Digital Distractions with Peer Influence: The Impact of Mobile App Usage on Academic and Labor Market Outcomes*

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Abstract

Concerns about excessive mobile phone use among youth are mounting. We present, to our knowledge, the first estimates of both behavioral and contextual peer effects, along with comprehensive evidence on how students' own and their peers' app usage affect academic performance, physical health, and labor market outcomes. Our analysis draws on administrative data from a Chinese university covering three student cohorts over four years. We exploit random roommate assignments, an exogenous policy shock, and an exogenous event for identification. App usage is contagious: a one s.d. increase in roommates' in-college app usage raises own usage by 5.8%. High app usage is harmful across all measured outcomes. A one s.d. increase in app usage reduces GPAs by 36.2% of a within-cohort-major s.d. and lowers wages by 2.3%. Roommates' app usage reduces a student's GPAs and wages through both disruptions and behavioral spillovers, generating a total negative effect that exceeds half the magnitude of the impact from the student's own app usage. Extending China's three-hour-per-week gaming restriction for minors to college students would boost their initial wages by 0.9%. High-frequency GPS and app usage data show that heavy app users spend less time in study halls, are more frequently late or absent from class, and get less sleep.

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Data Use Clarification. This paper makes secondary usage of data—pre-existing data and records that were previously collected for a different, non-research purpose. All data sets used in the analysis were pre-merged and anonymized by the data provider under strict rules to protect individual privacy. The authors were not involved in the data merge process. The merged and anonymized data are stored in a data lab in China that is fully secured and offline without USB access. Only authorized staff of the data provider can enter the secured lab. None of the authors has access to any form of the raw or processed data. The authors wrote executable files that were executed on the pre-merged data by the authorized staff and only had access to summary statistics, regression coefficients, and figures generated by these executable files. An exemption for the analyses conducted in this paper was granted by the Institutional Review Board of Social Science and Humanities at JiNan University (IRB No.A2408001-038). Data collection and analysis were conducted without oversight of the University of Wisconsin-Madison IRB, and oversight was not ceded to JiNan University, as required by UW-Madison policies and procedures.

1 Introduction

Mobile apps have brought significant convenience to our daily lives, yet concerns are growing about their over-usage.[1] There is mounting evidence across the globe that teenagers and young adults are especially prone to excessive and sometimes inappropriate use of mobile apps. According to a 2018 survey in China, 79% of college students reported playing mobile games during class, spending on average one-third of lecture time on their phones.[2] A 2019 UK study found that 39% of young adults reported experiencing smartphone addiction (Sohn et al., 2021). In the U.S., over 70% of high school teachers surveyed in 2023 identified phone distractions as a significant classroom issue (Lin et al., 2024). Similarly, a 2023 study across OECD countries reported that 65% of students were distracted by their own use of digital devices during math lessons, while 59% were distracted by other students' device use (OECD, 2023). Thus, digital distractions can be detrimental to *not only* individuals themselves *but also* their peers.

These concerns have triggered policies aimed at curbing mobile app usage. In September 2019, the Chinese Government introduced a game restriction policy for minors. As of August 2024, eleven US states have enacted or considered policies restricting phone use during school hours.[3]

Despite widespread alarm about app overuse and ongoing debates over potential policy responses, rigorous evidence on the long-term implications of app usage for individuals' and their peers' human capital development remains limited. Using data tracking three cohorts of college students over four years, we take a step toward addressing this gap. We present, to our knowledge, the first comprehensive evidence of how both individual and peer app usage affect academic performance, physical well-being, and early career outcomes.

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[1] For example, prolonged app usage can cause physical and mental health problems, see Sagioglou and Greitemeyer (2014); Tromholt (2016); Hunt et al. (2018); Vanman et al. (2018); Allcott et al. (2020); Mosquera et al. (2020); Allcott et al. (2022); Collis and Eggers (2022); Greitemeyer (2019).

[2] Source: `https://static.nfapp.southcn.com/content/201804/18/c1109284.html`.

[3] See `https://www.nytimes.com/2024/08/11/technology/school-phone-bans-indiana-louisiana.html`.

Empirical research on how individual and peer app usage affect human capital accumulation faces three key challenges. First, suitable data that report both phone usage and outcome measures are rare. To overcome this obstacle, we leverage a unique dataset that links individual-level, comprehensive mobile phone records to administrative data on students' demographic, academic backgrounds, in-college performances, and post-graduation labor market outcomes across multiple cohorts.

The second challenge arises from the endogeneity of mobile app usage. Factors such as stress from school, health shocks, or unobserved ability could influence both app usage and academic and labor market outcomes. To address this, we use two sets of instruments. The first set of instruments exploits the mid-sample launch of the blockbuster game "Yuanshen" – the most popular game in China, with the majority of its users under Age 25. We observe that heavy pre-college gamers are more affected by the release of Yuanshen compared to light pre-college gamers. Therefore, we interact Yuanshen's release date with students' *pre-college* app usage to construct a shift-share type of instruments, while controlling for student fixed effects and other time-varying confounding factors. Our identification assumption is that, conditional on student fixed effects and a rich set of controls, Yuanshen and pre-college usage affect students' GPA only through current app usage. This assumption is plausible. The launch of Yuanshen was an external shock unrelated to the university's academic environment and is likely orthogonal to any inter-temporal variation in unobserved factors that affect a student's GPA. In addition, any persistent factors correlated with pre-college app usage that affect GPA are absorbed by the student fixed effects.

The second set of instruments is based on China's 2019 game restriction policy for minors, which prohibits individuals under 18 from playing online games between 10 p.m. and 8 a.m. and limits their gaming time to 90 minutes per day on weekdays. This policy directly impacted 8% of students in our sample and indirectly affected all of them through their underage friends, as online gaming often occurs in social groups.[4] Event studies confirm the

[4] In a survey conducted by Chen and Hu (2024), 36% of respondents cited "interacting and competing with friends and others" as the primary motivation for playing mobile games.

policy's impact: students with more underage friends exhibited a significant reduction in app usage immediately after the policy. We use the minors' game restriction policy interacted with the evolving number of underage friends met before college as our instruments. The exclusion restriction is likely satisfied, given the inclusion of student fixed effects and extensive controls, because the game restriction policy represents another exogenous shock that is independent of the university's academic environment (similar to the Yuanshen shock), and students' pre-college friend network were established before college entry.

The third challenge stems from the well-known difficulties in identifying peer effects in empirical settings, including the endogeneity of peer group formation and the "reflection problem" first articulated by Manski (1993) – an individual's behavior both affects and is affected by their peers, making it difficult to establish causality. Disentangling the two classical types of peer effects, behavioral (endogenous) and contextual (exogenous) peer effects, is even more challenging (Manski, 1993; Bramoulle et al., 2020). In our context, the behavioral peer effects refer to how roommates' *action* of app playing influences a student's own app usage. Contextual peer effects, by contrast, capture how peers' pre-determined characteristics influence a student's outcomes independent of their actual behaviors. In our setting, the key regressor capturing contextual peer effects is roommates' pre-college game usage, which may reflect traits such as motivation, attitudes toward academics, or established study habits.

