Impacts of Algorithm-Powered Short Videos on Employment and Mental Health.

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Abstract

Algorithm-powered short videos, which leverage advanced algorithms and recommendation systems to analyze user preferences, have emerged as a dominant force in digital media. By comparing individuals before and after their exposure to short videos, this study provides causal evidence that short videos have increased employment, mainly part-time jobs, by 7.5% in China. A larger increase in employment is observed among marginalized groups with lower education levels and lower incomes, those from rural areas, and mothers with young children. We also observe that being exposed to short videos significantly reduces individual mental health, plausibly as a side effect of allocating more time to work and less time to sleep and exercise. We do not find a significant difference in the impact on mental health across population groups, suggesting an unbalanced welfare impact favoring marginalized groups. Finally, we find that reducing the frequency of short video consumption could substantially reduce the damage to mental health while maintaining most of the positive effects on employment.

Keywords: Short videos; Socioeconomic outcomes; Mental Health; Heterogeneity

JEL Codes:O12, L82, I12

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1 Introduction

Algorithm-powered short-form videos (short videos hereafter) have become a dominant force in digital media, engaging audiences with their creative storytelling, entertainment, and informational content within brief durations ranging from 15 seconds to 3 minutes. Unlike other digital social media platforms, short-video platforms such as TikTok, YouTube Shorts, and Instagram Reels employ advanced algorithms and recommendation systems to analyze user preferences, behavior, and content attributes to generate personalized recommendations. These recommendations can propel videos to viral status within minutes. For example, TikTok, launched in 2016, had reached 1.9 billion active users globally by 2024, and Instagram Reels, launched in 2020, had reached 1.8 billion active users by 2024. China, which aligns with the global trend, has recently experienced an explosive rise in short-video popularity, with nearly 0.8 billion active users in 2023.

Short video platforms have emerged as powerful drivers of employment opportunities and boost income generation. Their diverse mechanisms for economic participation cater to a broad spectrum of users, from digital content creators to small business owners and marginalized groups. As detailed in Section 2.2, we summarize that short video platforms facilitate employment through multiple channels: lowering the barriers to content creation, promoting job opportunities, enhancing vocational skills, fostering entrepreneurial ambition by exposing users to real-life success stories, and empowering marginalized groups who often face barriers in traditional labor markets. However, despite these potential positive effects on employment, the addictive nature of short videos still raises significant concerns about the adverse effects of excessive use, particularly regarding mental health.

This study examines the impact of short videos on employment and mental health. Our analysis is based on the longitudinal survey data from the China Family Panel Studies, which covers a population of about 33,600 in China from 2012 to 2022. The survey data show that more than half of adults in China watched short videos every day in 2022, and short videos have significantly penetrated all age groups and education groups. We estimate the impact of short videos on employment and mental health using a Staggered Difference-in-Differences (DID) model that compares individuals before and after watching short videos in regions with different levels of short-video exposure. Event studies suggest that individuals exposed to short videos early and later have no significant preexisting differences in employment and mental health. We also address the endogeneity concern by adopting a matched DID approach and employing the Instrumental Variable (IV) constructed from exogenous regional supply shocks of short videos.

The estimates suggest that short videos have significantly increased part-time employment. When defining those who worked at least one hour in the past week for income as employed, our preferred estimate indicates that short videos have increased the probability of being employed by 7.5%. The average working hours per week increased by only 0.67 hours for those employed (or 1.45% of the mean), confirming that most of the additional employment is part-time. We also find that short videos significantly increase the probability of engaging in off-farm work and self-employment. Heterogeneous analyses suggest that short videos have a more positive impact on the employment of those with a relatively lower education level, in lower income quartiles, from rural areas, and mothers of young children. We also find a larger impact on the young and unmarried but no significant gender differences. These findings suggest that short videos contribute to reducing employment inequality by disproportionately benefiting marginalized groups.

The employment benefits of short videos are not without cost. We show that short videos have significantly impaired mental health. Our analysis adopts a standard measure of mental health: the Center for Epidemiologic Studies Depression Scale (CESD), which is calculated based on the responses to a series of mental-health-related survey questions (Radloff, 1997; Haushofer and Shapiro, 2016; Huang et al., 2024a). The estimates suggest that short videos have significantly reduced mental health by 0.096 standard deviations. Similar results are found when estimating the impact on individual measures used to construct CESD, such as feeling unhappy, lonely, and poor sleep. We see no significant difference in the effects on mental health across different population groups. The negative impact on mental health seems to be a side effect of short videos on employment: short videos have significantly reduced the time individuals allocate to physical exercise and sleep and increased unhealthy behaviors related to work pressure (i.e., smoking and drinking).

Finally, we find that reducing the frequency of short video consumption could substantially reduce the damage to mental health while maintaining most of the positive effects on employment. We measure the frequency of watching short videos based on the survey question, "Do you watch short videos every day?" When separately estimating the impact for those who watch short videos every day and those who watch short videos but not every day, we find that the negative impact on mental health is approximately one-third as large for those who do not watch short videos every day compared to those who do. However, the positive effects on employment are very close for these two groups. These estimates suggest that reducing the time spent on short videos rather than completely banning them is a sensible choice.

This paper contributes to evaluating the impact of algorithm-powered short videos. Unlike other social media and traditional media, short videos employ advanced algorithms and recommendation systems to propel videos to viral status within minutes. Although short videos have become a dominant force in digital media in recent years, rigorous economic studies on their impact remain limited. Much of the current understanding of the impact of short videos is based on non-academic news reporting and publications from the psychology and medical fields. These studies predominantly focus on the effects of short videos on mental health and generally find negative effects, such as increased depression and anxiety, lower life satisfaction, and memory loss or impairment (e.g., Sha and Dong, 2021; Shychuk et al., 2022; Amsalem et al., 2024; Qu et al., 2024). Consistent with these studies, our analysis also finds that short videos reduce mental health. However, our analysis further reveals a substantial positive impact of short videos on employment, suggesting that reduced rest and increased work-related stress could explain the negative impact on mental health.

This paper is also related to the extensive literature on the impact of media on individual outcomes. Regarding traditional media such as newspapers, television, and the internet, existing studies have estimated their effects on various individual outcomes, including employment (Hjort and Poulsen, 2019), income (Aker and Mbiti, 2010), wages (Forman et al., 2012), and poverty (La Ferrara, 2016). For earlier social media platforms like Facebook, Twitter, and YouTube, numerous studies have investigated their impacts on mental health (Braghieri et al., 2022), individual well-being (Bao et al., 2021), crime (Müller and Schwarz, 2021), discrimination and prejudice (Ali and Qazi, 2023), and information dissemination (Gorodnichenko et al., 2021). Most of these findings present a concerning picture. With respect to the latest algorithm-powered short videos, little is known about their impact on individual economic outcomes. The findings from earlier social media platforms do not necessarily apply to short videos, as they differ substantially from previous platforms in key aspects such as algorithms, content, engagement rates, and user retention. Based on a large sample of longitudinal survey data and standard causal-effect identification strategies, this study uncovers a significantly positive impact of short videos on employment, particularly for marginalized groups that often encounter barriers in traditional labor markets.

2 Background

2.1 Prevalence of short videos

Unlike other social media platforms, algorithm-powered short videos, such as TikTok, YouTube Shorts, and Instagram Reels, employ advanced algorithms and recommendation systems to analyze user preferences, behavior, and content attributes, delivering personalized recommendations that can propel videos to viral status in minutes. Using hybrid recommendation techniques, including content-based filtering, similarity matching, and trend analysis, these platforms continuously refine user experiences through real-time feedback and adjustments. Key metrics such as watch time, engagement rate, and user retention serve as primary indicators of algorithm performance, while factors such as metadata, user interactions, and demographic trends influence recommendation outcomes.

Short videos have become a dominant force in digital media, engaging audiences with their creative storytelling, entertainment, and informational value within brief durations of 15 seconds to 3 minutes. Major short video platforms have experienced rapid expansion since their inception. For example, TikTok, launched in 2016, has amassed 1.9 billion active users globally by 2024; Instagram Reels, launched in 2020, has reached 1.8 billion active users by 2024. On average, users spend 1 hour and 16 minutes per day watching short videos, which is expected to account for 90% of all internet traffic.[1] The immense traffic generated by short video platforms worldwide translates into significant economic value.

China aligns with the global trend and has experienced an explosive rise in short video popularity in recent years. As presented in figure 1, the number of short video viewers in China has increased dramatically since 2018. Daily active users rose from about 30 million in 2018 to nearly 800 million in 2023, accounting up 57% of the total population in China. By December 2023, the total number of short video accounts nationwide had reached 1.55 billion, with 15.08 million professional content creators.

