)	0.020 (0.038)	0.140*** (0.018)	0.096** (0.040)
Age sq.	-0.002*** (0.000)	-0.001 (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Gender	-0.438*** (0.082)	-0.348*** (0.117)	-0.433*** (0.095)	-0.167 (0.151)
Income (ln)		-0.096** (0.041)		-0.046 (0.043)
Education level	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Num. obs.	8618	4741	6617	2864
R <sup>2</sup>	0.131	0.166	0.130	0.182

Notes: \*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ . Dependent variables in all columns are CESD8. Standard errors clustered at the person level are reported in the parenthesis.

Table 9: Short Video Daily Viewing and Perceptions of Social Issues in Urban Area

	Corruption	Environment	Inequality	Unemployment	Education	Healthcare	Housing	Social Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short Video	0.264*** (0.062)	0.168*** (0.060)	0.180*** (0.053)	0.102* (0.053)	0.175*** (0.062)	0.150** (0.061)	0.117** (0.059)	0.193*** (0.060)
Age	0.101*** (0.012)	0.032*** (0.011)	0.042*** (0.010)	0.016* (0.010)	0.077*** (0.012)	0.106*** (0.012)	0.043*** (0.011)	0.112*** (0.011)
Age sq.	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.000** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.059 (0.060)	0.016 (0.057)	0.315*** (0.051)	-0.185*** (0.051)	-0.234*** (0.059)	-0.182*** (0.059)	-0.017 (0.057)	-0.404*** (0.058)
Education level	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Num. obs.	7852	7953	7942	7921	7940	7948	7935	7934
R <sup>2</sup>	0.113	0.127	0.105	0.103	0.107	0.107	0.125	0.122

Notes: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . Standard errors clustered at the person level are reported in the parenthesis.

Table 10: Short Video Daily Viewing and Perceptions of Social Issues in Rural Area

	Corruption	Environment	Inequality	Unemployment	Education	Healthcare	Housing	Social Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short Video	0.119 (0.078)	0.094 (0.075)	0.075 (0.068)	-0.014 (0.067)	-0.031 (0.077)	-0.035 (0.075)	-0.018 (0.076)	0.006 (0.075)
Age	0.113*** (0.016)	0.053*** (0.015)	0.060*** (0.014)	0.013 (0.014)	0.098*** (0.016)	0.084*** (0.016)	0.070*** (0.016)	0.092*** (0.016)
Age sq.	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.000* (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.008 (0.075)	0.063 (0.072)	0.170*** (0.065)	-0.191*** (0.065)	-0.264*** (0.074)	-0.222*** (0.074)	-0.038 (0.074)	-0.223*** (0.072)
Education level	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Num. obs.	5731	5813	5795	5781	5795	5804	5790	5788
R <sup>2</sup>	0.090	0.105	0.083	0.087	0.092	0.085	0.098	0.083

Notes: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . Standard errors clustered at the person level are reported in the parenthesis.



Table 11: WeChat Moments Posting and Depression

Dependent variable: CESD8	
(1)	
WeChat Moments	0.054 (0.040)
Age	0.024 (0.038)
Age sq.	-0.001 (0.000)
Gender	-0.132 (0.132)
Urban	0.014 (0.141)
Income (ln)	-0.080** (0.040)
GDP	-0.000 (0.000)
GDP Per Capita	-0.012 (0.023)
Education level	YES
Num. obs.	3409
R <sup>2</sup>	0.030

Notes: \*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ . Standard errors clustered at the person level are reported in the parenthesis.

## Appendix

Table A1: 8-item CES-D in CFPS

NO	Question
1	I felt depressed.
2	I felt everything I did was an effort.
3	My sleep was restless.
4	I was happy.
5	I felt lonely.
6	I enjoyed life.
7	I felt sad.
8	I could not get "going".

Here are some descriptions of people's mental statuses. Please select according to your statuses in the past week among the following options: 1. Never (less than one day) 2. Sometimes (1-2 days) 3. Often (3-4 days) 4. Most of the time (5-7 days).

Table A2: Perceptions of Social Issues

NO	Question: How would you rate the severity of the “X” in China?
1	government corruption
2	environmental problem
3	inequality between the rich and the poor
4	employment problem
5	educational problem
6	medical service problem
7	housing problem
8	social security problem

How would you rate the severity of the above problems in our country? Let “0” be “not severe”, while “10” be “extremely severe”. Please choose a number that reflects your attitude.

Table A3: Differences in Characteristics and Perceptions of Social Issues between Two Groups

	Viewing Short Videos Daily		Difference (NO-YES)
	Yes	No	
CESD8	5.372 (3.864)	4.931 (3.704)	-0.440***
Screen Time	3.269 (2.912)	2.556 (2.633)	-0.713***
WeChat Moments	0.897 (1.729)	0.686 (1.491)	-0.212***
Age	36.327 (13.911)	35.170 (16.305)	-1.157***
Gender	0.526 (0.499)	0.510 (0.500)	-0.016*
Urban	0.546 (0.498)	0.589 (0.492)	0.043***
Income	47895.609 (42690.651)	53441.134 (55421.924)	5545.525***
Popularity	7.024 (1.731)	6.978 (1.784)	-0.046
Corruption Issue	6.382 (2.651)	6.164 (2.582)	-0.218***
Environment Issue	6.841 (2.562)	6.649 (2.557)	-0.192***
Inequality Issue	7.083 (2.282)	6.955 (2.262)	-0.128***
Unemployment Issue	6.568 (2.281)	6.477 (2.222)	-0.091*
Education Issue	6.575 (2.633)	6.459 (2.600)	-0.116**
Healthcare Issue	6.555 (2.614)	6.458 (2.536)	-0.098*
Housing Issue	6.450 (2.590)	6.346 (2.519)	-0.103*
Social Security Issue	6.100 (2.572)	5.923 (2.535)	-0.177***

Notes: \*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ . Standard errors are reported in the parenthesis.