We recover these two types of peer effects in three steps. First, leveraging the university's random dormitory assignment policy, we focus on a narrowly-defined peer group–roommates– and provide causal estimates of the reduced-form peer effects, which combine both behavioral and contextual peer effects. Second, we isolate behavioral peer effects by exploiting quasi-experimental variations based on the interaction of China's 2019 gaming restriction policy for minors and peers' friend network before college, which affected peers but not the focal student (Bramoulle et al., 2009; De Giorgi et al., 2020; Evtushenko and Kleinberg, 2021; Barwick et al., 2023). Finally, we recover the contextual peer effect by netting out the estimated behavioral component from the reduced-form estimates.

To our knowledge, this is the first study to empirically distinguish between behavioral and contextual peer effects within a unified framework. Disentangling these effects is crucial: conflating them can lead to biased estimates of the social returns to targeted interventions and, consequently, flawed policy evaluations.

Our analyses yield four key findings. First, mobile app usage is indeed contagious. Controlling for student fixed effects and utilizing the panel data structure, our IV estimates suggest that a one standard deviation (hereafter s.d.) increase in roommates' in-college app usage increases an individual's own app usage by 5.8%. This behavioral spillover effect dominates the contextual peer effect, which is modest and statistically insignificant. That is, peer influence in app usage is primarily driven by peers' actions rather than their characteristics.

Second, mobile app usage negatively affects GPAs. Unlike prior studies, we allow roommates' contemporaneous app usage to affect academic outcomes through two distinct channels. First, roommates' app usage affects a student's own app usage through the behavioral peer effects estimated above, which in turn affects his/her GPAs. Second, roommates' app usage could disrupt the study environment in the dorm or crowd out time spent in group studies, hence impairing a student's academic performance even when the student's own app usage is unaffected. Controlling for student fixed effects, our IV estimates indicate that a one s.d. increase in own app usage reduces GPAs for required courses in the same semester by 36.2% of a within-cohort-major s.d. Remarkably, combining both channels, a one s.d. increase in roommates' app usage results in a 22.7% s.d. reduction in one's GPA, more than half the magnitude of the impact from the student's own app usage.

Third, the effect of app usage on physical health, as proxied by physical education (PE) scores, is three times greater than its effect on the GPAs for required courses. In contrast, roommates' app usage has no direct effect on a student's PE scores, likely because disruptions from gaming are less relevant for outdoor activities.

Finally, utilizing the rare linkage of app usage with labor market outcomes upon graduation, our IV estimates imply that a one s.d. increase in own (roommates') in-college app usage reduces wage upon graduation by 2.3% (0.9%), or 12.1% (4.7%) of a within-cohort-major s.d. A back-of-the-envelope calculation suggests that if China's minors' game restriction policy were extended to college students, i.e., capping game time to 3 hours per week, students' initial wages would increase by 0.9%, equivalent to half of the wage premium from an extra year of work experience in developing countries (Lagakos et al., 2019).

To shed light on the mechanisms underlying these findings, we present three sets of evidence. App usage can affect academic performance via time allocation through both the extensive margin (time allocated to study halls) and the intensive margin (effective study time at a given location). Our first evidence comes from high-frequency location data collected by mobile phones' GPS, which allows us to precisely measure the extensive-margin time allocation. We find that app usage reduces students' time spent in study halls, increases time spent in dormitories, and increases late arrivals at and absences from lectures. Second, using supplemental high-frequency app-usage data to infer sleep patterns, we find that nighttime app usage is associated with shorter sleep duration and later wake-up time, another potential channel through which app usage may undermine academic performance. Our third set of evidence comes from the university's annual surveys, where heavier app users report poorer physical and mental health, submit fewer job applications, and are less satisfied with their job offers, aligning with our findings above. Notably, heavier users are more likely to recognize the addictive nature of gaming, suggesting a self-control problem rather than a lack of awareness.

Our paper contributes to the growing body of research on digital addiction. Studies have shown that Facebook usage can negatively impact emotional well-being, particularly among heavy users (Sagioglou and Greitemeyer, 2014; Tromholt, 2016; Hunt et al., 2018), that reducing Facebook usage lowers the consumption of politically-skewed news (Mosquera et al., 2020), and that temporarily deactivating Facebook accounts has lasting effects of reducing political polarization and improving subjective well-being (Allcott et al., 2020).

Braghieri et al. (2022) exploit the staggered roll-out of Facebook across U.S. colleges and find that the introduction of Facebook increased the likelihood of students experiencing poor mental health.[5] Our paper extends this line of research by accounting for peer effects and examining the consequences of app usage on academic achievements and physical health over multi-year periods and on early labor market outcomes, while also shedding light on the underlying channels.

We also contribute to the large literature on peer effects, as surveyed by Epple and Romano (2011), Sacerdote (2011), and Sacerdote (2014).[6] In more general settings, Brock and Durlauf (2006) and Brock and Durlauf (2007) provide methods for identifying social interactions in discrete choice models with endogenous group formation. A subset of this literature leverages random roommate assignment to identify peer effects (Sacerdote, 2001; Carrell et al., 2008; Kremer and Levy, 2008; Carrell et al., 2009; Feld and Zölitz, 2017; Booij et al., 2017). Stinebrickner and Stinebrickner (2008) find that a student's academic performance suffers if their (randomly-assigned) roommate brings a video game console to campus. Other studies use randomized field experiments, such as Duflo and Saez (2003), who show peer effects on colleagues' enrollment in tax deferred retirement plans after a benefits information fair, and Bursztyn et al. (2014), who identify two key channels of social influence in financial decision-making: social utility and social learning. Complementing the prior literature, we exploit random roommate assignment and combine it with additional quasi-random policy variations and a panel data structure to separate behavioral from contextual

[5]Other studies include Collis and Eggers (2022) that shows substitution toward instant messaging when social media is restricted, Kuznekoff and Titsworth (2013) that documents the negative effect of phone usage on note-taking during lectures, Aksoy et al. (2023) that finds an app that is designed to limit phone usage during class leads to improved self-reported outcomes and GPA, and Abrahamsson (2024) that shows banning smartphones in Norwegian middle schools significantly decreases the health care take-up for psychological symptoms and diseases among girls and improves their academic performance.