1. Data source: https://firework.com/blog/short-form-video-statistics.

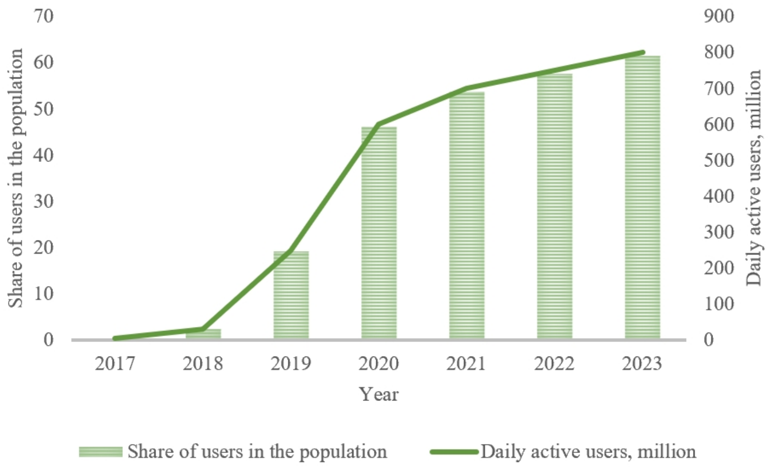

FIGURE 1 Popularity of algorithm-powered short videos in China

Notes: The data are derived from China Internet Network Information Center.

2.2 Potential impact of short videos

Short video platforms have emerged as powerful tools for fostering employment opportunities and enhancing income generation. Their diverse mechanisms for economic participation cater to a broad spectrum of users, from digital content creators to small business owners and marginalized groups. According to the Douyin Life Services Store Visit Data Report, from January to November 2024, more than 3 million people earned income through Douyin, generating over 133.3 billion yuan in revenue for offline businesses. Similarly, TikTok contributed $24.2 billion to US GDP last year and drove $14.7 billion in revenue for small business owners.[2]

Short video platforms could facilitate employment through the following channels. First, they have significantly lower barriers to content creation, allowing individuals of all backgrounds to generate income through digital media. Platforms such as Douyin provide intuitive editing tools that allow users to create high-quality videos without advanced technical skills. This reduced production threshold encourages mass participation, transforming everyday users into potential content creators. Unlike traditional media industries that rely on structured contracts, short video platforms directly distribute advertising revenue to creators.

Second, short videos help viewers improve their vocational skills and access job opportunities. Users can access various instructional content, including vocational training, professional development courses, and industry-specific skill building tu-

2. Data source: https://www.washingtonpost.com/technology/2024/03/13/tik-tok-economic-impact-report/

torials. For example, TikTok has become a popular platform for career advice. According to a 2023 EduBirdie study, 70% of the surveyed Generation Z people turned to TikTok for career advice. In addition, job–related content, such as career guidance, industry insight, and direct job postings, helps bridge labor market gaps by improving the efficiency of job matching. Some platforms have introduced live-streamed job fairs, enabling real-time interaction between employers and job seekers.

Third, short video platforms inspire entrepreneurial ambition by exposing users to real-life success stories and expanding market access for small businesses. Seeing others thrive in content creation, e-commerce, or digital marketing motivates people to explore similar income-generating opportunities. In addition, these platforms play a crucial role in expanding market access for small businesses and rural entrepreneurs. By eliminating traditional middlemen, farmers and artisans can sell their products directly to consumers via short videos and live-streaming sessions. For example, small and midsize business activity on TikTok contributed $24.2 billion to GDP in the US in 2023 while supporting 224,000 jobs.[3]

A particularly notable aspect of short video platforms is their ability to empower marginalized groups—including older people, stay-at-home mothers, and individuals with disabilities—who often face barriers in traditional labor markets. For example, stay-at-home mothers have used mom-blogging niches, where content centered on parenting, childcare, and family life generates substantial engagement and income. Beyond content creation, short video platforms also function as digital marketplaces for gig work and freelancing. Many individuals now use these platforms to recruit talent for small-scale work, such as designing PowerPoint presentations, writing online articles, or providing virtual assistance.

Despite these advantages of short videos, their potentially addictive nature leads to concerns about the side effects of excessive use, particularly on mental health. This concern is especially relevant considering that billions of people spend more than 1 hour on short videos every day. Previous studies on the impact of other social media generally find a negative impact of social media on mental health (e.g., Braghieri et al., 2022). The impact of exposure to short videos on mental health could be different from that of other social media because it is different in key metrics such as algorithms, content, engagement rate, and user retention.

3. Data source: https://tiktokeconomicimpact.com/

3 Data and Method

3.1 Data

3.1.1 The China Family Panel Studies

This paper utilizes data from the China Family Panel Studies (CFPS), the Chinese equivalent of the US Panel Study of Income Dynamics. Initiated in 2010 by the Institute of Social Science Survey at Peking University, CFPS is a nationally representative, biennial longitudinal survey. The main sample covers 14,798 households and 33,600 individuals from 162 counties and districts in 25 provinces of mainland China. Figure 2 presents the geographic distribution of the sample. The CFPS questionnaire has a rich set of questions that cover topics such as economic activities, education outcomes, family dynamics and relationships, migration, and health. This study uses data from the six waves of the survey in 2012, 2014, 2016, 2018, 2020, and 2022.[4]

4. The CFPS collects data on all genetic family members, whether they are at home or have left home for study, work, marriage, or other reasons. For those non-co-residing family members who are hard to reach for face-to-face interviews, the CFPS uses telephone or web interviews whenever possible. The response rate for each wave is approximately 81–84 percent at the individual level.

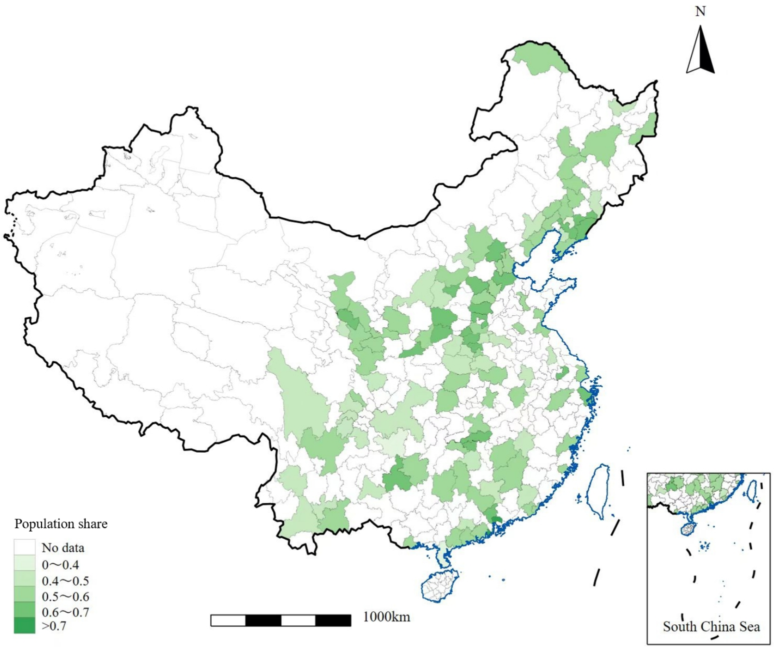

FIGURE 2 Sample cities of the CFPS survey and the average share of individuals watching short videos

Notes: This figure presents the distribution of prefectural-level cities containing the CFPS sample. It also presents the share of the surveyed individuals watching short videos in 2020 in each city.

The 2020 and 2022 waves of the CFPS asked respondents "whether you watched short videos" and "whether you watched short videos every day." The earlier waves of CFPS (2012, 2014, 2016, and 2018) do not collect such information as the prevalence of short videos in China occurred mainly after 2018 (Figure 1). A limitation of our dataset is that we do not know whether an individual watched short videos in the earlier waves, although there was only a small share of the population (1.8%) who watched short videos in 2018 according to Figure 1. In robustness checks, we exclude data from the 2018 survey and find very comparable results (Tables 2 and 5).

3.1.2 Summary statistics of key variables

Penetration rate of short videos. As presented in Figure 3, short videos are popular in most age groups and education groups. Panel A shows that 56.8% of the population watched short videos in 2022 on average, with 44.9% watching every day. Short videos are most popular among people under 40 years old, with more than 8% of them watching short videos. The popularity declines with age, but there are still more than 40% of those aged 50–60 watching short videos. Panel B shows that the share of the population watching short videos increases with the education level.