[6]See Sacerdote (2001), Zimmerman (2003), Stinebrickner and Stinebrickner (2006), Lyle (2007), Carrell et al. (2009), Beaman (2011), Imberman et al. (2012), Abdulkadiroğlu et al. (2014), Booij et al. (2017), and Feld and Zölitz (2017) for peer effects on human capital and labor market outcomes. See Figlio (2007), Kling et al. (2007), Carrell et al. (2008), Gould et al. (2009), Carrell and Hoekstra (2010), Lavy and Schlosser (2011), and Carrell et al. (2018) for peer effects on risky behaviors. Calvó-Armengol et al. (2009); Fruehwirth (2013); De Giorgi and Pellizzari (2014); Tincani (2018); Conley et al. (2024) examine students' effort choices in the presence of peer effects.

peer effects.

The rest of the paper proceeds as follows. Section 2 provides institutional background and describes the data. Section 3 separately identifies behavioral and contextual peer effects. Section 4 analyzes the effects of app usage on GPA and labor market outcomes. Section 5 investigates the underlying mechanisms and Section 6 concludes. Robustness checks, heterogeneity analysis, and additional details are presented in the appendices.

2 Institutional Background and Data Description

2.1 Background Information

Mobile Apps and Game Restriction Policy An average smartphone user spends over 3.5 hours per day on mobile apps in China in 2024. Of the 1.81 million apps in the Apple App Store, over 20% are game apps. In 2024, game app usage accounted for approximately 10% of the average daily mobile phone usage worldwide.[7] The game app market is dominated by blockbuster titles. One prominent example is Genshin Impact ("Yuanshen" in Chinese), an action role-playing game developed by the Chinese game developer miHoYo. Released on Android and iOS in September 2020, Yuanshen achieved overnight success, generating over $3 billion in revenue within a year (mostly from in-app ads), setting a record for all video games. By 2021, Yuanshen had become the most popular game in China with 13 million users and one of the most popular globally with over 100 million users worldwide, and the majority of its users are under Age 25.[8]

Gaming is often a group activity among young users for two main reasons. First, many of the most popular mobile games among this age group, such as Honor of Kings and Genshin Impact (Yuanshen), are multiplayer in nature and involve real-time cooperation or com-

[7]The full report by DataReportal is available at: `https://datareportal.com/reports/digital-2024-global-overview-report?utm_source=Global_Digital_Reports&utm_medium=Report&utm_campaign=Digital_2024&utm_content=Report_Promo`.

[8]See page 37 of the 2022 report by China Fortune Securities: `https://pdf.dfcfw.com/pdf/H3_AP202209301578791091_1.pdf`.

petition with others. Players often form teams, communicate through in-game chat, and coordinate strategies during gameplay. Second, even in single-player games, users frequently discuss progress, share tips, and compare achievements with their friends, creating a broader social ecosystem around the game. As a result, mobile gaming can foster both social interaction during gameplay and peer engagement outside the game.

With the rise of popular games, concerns about game addiction, particularly among teenagers, have grown rapidly. In response, China's National Press and Publication Administration imposed a minors' game restriction on October 25, 2019, prohibiting individuals under 18 from playing online games between 10 p.m. and 8 a.m. and limiting their gaming time to 90 minutes per day on weekdays. The policy was further tightened in September 2021 to a strict 3-hour weekly cap, which remains in effect today. Compliance is enforced through an ID requirement for account registration, enabling companies to verify users' ages and prevent minors from logging in once the restriction binds.

CEE and Random Dorm Assignment High school students in China select either the Science or Social Science/Humanities track and receive track-specific training accordingly. Upon graduation, college-bound students take the National College Entrance Exams (CEE), which assess skills in math, Chinese, English, and track-specific subjects.[9] College admissions are centralized within each province, where student-program assignments are determined by students' rank-ordered application lists and their CEE scores; see Chen and Kesten (2017) for a detailed overview.

The university in our study is a medium-sized, mid-tier institution by Chinese standards, located in a populous province in Southern China. The university offers both Bachelor's and Master's degrees, with 56 undergraduate majors in 10 categories.[10] An average full-time

[9]CEE scores are widely used as a proxy for pre-college academic ability (Li et al., 2012; Hoekstra et al., 2018; Bai et al., 2021). The exam content is standardized across the country, except for a few provinces and major cities that design their own tests.

[10]The 10 categories are science, engineering, literature, history, philosophy, law, medicine, arts, economics, and management. Most Bachelor's programs are four years, except for architecture and sculpture (five years) and clinical medicine (six years).

freshman cohort consists of approximately 2,500 students. In 2018, the majority of admitted students' CEE scores ranged between the 30^{th} and 80^{th} percentiles among college-admitted applicants in their home provinces.

The vast majority of students at this university live in on-campus dorms. Dorm rooms are equipped with multiple bunk beds and workstations, providing approximately 50-70 square feet of space per student. As is typical in Chinese universities, each dorm room accommodates 4 to 8 students, with 4 being the most common arrangement (Figure C.1).

Upon enrollment, Freshmen within each major are randomly divided into 5 administrative units, or "classes," each consisting of 20 to 50 students, depending on the major's size. Within each class, the university randomly assigns students to single-gender dorm rooms. Consistent with this assignment rule, within gender-class units, we find no correlation among roommates in their pre-college app usage, CEE scores, demographics, and socioeconomic backgrounds (Table C.1).

These initial dorm assignments typically remain in place throughout students' college years, except for rare re-assignments triggered by irreconcilable conflicts between roommates. According to a 2020 survey conducted at this university (Chen and Hu, 2024), 95% of non-senior students lived in dorms for over 5 days per week, while seniors on average lived in dorms for 3.5 days per week. Moreover, due to limited classroom and library space, students' self-study occurred mainly in their dorm rooms, averaging 2.4 hours per day.

2.2 Data

Our main analysis leverages an anonymized, pre-merged dataset that links administrative records for the 2018–2020 freshman cohorts at a Chinese university with detailed mobile phone usage data from a major telecommunications provider in the same province, covering the period 2018–2021. This dataset allows us to examine peer effects in app usage and evaluate its impact on academic and labor market outcomes. In addition, it includes geocoded location data recorded by mobile phone GPS systems and two waves of university-administered voluntary opt-in survey responses, which we use to explore potential mechanisms.[11] Throughout our analysis, we exclude the spring semester of 2020 for all cohorts, as students were off campus due to COVID-19.

Administrative Student Records The administrative data cover a total of 7,479 undergraduate students in the 2018-20 freshmen cohorts. The data consists of four components: 1) the complete history of roommate assignments;[12] 2) admission records, containing each student's CEE scores, high school track (social science or science), year of initial enrollment, major, gender, and city of origin; 3) college transcripts, containing grades for every course taken in each semester; 4) end-of-college outcomes for the 2018 and 2019 cohorts (who graduated in the summer of 2022 and 2023, respectively), including their employment status, post-graduate program admissions, and for those employed, their occupations, employer information, and initial wages.[13]

Phone Usage Data The phone usage data is provided by one of the largest wireless carriers in China, covering 75% of the population in the same province from 2018 to 2021. For each student, we observe monthly usage time for every app with at least 500 users. Following the classification systems used by the Android and Apple App Stores, we group mobile apps into four categories: social media, video, games, and others. Out of 7,479 students, 6,430 were successfully matched to their phone usage data. Most of the remaining students were not subscribers of this cellular carrier.[14] We exclude app usage data during

[11]All datasets used in this study were collected and merged by the university for internal educational quality improvement purposes. Students provided opt-in consent at enrollment and were informed of their right to opt out at any time during college. Data merging was carried out in a secure, offline data lab and followed by encryption and de-identification under a formal, tightly controlled protocol to safeguard individual privacy.

[12]Since fewer than 1.5% of students switched dorm rooms, we define roommates based on the initial dorm assignment.

[13]Students' administrative records contain detailed labor market outcomes because China requires a student-employer-university tripartite contract for college students' initial employment.

[14]To maximize sample size, we compute the average characteristics and phone usage of all roommates in each dorm room based on matched students. Results are similar when we exclude dorms with unmatched students.

winter and summer breaks (February, July, and August).

We use students' phone records to construct their friend network before college, restricting attention to pre-determined "private" friends. Specifically, we define student i's friends met before college (henceforth pre-college friends) as those who: 1) called i and received calls from i during the two months before i started college,[15] 2) had never been enrolled at the university under study by the end of our sample period, and 3) was connected — as defined by criterion 1) — only to i and no one else in our sample. We observe the age of students and their friends over time.

Location Data We leverage the geocoded location information collected by mobile devices at 5-minute intervals to identify students' locations. We divide the campus into three regions using the cell towers' coverage areas: study halls, dorms, and other areas (gym/entertainment/shopping facilities). Based on daily geolocation data and class schedules for 2,103 courses across 56 majors over six semesters from 2018 to 2021, we construct six indicators of on-time performance: time of first arrival at the study hall, time of last return to the dorm, duration at study halls (dorms), lateness by at least ten minutes for major-required courses, and absences from major-required courses.

Sleep Patterns For the 2020 cohort (2,153 students), we observe detailed hourly app usage data from November 1, 2023, to June 30, 2024 (the other cohorts had graduated by then). We construct sleep and wake-up times from hourly app usage using the following algorithm. For each student on each day, sleep onset is defined as the first hour within a three-hour window after 9 p.m. during which total app usage falls below 10% of the student's average daily usage over the prior month. Wake-up time is defined as the first hour in a three-hour window after 6 a.m. during which app usage exceeds 50% of the student's average daily usage. If no low-usage window occurs by 3 a.m., sleep onset is coded as missing, indicating

[15] Not all high school students own mobile phones, but nearly all acquire one during the summer following high school graduation.

the student likely did not sleep through the night. Similarly, if no high-usage window is found by 6 p.m., wake-up time is also coded as missing.

Field Surveys Our analyses also exploit two rounds of the universities' regular annual online surveys (see Table C.2 for a summary). These surveys were administered by university staff in mid-June of 2022 (for the 2018 cohort) and 2023 (for the 2019 and 2020 cohorts), when most graduates had secured a job. In total, 1,798 out of 7,479 students participated, yielding a response rate of 24%.

A limitation of the survey data is that respondents are not representative: those from less advantaged backgrounds, as measured by rural residence and parental education, are overrepresented. We re-weight the survey sample to match the distribution of rural status and parental wealth in the full student population. On the upside, survey quality is high: students' self-reported answers closely align with corresponding administrative records. The survey complements the main datasets by providing additional information on: 1) personality (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) (Goldberg, 1993); 2) physical and mental health; 3) professional certifications, job search processes, and satisfaction with job offers; 4) attitudes toward gaming; and 5) interactions among roommates.

2.3 Summary Statistics on Demographics and App Usage

Table 1 presents summary statistics for the 6,430 students in our main sample.

Demographics Panel A shows that compared to an average university in China (2021 China Education Statistical Yearbook), students at this university are less likely to be female (42% in our sample vs. 53% in the national college student population), less likely to have followed a social science track in high school (25% vs. 29%), and more likely to be rural residents (40% vs. 27%). Their average CEE score was 506 out of a total of 750, consistent with the mid-tier ranking of this university. We use the average housing price in the student's pre-college residential community (equivalent to a census block in the U.S.) as a proxy for parental wealth. The average housing price was ¥5.7 million ($810,000 USD).[16] On average, students have four underage pre-college friends.

App Usage Panel B documents students' monthly usage of each app category during our sample period. On average, students spend 92.9 hours per month on all mobile apps, with significant dispersion (the s.d. is 108.5 hours). Breaking this down by major app categories, students spend an average of 33.4 hours on social media, 22.4 hours on videos, 12.1 hours on games, and 25 hours on the remaining "other" category. Notably, time spent on educational apps in the "other" category is modest at 1.2 hours per month.

A potential concern is that we do not observe app usage on devices other than mobile phones. With due caveats remaining, two pieces of evidence help alleviate this concern. First, according to the *2020 China Gaming Industry Report* by the China Audio-video and Digital Publishing Association, Chinese gamers exhibit a clear preference for mobile gaming over PC or console gaming. In 2020, mobile games accounted for 75.4% of total revenue in the Chinese gaming market, while PC and console games combined made up only one-fourth.[17] A 2020 government report by the China Internet Network Information Center (CNNIC) confirms this pattern among youth users: over 60% of high school students play games on mobile phones, while fewer than 30% use computers.[18] Second, app usage is likely positively correlated across devices. Based on the 2018 wave of the China Family Panel Study, a nationally representative longitudinal survey of Chinese families and individuals, the correlation between smartphone and computer use is around 0.46. Similarly, a 2019 industry survey by TECHnalysis Research finds that many players regularly switch between mobile and PC/console gaming. As long as game usage across devices is not perfectly substitutable, i.e., increases in smartphone usage are not fully offset by reductions in computer gaming

[16] The exchange rate in 2023 is ¥7.07 per USD. Throughout the paper, all monetary values are measured in 2023 RMB.

[17] The full report is available at: `http://www.ce.cn/culture/whwx/tu/202004/20/P020200420540028693888.pdf`. See page 17 for relevant statistics.

[18] The full report is available at: `https://www.cac.gov.cn/2020-05/13/c_1590919071365700.htm`.

time, our findings should remain robust.

GPA Panel C summarizes students' grades (on a 0-100 scale) across all courses, required courses, required major-specific courses, and physical education (PE). Each observation represents a student-semester, excluding the spring of 2020 (COVID). Throughout the paper, we use course credits as weights to calculate GPAs. The average GPA for all courses is 78, with a standard deviation of 6.6.