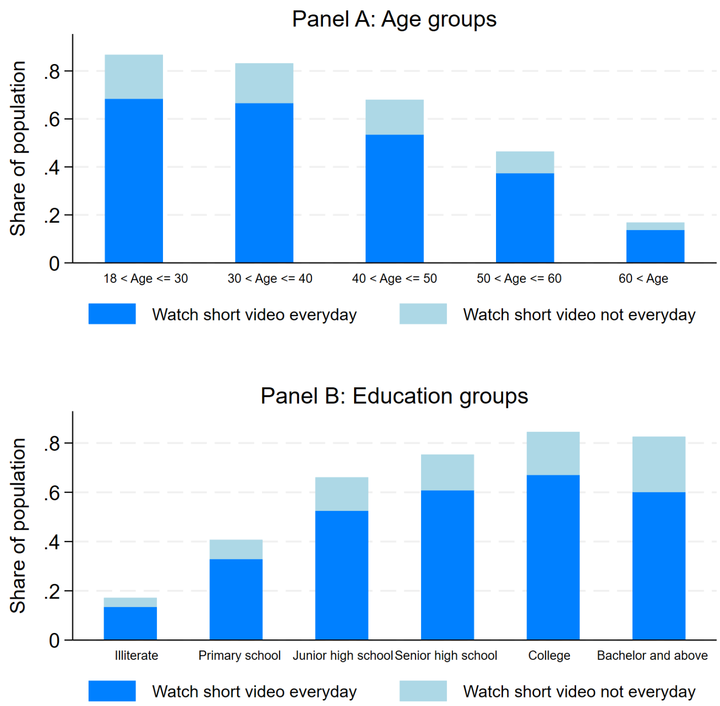

FIGURE 3 Share of the population watching short videos in 2022 in each age and education group

Notes: This figure is based on the data from the 2022 CFPS survey. Those watching short videos are further classified as watching every day and not every day.

Figure 4 presents the estimated hours spent on short videos. The survey does not contain information on the time each individual spent watching short videos; we estimate the time spent on short videos by regressing the time spent on a smartphone each day on the dummy variable of watching short videos (based on model (1)). Panel A shows that those watching short videos spend about one hour every day on short videos, with the longest watching hours found for those older than 60. Panel B shows that watching short videos significantly increased the time spent on smartphones by those with a relatively low education level, but had no significant effect on those who received a college education or above.

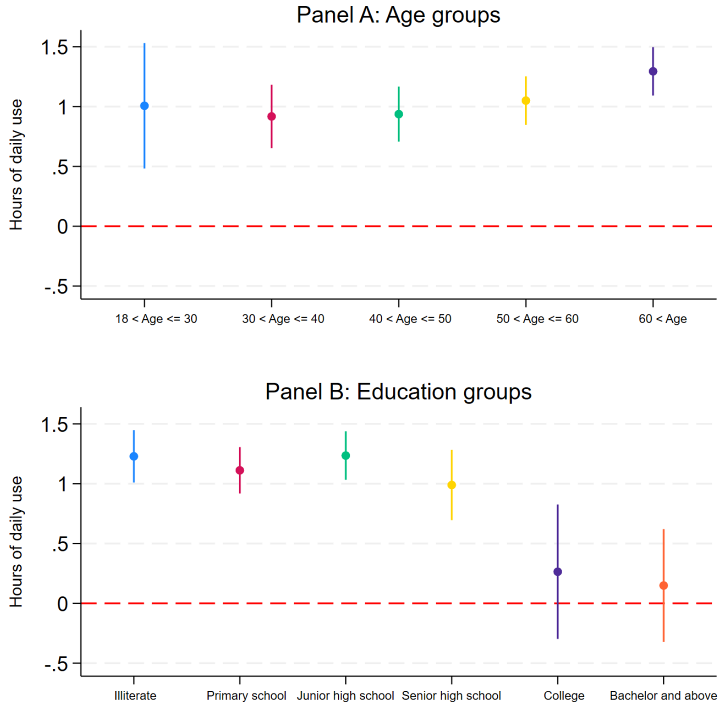

FIGURE 4 Effect of short videos on individual time spent on smartphone
Notes: This figure presents the effect of watching short videos on individual time spent on a smartphone, estimated based on model (1) for each population group.

Potential impact on employment. Figure 5 presents the changes in the distribution of employment before and after individuals' access to short videos. Specifically, for those recorded as watching short videos, we obtain their employment status (employed or not) in the survey waves just before and just after watching. The survey defines an individual as employed if he or she worked at least one hour in the past week for income. We then plot the distribution of the chance of being employed before and after watching short videos, respectively, across age groups. The figure suggests that short videos significantly increased the chance of being employed for people older than 23 years. To address the concern that the increase in employment after watching could be caused by the time trend, Appendix Figure A.1 (Panel A) compares people watching short videos or not in the same year (2022) and finds a similar result. In addition, Appendix Figure A.1 (Panel B) also shows that those watching short videos or not have no significant differences in employment before short videos become available.

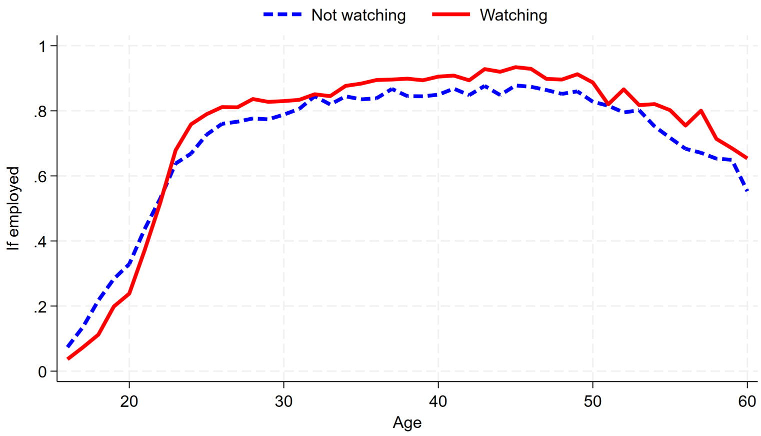

FIGURE 5 Employment distributions before and after access to short videos
Notes: This figure plots the distribution of the chance of being employed just before and after watching short videos, respectively, across age groups.

Potential impact on mental health We adopt a standard mental health measure widely used in the literature (Radloff, 1997; Haushofer and Shapiro, 2016; Huang et al., 2024a): The Center for Epidemiological Studies Depression Scale (CESD), which is constructed based on a series of questions that require individuals to rate how often, over the past week, they experienced symptoms associated with depression. Specifically, we calculate CESD based on answers to eight standard questions: *I feel down*, *I find it difficult to do anything*, *I have trouble sleeping*, *I feel happy*, *I feel lonely*, *I enjoy life*, *I feel sad*, and *I feel life is unbearable.* Each question provided four response options: 1 = almost never (less than 1 day), 2 = sometimes (1–2 days), 3 = often (3–4 days), and 4 = most of the time (5–7 days). For the two positively framed items, *I feel happy* and *I enjoy life*, we reverse the scoring direction. The CESD is then calculated as the sum of the answers to these questions (Liu et al., 2025). As such, a higher value of CESD corresponds to a worse mental health status. To facilitate interpretation, we normalized the CESD by subtracting the mean and dividing the standard deviation. When analyzing the effect on mental health, we excluded data from the 2014 wave, which does not contain comparable mental health measures.

Figure 6 presents the density distribution of CESD for individuals before and after watching short videos. Specifically, for those recorded as watched short videos, we keep their CESD value from survey waves just before and after watching. We then plot the distribution of the CESD before and after watching short videos, respectively. Note that the figure excludes people who have never watched short videos to ensure comparability. We find a significant shift to the right in the distribution of CESD, suggesting a detrimental impact of short videos on mental health.

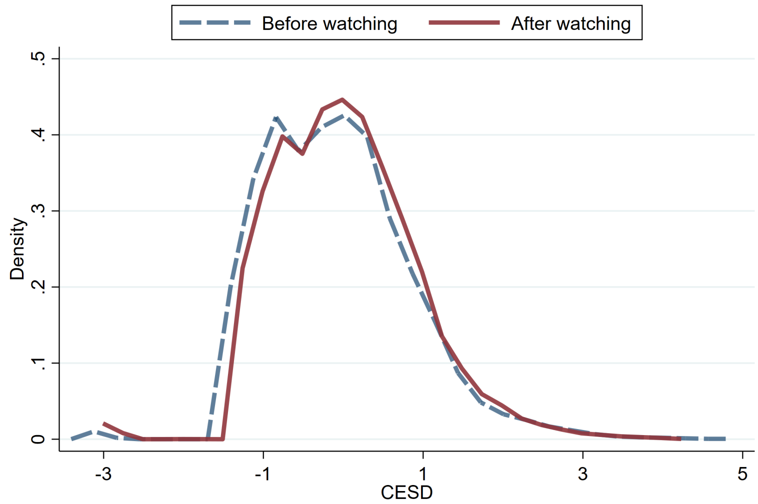

FIGURE 6 Distributions of the standardized CESD before and after individuals watching short videos

Notes: This figure presents the density distribution of CESD for individuals before and after watching short videos.

3.2 Method

3.2.1 Staggered Difference-in-Differences estimation

Our baseline analysis is based on a staggered DID model:

$$Y_{ict} = \beta Treated_{ict} + \theta_i + \theta_c + \theta_t + X_{ict}\gamma + \epsilon_{ict} \tag{1}$$

where Y_{ict} is the outcome variable of interest for individual i from cohort c in year t. The key outcome variables are employment status and CESD; various other outcome variables will be used in the supplementary analysis. The dummy variable $Treated_{ict}$ equals one if the individual i watches short videos in year t. The model also controls for individual fixed effects (θ_i), cohort fixed effects (θ_c), year fixed effects (θ_t) and a set of time-varying factors (Hukou, marriage status and education level, included in X_{it}) that will be detailed later.[5] Finally, ϵ_{ict} is the error term. Standard errors will be clustered at the county level in the main analysis.

The coefficient of interest β captures the effect of short videos. Identification is

5. Hukou is the household registration system in China. There are two main types: rural hukou and urban hukou. Historically, these two types were associated with different levels of access to resources and social welfare. Individuals can adjust their Hukou under certain conditions.

based on the plausibly exogenous variation in the penetration rate of short videos over time and across regions. As presented in Figure 2, the share of individuals watching short videos varies substantially across regions. The underlying assumption is that people exposed to short videos early and later (or never) would follow the same trend without short videos. To make this assumption more realistic, the estimation model includes individual and cohort fixed effects to account for time-invariant differences across individuals and includes year-fixed effects to account for shocks common to all individuals.

3.2.2 Event-study estimation

To verify the identification assumption, we estimate the following event-study model:

$$Y_{ict} = \sum_{k=-4, k \neq -1}^{2} \beta_k D_{ict} + \theta_i + \theta_c + \theta_t + X_{ict}\gamma + \epsilon_{ict} \tag{2}$$

D_{ict} is an indicator variable for the k^{th} period (survey wave) relative to the event time (start to watch short videos). The coefficients β_k for $k \geq 0$ capture the dynamic effects of treatment. The coefficients β_k for $k < 0$ serve as a falsification test. The period $k = -1$ is set as the baseline and omitted from the regression. All other model settings are the same as the baseline DID model (1). As presented in Figures 9 and 12, we find that all estimates of β_k for $k < 0$ are close to zero and statistically insignificant for employment and CESD. This finding is robust to different methods addressing heterogeneous treatment effects (Clarke and Tapia Schythe, 2023; Cengiz et al., 2019) (also presented in Figures 9 and 12).

3.2.3 Matched Difference-in-Differences estimation

To further address the concern of endogeneity bias, we also adopt a matched DID estimation. Specifically, we use the propensity score matching (PSM) method (Dehejia and Wahba, 2002) to reconstruct the more comparable treated and control groups. We match individuals based on five characteristics that are likely to affect individual chances of watching short videos: gender, years of schooling, rural or urban residents, marital status, and age and its square. As presented in Figure 7, the matching process substantially reduced the differences between people who watch short videos and those who do not. The matched DID estimate addresses the concern that people watching short videos or not are not randomly assigned.

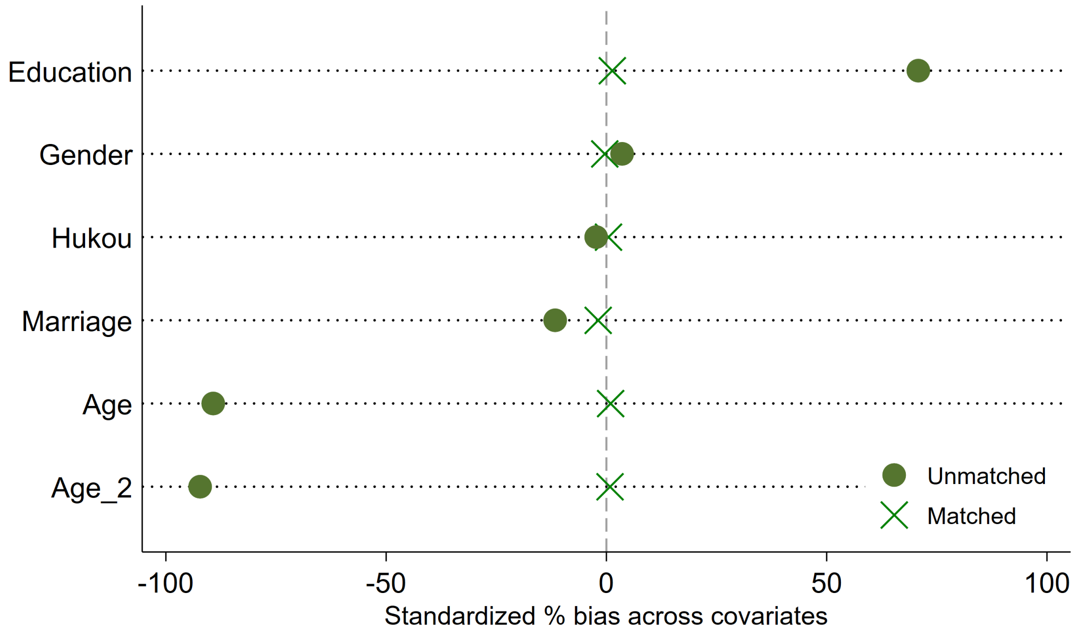

FIGURE 7 Efficiency of the Propensity Score Matching

Notes: This figure presents the Difference in key features between individuals watching short videos or not before and after the Propensity Score Matching. We adopt the propensity score matching method of (Dehejia and Wahba, 2002) for five features that could affect the individual chance of watching short videos: gender, years of schooling, rural or urban residents, marital status, and age and its square.

3.2.4 Instrumental Variable estimation

Finally, we adopt an IV estimate to address the endogeneity concern further. We construct the IV for watching short videos based on plausibly exogenous supply shocks from the establishment of cultural and entertainment brokerage companies (also known as Multichannel Network (MCN) companies). MCN companies are major suppliers of short videos in China. MCN companies contract and manage a large number of content creators, providing services such as daily operations, content creation, and advertising to help creators gain more exposure and revenue across various platforms. According to the *China MCN Industry Development Report* published by Fudan University, the establishment of MCN companies is closely tied to the rise of short videos in different regions. MCN companies began to establish on a large scale from 2019. The total national number of MCN companies increased from 2,896 in 2019 to 14,233 in 2022.

We construct the IV in the following steps. First, we collect annual data on the number and size of MCN companies in each city from the Tianyancha platform.[6]

6. Tianyancha is a platform providing the most comprehensive business registration information in China. The website is `https://www.tianyancha.com/`.

Figure 8 shows the significant variation in the number of MCN companies in cities. Second, we calculate the size-weighted total number of MCN companies in each city.[7] Third, we calculate the closest distance by road from one city to each of the other cities based on ArcGIS and the latest road maps. Finally, we construct the IV for individuals in city k as the inverse-distance-weighted total number of size-weighted MCN companies from all other cities.[8] Note that the calculation excludes MCN companies from city k itself to avoid the concern that they are endogenous to individuals in the city. The IV allows for a larger effect of MCN companies from nearby cities, consistent with the fact that people tend to be more interested in short videos created based on topics related to their attachments. As presented in Table 3, the estimates in the first stage suggest that the IV is strongly and positively correlated with the chance to watch short videos.

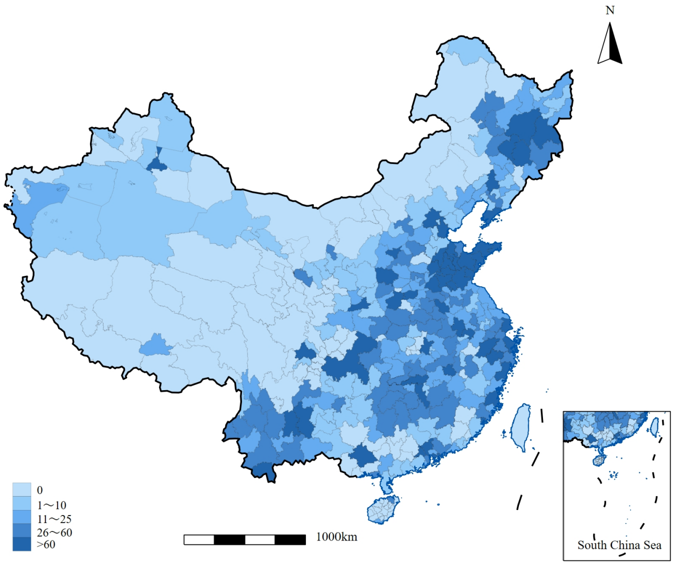

FIGURE 8 Number of MNC companies in each city in 2020

Notes: The data are derived from the Tianyancha platform.

7. In the data, each MCN company is classified as a micro-enterprise, small enterprise, medium enterprise, or large enterprise. We follow the literature to sign a weight of 0.5, 1, 1.5, and 2 for each type of enterprise (Astakhov et al., 2019).