Job Outcomes Panel D reports job market outcomes for the 2018 and 2019 cohorts, who graduated in 2022 and 2023, respectively. Of these graduates, 14% were admitted to some post-graduate programs, 79% found a job, and 7% were neither admitted to post-graduate programs nor employed upon graduation. Among those employed, the average initial monthly wage was ¥5,377 (see Figure C.2 for the distribution of initial wages). For comparison, the average initial monthly wage for college graduates in China in 2021 was ¥5,885 (MyCos, 2021).

Time Allocation Panel E in Table 1 provides summary statistics on students' typical weekday time allocation during the semester. On average, students arrive at study halls at 10:56 a.m. and return to their dormitories at 5:49 p.m. They spend 6.9 hours in study halls and 14.6 hours in dorms. Tardiness and absenteeism are somewhat common: students skip major-required classes 9% of the time and show up at least 10 minutes late a quarter of the time.

Sleep Patterns Table C.3 reports summary statistics on daily app usage and sleep patterns during a typical school day in the semester. Weekends and the winter break (February 2024) are excluded. On average, students spent 1 hour on mobile apps between 9 p.m. and 3 a.m., including 15 minutes on game apps. During the day, between 8 a.m. and 9 p.m., they averaged 2.2 hours of total app usage, with 30 minutes on games. They typically fell asleep after 11 p.m. and woke up before 7 a.m., averaging 6.8 hours of sleep per night. In 15% of student-day observations, sleep began after midnight, and in 16% of observations, wake-up time was after 9 a.m.

In all regression analyses in this paper, mobile app usage is measured in log hours, GPAs are in points on a scale from 0 to 100, and wages are in log RMB.

3 Peer Effects on App Usage

There is ample evidence that peer effects play an important role in youths' mobile app usage (Haidt, 2024). Figure C.3 presents residualized binscatter plots (and OLS estimates) of students' monthly mobile app usage during college against that of their roommates, controlling for month-of-sample and individual fixed effects. Consistent with anecdotal evidence, a student's app usage is strongly correlated with that of their roommates across all app categories we study. While suggestive, these correlations do not necessarily imply causal peer effects, due to the well-known "reflection problem" (Manski, 1993). As students simultaneously influence and are influenced by their peers, causal estimation requires exogenous variation in peers' usage.

Following Manski (1993), the literature distinguishes between two types of peer effects: behavioral (endogenous) and contextual (exogenous) (Bramoulle et al., 2020). In our context, behavioral peer effects refer to how roommates' *action* of playing apps influences a student's own app usage. Contextual peer effects, in contrast, capture the influence of peers' predetermined characteristics on a student's outcome, independent of their actual behaviors. The key regressor capturing contextual peer effects in our setting is roommates' pre-college game usage, which may reflect traits such as motivation, attitudes toward academics, or established study habits.

Distinguishing between these two peer effects is challenging. A common compromise substitutes contemporaneous peer outcomes as a function of pre-determined characteristics, and estimates a reduced-form peer effect by regressing individual outcomes on both own and peers' pre-determined attributes. This reduced-form estimate combines both behavioral and contextual effects. To address the endogeneity of peer group formation, researchers typically rely on random peer assignment – a strategy that we also adopt below.

We contribute to this literature by moving beyond the reduced-form and separately identifying behavioral and contextual peer effects. Our estimation proceeds in three steps. First, we leverage the university's random dormitory assignment to estimate reduced-form peer effects, using exogenous variation in roommates' pre-college app usage. Appendix B formally derives the relationship between the reduced-form coefficient and the two types of peer effects. Second, to isolate behavioral peer effects, we exploit quasi-experimental variation generated by interacting China's 2019 gaming restriction policy for minors with peers' pre-college friend networks. This instrument affects peers but not the focal student. Third, we recover contextual effects by subtracting the estimated behavioral effect from the reduced-form estimate.

While there is a large literature on peer effects, we are not aware of any prior studies that separately identify behavioral and contextual peer effects within a unified empirical framework. Beyond its methodological contribution, this distinction has important policy implications. If peer effects are primarily contextual (i.e., driven by peers' background characteristics rather than their behaviors), interventions targeting peer behavior, such as the minors' game restriction policy, may have limited spillovers. In contrast, if behavioral peer effects dominate, such interventions could generate meaningful multiplier effects through peer influence.

3.1 Reduced-Form Estimates

We hypothesize that an individual's in-college app usage in month t, y_{it}, is affected by his pre-determined characteristics x_{it}, roommates' app usage y_{jt}, and roommates' pre-determined characteristics x_{jt}. Specifically, we focus on one pre-determined characteristic for notation simplicity (and include other attributes in the empirical analyses): pre-college app usage, which could reflect personal traits, such as motivation, unobserved ability, and study habits. Letting N_i, of size $|N_i|$, denote the set of individual i's roommates, we have:

$$y_{it} = \alpha + \gamma x_i + \beta \frac{1}{|N_i|} \sum_{j \in N_i} y_{jt} + \delta \frac{1}{|N_i|} \sum_{j \in N_i} x_j + \epsilon_{it}, \tag{1}$$

where β is the behavioral peer effect and δ measures the contextual effect.

Substituting roommates' app usage y_{jt} using Equation (1) and after some algebra, we obtain the reduced-form equation (see Appendix B for derivations):

$$y_{it} = \theta_\alpha + \theta_{\gamma_1} x_i + \theta_{\gamma_2} \frac{1}{|N_i|} \sum_{j \in N_i} x_j + \mathbf{z}'_{it}\rho + \eta_{cg} + \eta_m + \eta_t + \varepsilon_{it}, \tag{2}$$

where parameter θ_{γ_2} is the reduced-form peer effect and a function of both β and δ. Vector $\mathbf{z}_{it}$ is a rich set of demographic attributes, including age, rural residency, social science/science track in high school, CEE scores, and housing price (a proxy of parental wealth). We also control three sets of fixed effects: class-by-gender fixed effects where "class" is a cohort-major-administrative unit (η_{cg}), dorm-size fixed effects (η_m), and month-of-sample fixed effects (η_t).

The random assignment of roommates enables a causal estimate of the reduced-form peer effects. Table 2 presents the results.[19] Standard errors are clustered at the class level to allow for potential temporal correlations. Column (1) reports the result for total app usage, and Columns (2)-(4) present the estimates for each major app category separately. According to Column (1), if student A's total app usage before college is twice that of student B, student A would use apps 19% more frequently than student B during college, ceteris paribus. The coefficient of roommates' pre-college mobile app usage (0.035) implies that being assigned to roommates whose pre-college app usage is one s.d. higher increases a student's in-college

[19]While our estimates reflect intent-to-treat effects, they are likely similar to the treatment-on-the-treated, given the rarity of room changes. Our main results are robust when restricted to dorm rooms with no roommate changes.

app usage by 4.0%, or 18.4% of the own effect.[20]

To provide a visual representation of reduced-form peer effects in our sample, Figure 1 plots students' residualized in-college app usage against their roommates' pre-college usage across all app categories, controlling for class-by-gender, dorm size, and month-of-sample fixed effects. A clear pattern emerges: students' app usage is strongly and positively associated with their roommates' prior usage, consistent with Table 2. Notably, the peer effect appears stronger among students who were heavy users before college, a topic we explore formally in Appendix C.