8. The IV for all individuals in city k and year t is calculated as $IV_{kt} = \sum_{\text{other cities } j} \left(\frac{1}{d_{k,j}} \times \text{MCN}_{jt}\right)$, where $d_{k,j}$ is the distance between city k and city j, and MCN_j is the size-weighted MCN number in city j.

4 Results

4.1 Impact on employment

4.1.1 Baseline estimates

Table 1 presents the effect of short videos on employment, estimated based on model (1). Column 1 suggests that exposure to short videos increases the likelihood of being employed 7.5%. Recall that the survey defines an individual as employed if he or she worked more than 1 hour per week for income. This definition is suitable for examining the effect of short videos, which tend to increase part-time employment (see subsection 2.2 for details). Column 2 confirms this by showing that short videos only increase weekly working hours by 0.68 (or 1.45% of the mean). Columns 3 and 4 show that short videos significantly increased the chances of having off-farm work and self-employment, respectively. Appendix Table B.1 shows that exposed to short videos significantly increased income and consumption.

TABLE 1 Impact of short videos on employment

	If employed	Working hours per week	If with off-farm work	If self-employed
	(1)	(2)	(3)	(4)
Short video	0.075***	0.678**	0.071***	0.010**
	(0.006)	(0.329)	(0.005)	(0.004)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Dep.Var.Mean	0.662	46.588	0.491	0.109
Observations	153,455	69,025	116,756	99,634
R-squared	0.602	0.584	0.767	0.675

Notes: This table presents the effect of short videos on employment, estimated based on model (1). Standard errors reported in parentheses are clustered at the county level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.1.2 Robustness checks

We examine the robustness of the estimated effect on employment to omitted variables, measurement error, and alternative estimation methods (i.e., event study, heterogeneous treatment effect, PSM, and IV estimations). To save space, all robustness checks focus on the outcome variable if employed. All robustness checks have the same model setting as the baseline estimation except for the one specified in each check.

Robust to omitted variables. Column 1 of Table 2 excludes the time-varying control variables, column 2 additionally controls the dummy of using the Internet, and column 3 additionally controls for the infection rate of COVID-19 in each city.[9] The resulting estimates are all comparable to the baseline estimate. Column 4 replaces the individual-fixed effects with the county-fixed effects, which are less able to account for time-invariant differences between individuals. The resulting estimates are similar, suggesting that the estimated effect is not primarily driven by preexisting differences between individuals. Column 5 clusters the standard error at the county-year level and does not significantly alter the estimated standard error. Finally, column 6 excludes data from the 2018 survey to address the concern that the status of watching short videos was not precisely measured in that year (see subsection 3.1.2 for details). The resulting estimates are comparable.

TABLE 2 Robustness of the effect on employment

	If employ					
	Excluding control variables	Control for internet use	Control for COVID-19	County FE	County-year cluster	Drop 2018 data
	(1)	(2)	(3)	(4)	(5)	(6)
Short video	0.108***	0.074***	0.056***	0.074***	0.075***	0.082***
	(0.006)	(0.006)	(0.008)	(0.006)	(0.005)	(0.007)
Individual FE	Yes	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	Yes	No	No
Observations	161,800	153,455	131,184	162,220	153,455	128,493
R-squared	0.594	0.602	0.622	0.253	0.602	0.609

Notes: This table examines the robustness of the effect of short videos on employment based on model (1). The sample size varies across columns due to the different availability of control variables. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Robust to estimation methods. Figure 9 presents even-study estimates based on model (2). The baseline event-study estimates suggest that the effect increases over time after exposure to short videos, while no significant effects are observed before that. To address the concern that individuals watching short videos

9. The city-year level COVID-19 infection rate data are collected from the official websites of each city.

or not may not be comparable, the figure also presents the event-study estimates based on the PSM sample (see subsection 3.2.3 for details). The resulting event-study estimates are very similar. In addition, we address the potential bias from heterogeneous treatment effects by adopting the frequently used methods proposed by Clarke and Tapia Schythe (2023) and Cengiz et al. (2019), respectively. The resulting estimates are close to the baseline event study estimates.

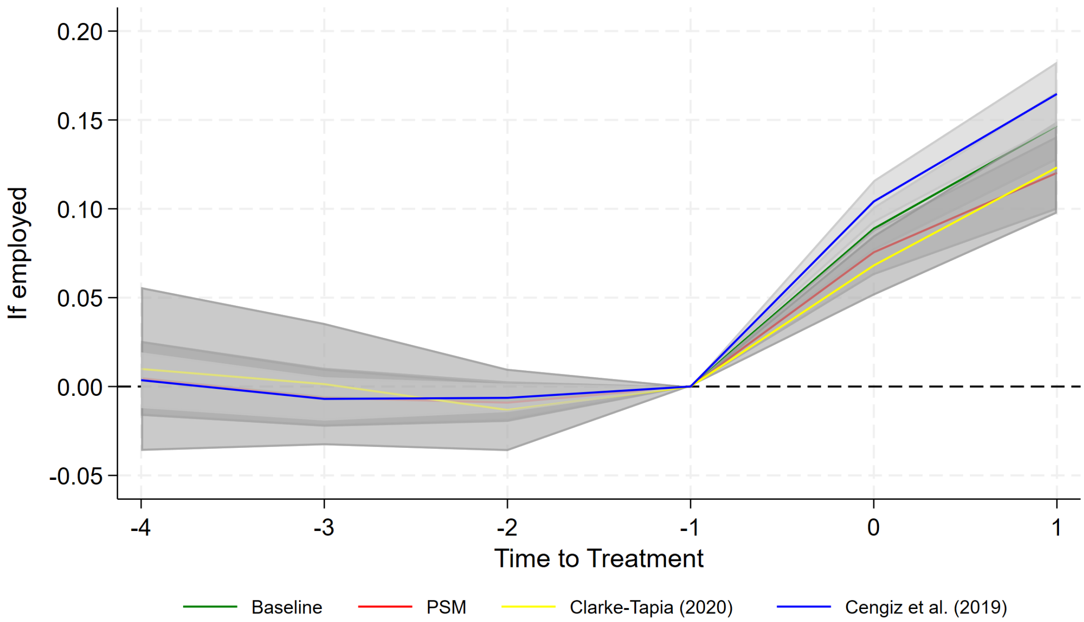

FIGURE 9 Dynamic effects of short videos on employment

Notes: This figure presents the dynamic effects of short videos on employment, estimated based on the event-study model (2). Besides the baseline event-study estimates, the figure also presents the PSM event-study estimates and the event-study estimates addressing heterogeneous treatment effects proposed by Clarke and Tapia Schythe (2023) and Cengiz et al. (2019). The shadow areas denote the 95% confidence intervals calculated based on standard errors clustered at the county level.

Instrumental Variable estimates. Columns 1 and 2 of Table 3 present the IV estimates. As detailed in subsection 3.2.4, the IV is constructed based on the inverse-distance weighted supply shocks of short videos from other cities. Panel B of the table presents the first-stage estimates, suggesting a positive and strong effect of the IV on the chance of watching short videos. The IV estimates presented in column 1 of Panel A confirm that short videos significantly increased the chance of being employed, although the IV estimate is larger than the baseline estimate.[10] Column 2 excludes data from 2018 and obtains a very comparable IV estimate.

10. Existing studies suggest that adopting an IV approach tends to enlarge the estimated effect (Huang et al., 2024b; Zhang and Assaad, 2024; Jiang, 2017).

TABLE 3 Instrumental Variable estimates

Panel A	If employed		CESD	
	Baseline	Drop 2018 data	Baseline	Drop 2018 data
Second stage	(1)	(2)	(3)	(4)
Short video	0.298***	0.264**	0.660**	0.718**
	(0.101)	(0.105)	(0.314)	(0.331)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Observations	155,489	129,895	114,693	87,697
Wald F	117.5	122.6	66.6	69.4

Panel B	Short video			
First stage	(1)	(2)	(3)	(4)
IV	0.160***	0.161***	0.123***	0.124***
	(0.015)	(0.015)	(0.015)	(0.015)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Observations	155,489	129,895	114,693	87,697

Notes: This table presents the IV estimates of model (1), based on the IV constructed in subsection 3.2.4. Columns 1 and 2 estimate the effect on employment, while columns 3 and 4 estimate the effect on CESD. Columns 1 and 3 utilize the full sample, while columns 2 and 4 drop the data from 2018. Standard errors reported in parentheses are clustered at the county level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.1.3 Heterogeneity of the effect

Figure 10 presents the heterogeneity of the effect across education and income groups, estimated based on the model (1) using data from each group. Panel A shows that short videos have no significant effect on those with a bachelor's or higher degree but increase the employment of all other education groups. Panel B shows that the positive impact on those with a low income is much higher than on those with a high income. These estimates suggest that short videos tend to reduce the level of inequality in employment between educational and income groups. This finding is consistent with the fact that short videos tend to empower marginalized groups (see subsection 2.2 for details).