Since the estimates are largely similar across app categories and our instrumental variables primarily pertain to game usage, we focus on total app usage, game app usage, and game+video app usage for the remainder of the analysis and present the effects of social media and video app usage in Appendix C.

3.2 Behavioral Spillover Effects

To isolate behavioral spillover effects, we exploit the panel data structure and use student fixed effects to absorb both their own and roommates' time-invariant characteristics, including pre-college app usage. Specifically, we estimate the following equation:

$$y_{it} = \eta_i + \beta \frac{1}{|N_i|} \sum_{j \in N_i} y_{jt} + \epsilon_{it}, \tag{3}$$

where η_i is a student fixed effect and β captures the behavioral peer effect. To address concerns about endogeneity and reverse causality associated with roommates' in-college app usage y_{jt}, we estimate Equation (3) via 2SLS.

We construct a shift-share-type of instrument by interacting the timing of the minors' game restriction policy with the (evolving) number of minors among roommates' pre-college friends. The policy was implemented midway through the sample period (see Section 2.1).

[20]The effect of one s.d. increase in pre-college mobile app usage = 0.035 (Column 1) $\times \frac{96.7\text{(one s.d. of pre-college mobile app time)}}{85.2\text{(mean of pre-college mobile app time)}} = 0.040$.

Although the policy had limited direct impact on students in our sample (only 8% were under 18 when the policy started), it indirectly affected many of them through their underage pre-college friends, as illustrated in Figure 2 below. Crucially, this instrument is orthogonal to the error term by construction: roommates are randomly assigned, and their pre-college friend networks are predetermined and do not overlap with that of individual i.

Panel A of Figure 2 reports the event study coefficients for the interaction between the game restriction policy and the (evolving) number of a student's underage pre-college friends. Three patterns emerge. First, there is no evidence of differential pre-trends in app usage by exposure to underage friends. Second, immediately following the policy, students with more underage friends experienced significantly larger reductions in app usage. Third, this effect dissipates after approximately seven months, consistent with those friends aging out of the policy's targeted age group.

Panel A of Table 3 presents IV estimates of the behavioral effect of roommates' app usage. Panel B reports the first-stage results. All columns include student fixed effects and month-of-sample fixed effects. Columns (1) to (3) use the (evolving) number of roommates' underage pre-college friends and its interaction with the minors' restriction policy as IVs. Columns (4) to (6) employ similar IVs, except that the number of friends is weighted by phone call frequency before college. The results confirm that app usage is indeed contagious. A one s.d. increase in roommates' app usage increases one's contemporaneous app usage by 5.8%, 10.7%, and 6.5% for all apps, games, and games+video, respectively.[21]

3.3 Recovering Contextual Effect

Using the estimated reduced-form peer effects in Table 2 and behavioral peer effects in Table 3, we can now recover contextual peer effects.[22] Table 4 shows that relative to behavioral

[21]The effect of one s.d. increase in total app usage = 0.05 (Column 4) $\times \frac{108.5(\text{one s.d. of total app time})}{92.9(\text{mean of total app time})} =$ 0.058. The effect of one s.d. increase in game and game+video app usage is calculated analogously.

[22]In our analysis, we identify a specific form of behavioral effect – namely, through app usage. After isolating this channel from the reduced-form peer effect estimated using random roommate assignment, we define the remaining component as the contextual peer effect, which may include effects of roommates'

peer effects, contextual peer effects are much smaller and statistically insignificant. These findings suggest that in the context of mobile app usage, it is the direct actions of peers' app usage that drive peer influences, presumably due to the situational and spontaneous nature of mobile app usage, where peer behaviors provide more immediate social cues than peers' characteristics.

4 Effects on Academic and Labor Market Outcomes

4.1 App Usage and Academic Performance

Having quantified peer effects in app usage, we now turn to examining how both a student's own and their roommates' app usage affect academic outcomes. Roommates' app usage can influence academic performance through two distinct channels. The first is an indirect channel: roommates' app usage affects the student's own usage, which in turn impacts their GPA. The second is a direct channel: holding own usage constant, roommates' app usage disrupts the study environment (a concern echoed by a non-trivial fraction of students in our survey who reported being disturbed by roommates' gaming in the dorm, see Section 5.3), or crowds out time spend in group studies and hence decreases positive peer influences.

As a first step, we run the following OLS regression of GPA on app usage:

$$\text{GPA}_{is} = \alpha_1 \text{Phone}_{is} + \alpha_2 \frac{1}{|N_i|} \sum_{j \in N_i} \text{Phone}_{js} + \alpha_3 \text{CEE}_i \times \eta_s + \eta_i + \eta_{cs} + \epsilon_{is} \tag{4}$$

where i is a student, s is a semester (e.g., spring semester in the junior year), and Phone_{is} is individual i's app usage in semester s. Throughout, we use student fixed effects η_i to control for unobserved permanent individual traits (e.g., ability) that affect academic performance. We also include class-semester fixed effects (η_{cs}) where "class" c is a cohort-major-administrative-unit triplet that capture systematic differences in course difficulty, grading

non-app usage behaviors.

standards, etc. Finally, we include an interaction between individual i's CEE score and a linear semester trend to control for potentially differential GPA trends between students who were well-prepared for college and those who were less prepared (where, with a slight abuse of notation, we use η_s to denote the linear semester trend).

OLS Estimates Columns (1)-(3) in Panel A of Table 5 report the OLS estimates of how app usage affects GPA for required courses.[23] Doubling a student's total app usage in college is associated with a 0.546-point drop in GPA for required courses. In other words, one s.d. increase in total app usage is associated with a 32.2% of a within-cohort-major s.d. reduction in GPA.[24] The corresponding magnitudes for game and game+video apps range are 42.7% and 31.2% s.d., respectively. The association between peers' app usage and academic outcomes is economically significant, ranging from one-fifth to one-fourth the size of the individuals' own effect. These patterns are also evident in the residualized binscatter plots in Figure 3, which reveal a tight and negative relationship between GPA and both own app usage and roommates' app usage.

Columns (4)-(6) examine the effect of app usage on performance in physical education (PE), a required course at the university.[25] Doubling a student's total app usage in college is associated with a 1.577-point drop in his/her PE grade. In contrast, we find no direct effects of roommates' app usage on PE scores. This result is intuitive: while roommates' game-playing creates noise and hinders students' concentration on studying, such disruptions are less relevant for outdoor physical activities. Although it is conceivable that roommates' app usage could affect PE scores by crowding out positive peer influence (e.g., via team sports), our estimate suggests that such peer influences are limited.