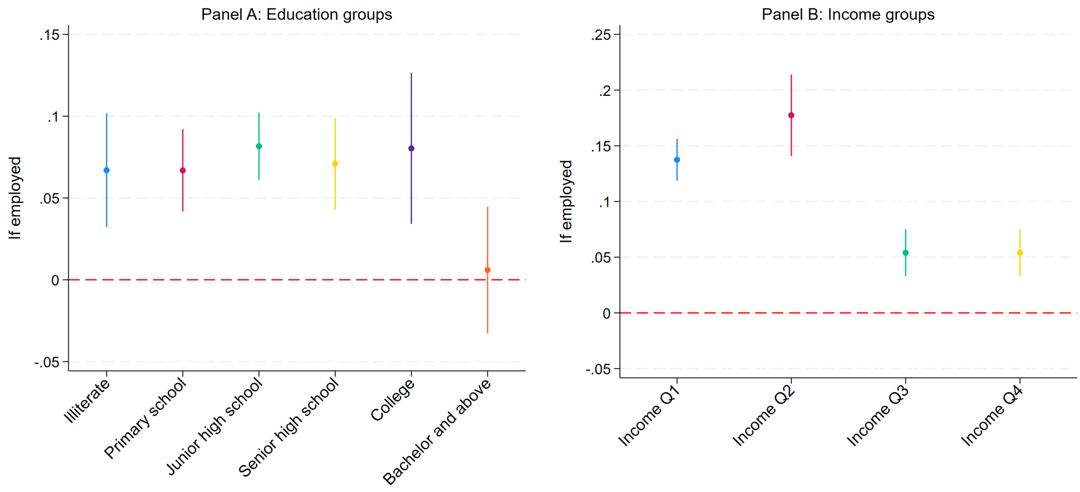

FIGURE 10 Effects of short videos on the employment of different education and income groups

Notes: This figure presents the effect of short videos on the employment of different education groups (Panel A) and income groups (Panel B), estimated based on model (1) for each group. The vertical lines denote the 95% confidence intervals calculated based on standard errors clustered at the county level.

Figure 11 examines the heterogeneity of the effect across different individual characteristics. The effects of heterogeneity are estimated based on a modified version of the model (1) that additionally includes the interaction between the dummy watching short videos and the dummy of each characteristic. We find a significantly larger effect on those with a rural hukou than on those with an urban hukou. Those with a rural hukou usually have relatively low levels of education and income. We also find a larger positive effect on mothers with young children. These findings further highlight that short videos increase the employment of marginalized groups. In addition, we find significantly large effects on the young and unmarried but similar effects between genders.

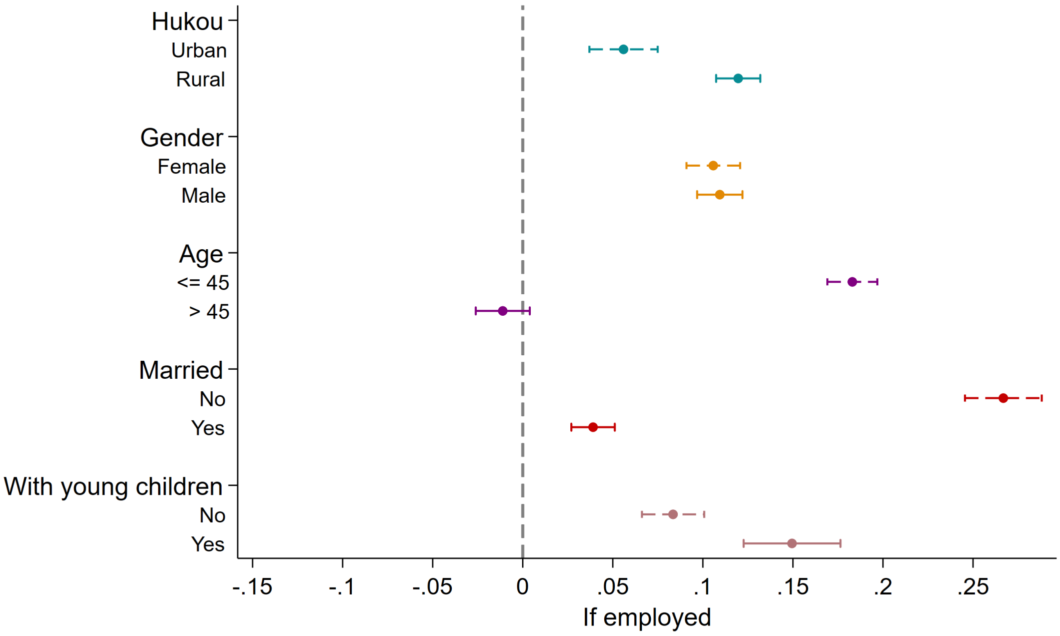

FIGURE 11 Heterogeneity of the effect of short videos on employment

Notes: This figure examines the heterogeneity of the effect of short videos on employment across different individual characteristics, estimated based on a modified version of model (1) that additionally includes the interaction between the dummy of watching short videos and the dummy of each characteristic. The corresponding point estimates are reported in Appendix Table B.2. The horizontal lines denote the 95% confidence intervals calculated based on standard errors clustered at the county level.

4.2 Impact on mental health

Table 4 presents the effects of short videos on mental health, estimated based on the model (1). Column 1 shows that watching short videos significantly increases the CESD by 0.096 standard deviation. As a larger CESD corresponds to worse mental health, this estimate suggests that short videos significantly reduce the mental health of individuals. Columns 2–9 of the table present the estimated effect for each of the eight components of CESD, respectively. All these components are standardized, and a larger value corresponds to a worse mental health outcome. We find that short videos have a positive effect on each of the eight components, although the effect on the last component is not statistically significant.

TABLE 4 Effect of short videos on mental health

	CESD	Feel down	Difficult to do anything	Poor sleep	Feel unhappy
	(1)	(2)	(3)	(4)	(5)
Short video	0.096***	0.077***	0.050***	0.067***	0.090***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.014)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	115,601	121,534	121,569	121,728	121,652
R-squared	0.581	0.451	0.472	0.530	0.426

	Feel lonely	Lack of joy in life	Feel sad	Feel life is unbearable
	(6)	(7)	(8)	(9)
Short video	0.053***	0.116***	0.047***	0.020
	(0.015)	(0.014)	(0.014)	(0.013)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Observations	121,584	121,633	121,667	121,561
R-squared	0.479	0.434	0.481	0.456

Notes: This table presents the effect of watching short videos on mental health, estimated based on model (1). Column 1 estimates the effect on CESD, while columns 2–9 estimate the effect on each of the mental health measures used to construct CESD. The sample size is smaller than that of the above analysis as comparable mental health data are not available in the 2014 survey. Standard errors reported in parentheses are clustered at the county level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Tables 3 and 5 and Figure 12 examine the robustness of the estimated effect on mental health. Table 5 shows that the estimated effect is robust to excluding control variables (column 1), control for Internet use (column 2), control for the COVID-19 infection rate (column 3), replacing individual-fixed effects by county-fixed effects (column 4), clustering the standard error at the county-year level (column 5), and excluding data from 2018 (column 6). Columns 3 and 4 of Table 3 present IV estimates that also suggest a significant detrimental effect of short videos on mental health. Figure 12 presents the event-study estimates and shows that the estimates are robust to adopting the PSM sample and addressing the potential bias from the effects of heterogeneous treatment.

TABLE 5 Robustness of the effect on mental health

	CESD					
	Excluding control variables	Control for internet use	Control for COVID-19	County FE	County-year cluster	Drop 2018 data
	(1)	(2)	(3)	(4)	(5)	(6)
Short video	0.108***	0.061***	0.077***	0.144***	0.096***	0.114***
	(0.015)	(0.017)	(0.022)	(0.014)	(0.013)	(0.017)
Individual FE	Yes	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	Yes	No	No
Observations	121,107	115,601	92,575	125,813	115,601	89,677
R-squared	0.575	0.581	0.610	0.089	0.581	0.605

Notes: This table examines the robustness of the effect on mental health. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

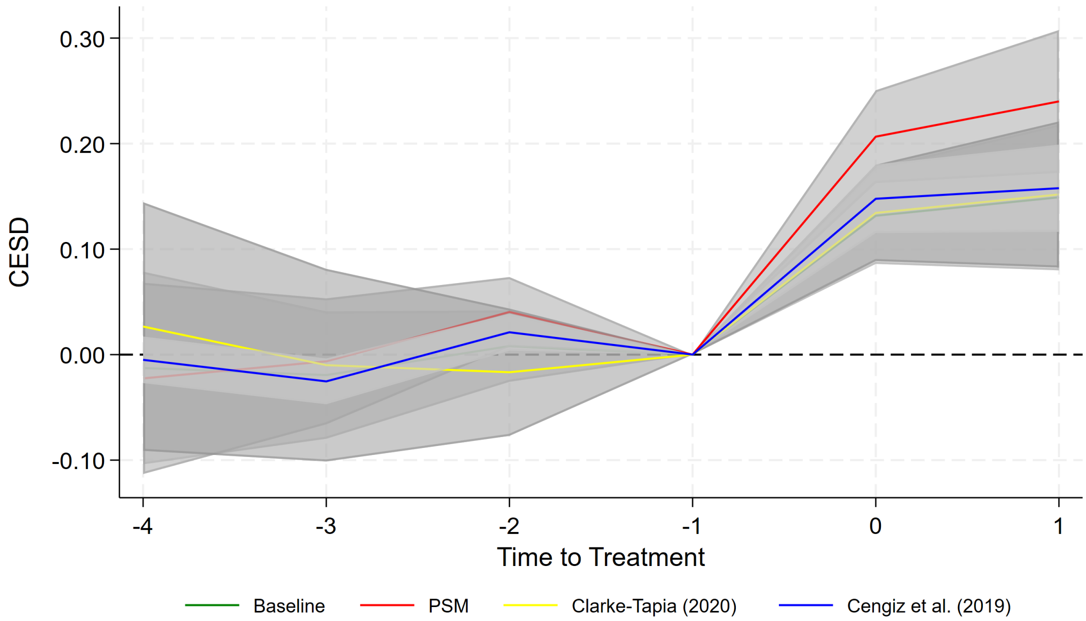

FIGURE 12 Dynamic effects of short videos on mental health

Notes: This figure presents the dynamic effects of short videos on mental health, estimated based on different versions of the event study model (2). Besides the baseline event-study estimates and the PSM event-study estimates, we also present the event-study estimates of Clarke and Tapia Schythe (2023) and Cengiz et al. (2019) to address the heterogeneous treatment effects. The shadow areas denote the 95% confidence intervals calculated based on standard errors clustered at the county level.

Figures 13 and 14 present the heterogeneity of the effect of short videos on mental health. Figure 13 shows that the effect of short videos on mental health varies across education groups (Panel A) and income groups (Panel B), but the differences are not statistically significant. Figure 14 shows that the impacts are similar between those with different Hukou, gender, and marital status. Although we find larger detrimental effects for young people and mothers with young children, the differences are also not statistically significant.

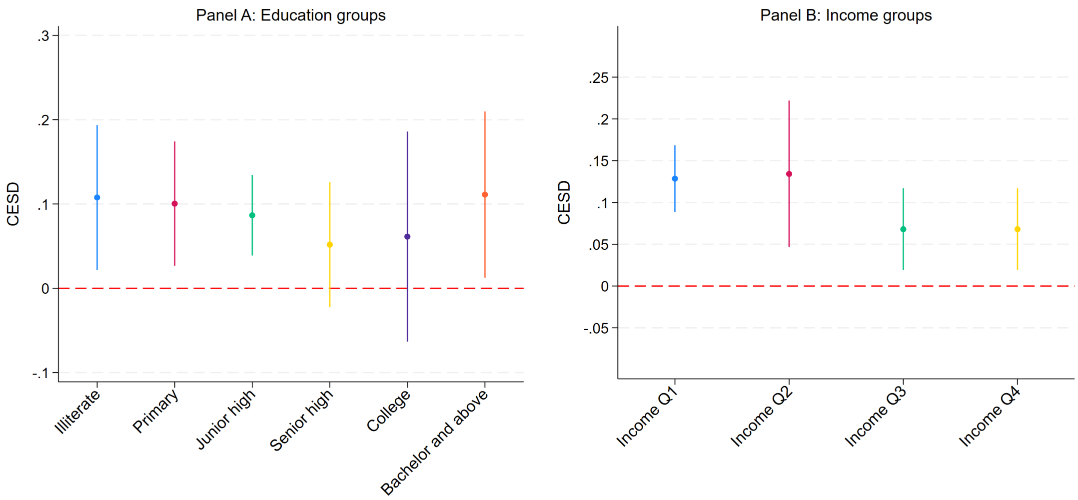

FIGURE 13 Effects of short videos on the mental health of different age and education groups

Notes: This figure presents the effect of short videos on the mental health of different age groups (Panel A) and education groups (Panel B), estimated based on model (1) for each group. The vertical lines denote the 95% confidence intervals calculated based on standard errors clustered at the county level.

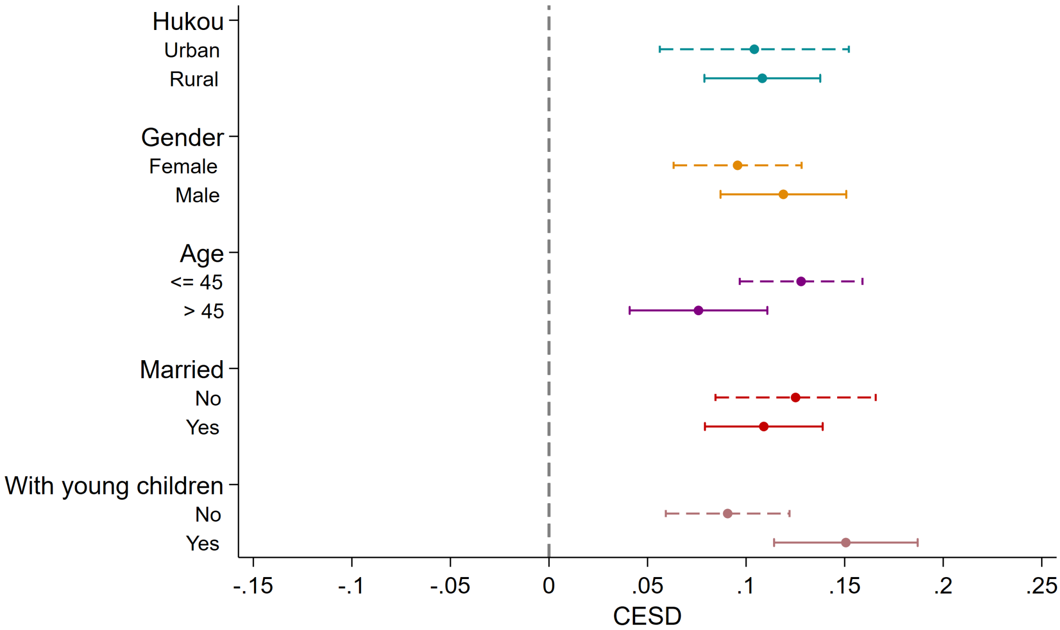

FIGURE 14 Heterogeneity of the effect of short videos on mental health

Notes: This figure examines the heterogeneity of the effect of short videos on mental health across different individual characteristics, estimated based on a modified version of model (1) that additionally includes the interaction between the dummy of watching short videos and the dummy of each characteristic. The corresponding point estimates are reported in Appendix Table B.3. The horizontal lines denote the 95% confidence intervals calculated based on standard errors clustered at the county level.

4.3 Discussion

This subsection highlights three important implications of our study. First, short videos have a more positive impact on the employment of marginalized groups but do not have a more negative impact on their mental health. As presented in Figures 10 and 11, we find that short videos have a more positive impact on the employment of those with a relatively low education level, in low-income groups, from rural areas, and mothers with young children. In contrast, as presented in Figures 13 and 14, we did not find such significant differences in the impact on mental health across population groups. These findings suggest that marginalized groups have a larger net gain from short videos.

Second, the impact on mental health seems to be a side effect of the impact on employment. We have shown that short videos significantly increase the time individuals allocate to work (column 2 of Table 1). A longer work time could reduce the time allocated to rest and physical exercise and increase work pressure. These changes could negatively impact mental health (Carrieri et al., 2020; Harvey et al., 2017; Birnbaum et al., 2010). Appendix Table B.4 presents evidence supporting this. We show that watching short videos significantly reduces the time individuals allocate to physical exercise and sleep and increases unhealthy behavior related to work pressure (i.e., smoking and drinking).

Finally, it is possible to mitigate the negative effect while keeping the positive effect by reducing the frequency of watching short videos. Based on answers to the survey questions of "if you watch short videos" and "if you watch short videos every day", we examine the impact difference between those watching short videos every day and those watching but not every day. As presented in Figure 15, for those watching short videos but not every day, short videos have a much smaller (about one-third) effect on their mental health (Panel B), but the positive effect on their employment is similar (Panel A). These findings suggest the possibility of increasing the net benefit from short videos by reducing the frequency of watching short videos.