[23]To mitigate endogeneity from students' strategic course selection, we use the GPA for required courses as our primary outcome. Alternative GPA measures and course selection are examined in the robustness section.

[24]The effect of one s.d. increase in total app usage = $[0.546 \text{ (Column 1)} \times \frac{108.5\text{(one s.d. of total app time)}}{92.9\text{(mean of total app time)}}]$ / 1.98 (average within-cohort-major s.d. of GPA) = 32.2%.

[25]We lose 3,220 obs for this analysis due to missing PE scores for the 2018 cohort in some departments.

IV Validity The estimates of α_1 and α_2 in Equation (4) could be subject to the omitted variable bias from time-varying unobserved factors that influence both app usage and academic performance, such as stress from school, extracurricular activities, course schedules, etc. We pursue an IV strategy to identify causal effects. The first set of IVs, similar to the analysis of peer effects in Section 3.2, is the interaction between the timing of minors' game restriction policy and the (evolving) number of pre-college minor friends.

Our second set of IVs leverages the introduction of Yuanshen midway through the sample period (Section 2.1). We interact the timing of Yuanshen with one's pre-college app usage as an instrument, which is motivated by the observation that heavy pre-college gamers are more affected by the release of Yuanshen compared to light pre-college gamers, as shown in event-study Figure 2 below.[26] Our identification assumption is that, conditional on student fixed effects and a rich set of controls, Yuanshen and pre-college usage affect students' GPA only through current app usage. This assumption is plausible. The launch of Yuanshen was an external shock unrelated to the university's academic environment and is likely orthogonal to any inter-temporal variation in unobserved factors that affect a student's GPA. In addition, any potential effect of pre-college app usage on GPA is absorbed by the student fixed effects.

Specifically, the first stage uses the following regression:

$$\begin{aligned} y_{is} &= \lambda_1 \text{YS}_s \times \text{PrePhone}_i + \lambda_2 \text{YS}_s \times \frac{1}{|N_i|}\sum_{j \in N_i} \text{PrePhone}_j + \lambda_3 \text{Policy}_s \times \text{Minor}_{is} \\ &+ \lambda_4 \text{Policy}_s \times \frac{1}{|N_i|}\sum_{j \in N_i} \text{Minor}_{js} + \lambda_5 \text{Minor}_{is} + \lambda_6 \frac{1}{|N_i|}\sum_{j \in N_i} \text{Minor}_{js} \\ &+ \text{CEE} \times \eta_s + \eta_i + \eta_{cs} + \epsilon_{is} \end{aligned} \tag{5}$$

where y_{is} is i's app usage in semester s, YS and Policy stand for the Yuanshen and game-restriction policy shocks, PrePhone_i is i's pre-college app usage, and Minor_{is} is the evolving number of i's pre-college friends who are under 18. We instrument for roommates' in-college

[26] Around 32% of students in the sample played Yuanshen. We do not use Yuanshen as an IV for the peer effect analyses in Section 3.2, because Yuanshen directly affects both individuals' and their roommates' app usage, violating the exclusion restriction for an IV.

usage analogously using a) the interaction of the minors' game restriction policy and the evolving number of roommates' pre-college minor friends, and b) the interaction of Yuanshen with roommates' pre-college app usage.

As in Section 3.2, we conduct an event study in Panel B of Figure 2 to validate the set of Yuanshen IVs. Reassuringly, we find no evidence of a pre-trend. The launch of Yuanshen disproportionately increased app usage among students with higher pre-college app usage, with these differential impacts persisting and strengthening over time. Table C.4 conducts a placebo test showing that the Yuanshen launch and the minors' game restriction policy affect the usage of gaming apps and closely related social media and video apps, but not shopping or news apps. Together, these patterns indicate that these shocks generate exogenous variations in students' app usage that are unlikely to be driven by other confounding factors.

IV Estimates Columns (1)-(3) in panel B of Table 5 present the IV results on the effects of mobile app usage (total apps, gaming apps, and game + video apps) on GPAs for required courses. Students' own app usage has a strong negative impact on GPAs, with all coefficients statistically significant at the 1% level. A one s.d increase in app usage reduces GPA by 0.716 points, equivalent to 36.2% of a within-cohort-major GPA s.d.[27] Additionally, a one s.d increase in roommates' app usage *directly* lowers the student's GPA by 0.408 points, or 20.6% of a within-cohort-major GPA s.d. The behavioral peer effect estimated in Section 3.2 indicates that a one s.d. increase in roommates' app usage raises a student's own app usage by 5.8%. Taking into consideration this contagion effect, the total impact of a one s.d. increase in roommates' app usage is a 0.450-point reduction in GPA, approximately 22.7% of a within-cohort-major GPA s.d. This effect size is substantial and amounts to over 60% of the own app usage effect, echoing findings in the literature regarding the significant role of peer effects in academic performance (Sacerdote, 2001; Conley et al., 2024). The negative impact of game app usage is even larger: a one s.d. increase in gaming time leads to a

[27]The effect of one s.d. increase in app usage = 0.613 (Column 1) $\times \frac{108.5(\text{one s.d. of total app time})}{92.9(\text{mean of total app time})} = 0.716$. The effect of one s.d. increase in game app usage and roommates' app usage is calculated analogously.

1.119-point reduction in GPAs, or 56.6% of a within-cohort-major GPA s.d. The effect of roommates' game usage is similar to that in Column (1) on total app usage. Relative to IV estimates, OLS estimates are biased toward zero. This may arise from shocks that lower both GPA and app usage (such as a negative health shock).

Columns (4)-(6) in panel B provide IV estimates on the effect of app usage on physical education. A one s.d. increase in app usage reduces PE scores by 2.74 points, almost four times as large as the effect on required GPA, echoing the detrimental health effect of excessive screen exposure (Nakshine et al., 2022). Similar to the OLS estimates, we do not find direct effects of roommates' app usage on PE scores.

4.2 App Usage and Labor Market Outcomes

As in Section 4.1, Figure 4 presents the residualized binscatter plots of wages upon graduation against app usage. Wages are negatively associated with both individuals' and roommates' mobile app usage. Now, we examine this relationship formally and estimate the following equation:

$$y_i = \gamma_1 \text{Phone}_i + \gamma_2 \frac{1}{|N_i|} \sum_{j \in N_i} \text{Phone}_j + X_i' \gamma_X + \eta_{cg} + \eta_m + \hat{\eta}_i + \varepsilon_i, \quad (6)$$

where y_i represents individual i's post-college labor market outcome, such as the (log) initial wage upon graduation,[28] and Phone_i (Phone_j) is individual i's (roommates') average app usage during college.