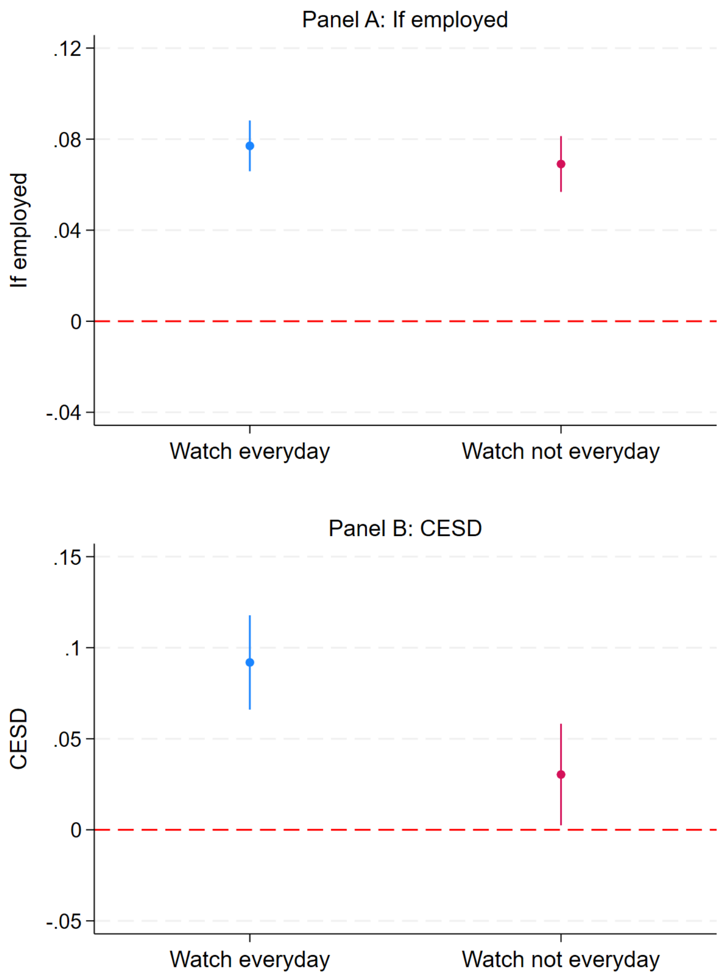

FIGURE 15 Different impacts for people watching short videos every day and not every day

Notes: This figure presents the impact of short videos on those watching every day and those watching but not every day, respectively, estimated based on model (1). The corresponding point estimates are reported in Appendix Tables B.2 and B.3. The vertical lines denote the 95% confidence intervals calculated based on standard errors clustered at the county level.

5 Concluding Remarks

Algorithm-powered short-form videos have become a dominant force in digital media. Unlike other digital media, short video platforms employ advanced algorithms and recommendation systems to analyze user preferences and deliver personalized recommendations that can propel videos to viral status in minutes. Short video platforms have emerged as powerful tools to foster employment opportunities and boost income generation. Their diverse mechanisms for economic participation cater to a broad spectrum of users, from digital content creators to small business owners and marginalized groups. In addition, the addictive nature of short videos also leads to substantial concerns about the side effects of excessive use, particularly on mental health. However, rigorous economic studies on the impact of short videos are scarce. Most of our understanding of the impact of short videos comes from judgment in news reports and publications in the psychology and medical fields.

Based on field survey data for about 27,000 individuals in China from 2012 to 2022, we estimate the impact of short videos on employment and mental health. We find that short videos significantly increased part-time employment, especially for the marginalized groups in lower-income quartiles, from rural areas, and mothers of young children. We show that short videos significantly reduced mental health, but the impact on mental health does not differ significantly across population groups. We present evidence that the negative impact on mental health seems like a side effect of short videos on employment and that reducing the frequency of watching short videos could substantially lower the damage to mental health while keeping most of the positive effects on employment.

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Online Appendix

A Data appendix

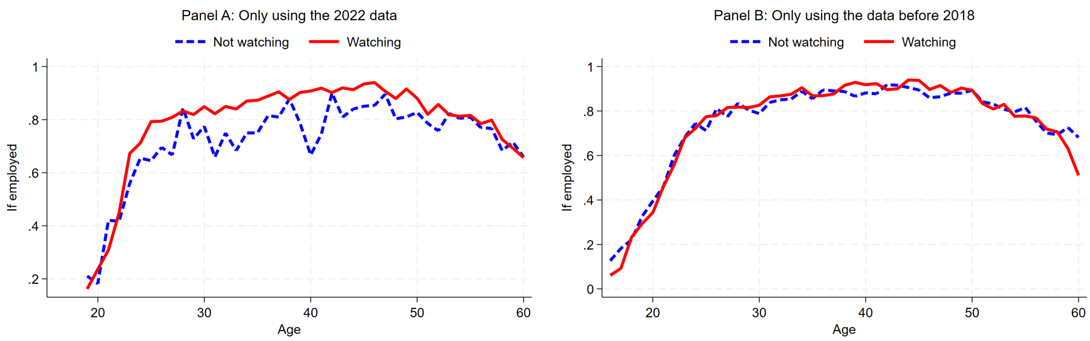

FIGURE A.1 Potential impact of watching short videos on employment

Notes: Panel A presents the chance of being employed for those watching short videos and not, respectively, in 2022. Panel B classifies individuals as watching short videos or not based on the 2022 data. It then plots the distribution of employment in 2016 for those classified as watching or not, respectively.

B Result appendix

TABLE B.1 Effect of short videos on income

	Monthly per capita net income (1)	Monthly employment income (2)	Monthly operate income (3)	Monthly per capita expenditure (4)	If online shopping (5)
Short video	456.3***	549.0***	105.3***	321.9***	0.093***
	(30.8)	(51.1)	(33.8)	(25.8)	(0.014)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes
Dep.Var.Mean	1741.0	1971.4	615.7	1596.4	0.593
Observations	154,987	74,292	57,982	154,854	55,782
R-squared	0.637	0.744	0.603	0.575	0.554

Notes: This table presents the effect of exposed to short videos on income, estimated based on model (1). Standard errors reported in parentheses are clustered at the county level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE B.2 Heterogeneity of the impact on employment

	If employed						
	Rural hukou (1)	Male (2)	Age > 45 (3)	Married (4)	Mother with young children (5)	Short video everyday (6)	Short video not everyday (7)
Short video	0.056***	0.106***	0.183***	0.267***	0.083***		
	(0.010)	(0.008)	(0.007)	(0.011)	(0.009)		
Key	-0.056***	-0.015	0.032***	0.093***	-0.060***	0.077***	0.069***
	(0.008)	(0.045)	(0.008)	(0.008)	(0.010)	(0.006)	(0.006)
Short video ×Key	0.064***	0.004	-0.194***	-0.228***	0.066***		
	(0.010)	(0.008)	(0.009)	(0.011)	(0.015)		
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	161,800	161,800	161,800	159,737	81,526	161,800	161,800
R-squared	0.594	0.594	0.597	0.599	0.578	0.592	0.592

Notes: This table examines the heterogeneity of the effect of short videos on employment across different individual characteristics, columns 1-5 are estimated based on a modified version of model (1) that additionally includes the interaction between the dummy of watching short videos and the dummy of each characteristic. Columns 6-7 are estimated based on model (1) using sub-samples. Standard errors reported in parentheses are clustered at the county level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE B.3 Heterogeneity of the impact on mental health

	CESD				
Key	Rural hukou	Gender	Age > 45	Marriage	Mother with young children
	(1)	(2)	(3)	(4)	(5)
Short video	0.104***	0.096***	0.128***	0.125***	0.091***
	(0.024)	(0.017)	(0.016)	(0.021)	(0.016)
Key	0.001	-0.073	0.004	-0.149***	0.001
	(0.017)	(0.112)	(0.016)	(0.021)	(0.014)
Short video	0.004	0.023	-0.052***	-0.016	0.060***
×Key	(0.023)	(0.015)	(0.016)	(0.018)	(0.018)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	121,107	121,107	121,107	121,078	121,107
R-squared	0.575	0.575	0.575	0.576	0.575

	CESD		Time spent on mobile phone	
Key	Short video everyday	Short video not everyday	Short video everyday	Short video not everyday
	(5)	(6)	(7)	(8)
Key	0.092***	0.030**	0.847***	0.023
	(0.013)	(0.014)	(0.057)	(0.070)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Observations	121,107	121,107	30,292	30,292
R-squared	0.575	0.575	0.784	0.777

Notes: This table examines the heterogeneity of the effect of short videos on mental health across different individual characteristics. Standard errors reported in parentheses are clustered at the county level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE B.4 Other related impacts of short videos

	Hours of sleep	Times of exercise	Smoking	Drinking
	(1)	(2)	(3)	(4)
Short video	-0.082***	-0.542***	0.036***	0.020***
	(0.031)	(0.039)	(0.003)	(0.004)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Observations	45,470	67,359	154,333	154,326
R-squared	0.637	0.518	0.846	0.638

Notes: This table presents the effect of short videos on several other outcome variables, estimated based on model (1) with different dependent variables. The dependent variables are hours of sleep per day (column 1),frequency of physical exercise per week (column 2), whether smoked in the past month (column 3), and whether drank alcohol more than three times per week in the past month (column 4).