Since labor market outcomes are measured only once for each student, we cannot use student fixed effects. Instead, we control a rich set of student attributes X_i, which include age at college enrollment, rural residency, social science/science track in high school, CEE scores, parents' housing prices, and hometown fixed effects, along with both own and roommates' pre-college app usage.[29] Variables η_{cg} and η_m denote class-gender and dorm-size fixed

[28]We focus on graduates because there were only four dropouts in the sample. We have examined the probability of being unemployed or pursuing post-graduate studies but lacked statistical power (the estimates are noisy), as these scenarios apply to a small fraction of students.

[29]We include hometown fixed effects in wage regressions to capture potential "birthplace" effects as some

effects, respectively. Finally, to capture unobserved ability that could be correlated with job placement outcomes, we control for the estimated student fixed effect $\hat{\eta}_i$ from the IV estimation of the GPA Equation (4).[30]

Since both Phone_i and Phone_j may be correlated with unobserved factors that affect job market outcomes, we instrument them using predicted mobile app usage. The prediction is based on exogenous variation introduced by the release of Yuanshen (interacted with pre-college usage) and the minors' restriction policy (interacted with the number of pre-existing friends who are under 18), as argued in the GPA analysis in Section 4.1.[31]

OLS Estimates Columns (1)-(3) in Table 6 report the OLS estimates. Doubling a student's total app usage in college is associated with a 1.5% drop in wages upon graduation. The magnitudes are similar across app categories. The association between peers' app usage and wages is economically significant, around half the size of the individuals' own effect.

IV Estimates Columns (4)-(6) in Table 6 present IV results. Doubling total app usage during college reduces wages upon graduation by 2%. In other words, a one s.d. increase in own app usage is associated with a 2.3% reduction in the initial wage, equivalent to 12.1% of the within-cohort-major s.d.[32] This detrimental effect is also reflected in the increased probability of being in the bottom quartile of the wage distribution (see Table C.5, which examines the likelihood of earning an initial wage in the top or bottom quartile of the graduating cohort wage distribution). Roommates matter as well: a one s.d. increase in roommates' app usage reduces one's wage upon graduation by 0.9%, or 4.8% of the within-cohort-major s.d. Taking into account the indirect channel where roommates' behavior

students return to their home counties to work.

[30]The student fixed effect derived from Equation (4) captures all time-invariant, unobserved characteristics that systematically influence GPA. In practice, this includes factors such as innate ability or talent, consistent motivation or work ethic, family background or socioeconomic status, and stable personality traits. These time-invariant characteristics are also likely to influence labor market outcomes.

[31]We use Equation (5) to predict mobile app usage for all apps, game apps, and game+video apps in each semester and then average across all semesters.

[32]The effect of one s.d. increase in total app usage = [5376.93 (mean of wage) $\times$ 0.02 (Column 1) $\times \frac{108.5(\textit{one s.d. of total app time})}{92.9(\textit{mean of total app time})}$] / 1039 (average within-cohort-major s.d. of wage) = 12.1%.

affects students' own app usage, the total effect of a one s.d. increase in roommates' app usage results in a 1% wage reduction, or 5.3% of the within-cohort-major s.d. Relative to IV estimates, OLS estimates are only moderately biased toward zero.

Next, we compare specifications with and without controlling for cumulative GPA, which isolates the effect of app usage on wage outcomes beyond its impact through academic performance. As shown in Table C.6, controlling for GPA reduces the estimated effect of game usage on wage outcomes by approximately one-third. This suggests that academic performance in college is an important but not the only channel linking gaming behavior to labor market outcomes.

Robustness and Effect Heterogeneity Appendix C presents a series of robustness checks and explores effect heterogeneity. We conduct an ITT event study for the instruments, re-estimate the GPA effects using only cumulative GPA (exploiting only between-student variation) and other alternative GPA measures, rule out course selection as a confounding factor, and demonstrate that our results are robust to alternative choices of IVs. We also show that the effect of social media app usage is comparable to that of game app usage.

Regarding heterogeneity across student groups, students from wealthy families (above-median parental housing wealth) spend about twice as much time on mobile apps during college as those from less-wealthy families, with similar contrasts between heavy and light pre-college users. Differences by other attributes, such as gender, science vs. social science track, urban vs. rural status, or high vs. low CEE scores, are small. The negative effect of app usage on GPA is roughly two-thirds larger for students from wealthy families than for less-wealthy students, with a comparable gap between heavy and light pre-college users.

Implications of the Game Restriction Policy We perform a back-of-the-envelope calculation to assess the potential impact of extending the minors' game restriction policy that caps gaming time at three hours per week to college students. The exercise proceeds in three steps.

First, we cap each student's monthly usage of game apps at 12 hours. This restriction binds in 34.3% of student-month observations and reduces average monthly gaming time from 12.1 hours to 8 hours, about a one-third decrease.

Second, we incorporate the behavioral peer effect for gaming apps (estimated at 0.078 in Table 4) to account for the spillover effect among peers. The average gaming time would further decline to approximately 7.68 hours ($= 8-(12.1-8)*0.078$) and eventually converge to 7.65 hours in steady state.[33] Since behavioral peer effects are stronger among heavy users (see Appendix C.2) who are disproportionately affected by the policy, we view this estimate as a conservative lower bound of the total effect.

Third, we translate the reduction in gaming time into wage changes by multiplying it by the combined coefficients on own and roommates' game usage from the wage regression (Column (5) of Table 6). The results suggest that imposing a three-hour weekly cap on gaming would raise post-graduation wages by 0.9%, equivalent to 4.8% of the within-cohort-major s.d.. This effect size is economically meaningful, at about half the magnitude of the wage premium associated with one additional year of work experience in developing countries (Lagakos et al., 2019).[34]

5 Evidence on Underlying Mechanisms

Our analyses so far indicate that app usage is contagious among peers and detrimental to academic performance, physical health, and labor market outcomes. To shed light on the underlying mechanisms, we draw on three complementary sources of evidence: high-frequency location data, nighttime app usage and sleep patterns, and field surveys.

[33] According to Equation (3), the total reduction at the steady state is 4.1/(1-0.078)= 4.45 hours. Thus, the average monthly gaming time converges to $12.1 - 4.45 = 7.65$ hours.

[34] Lagakos et al. (2019) reports that the return to an additional year of work experience ranges from 1.3% to 2% in developing countries such as Brazil, Chile, and Mexico.

5.1 Evidence from High-Frequency Location Information

Time allocation is one direct channel through which app usage affects students' academic performance. This can happen along both the extensive margin (how much time students spend in study halls vs. dorms) and the intensive margin (efforts they devote to studying at a given location). The GPS data allows us to precisely measure the former.

We adopt the same specification used in the GPA analyses in Section 4.1 and leverage the same quasi-experimental variation generated by the Yuanshen and policy shock to examine changes in students' time allocation following these shocks. Specifically, we estimate Equation (5), replacing the dependent variable with student i's extensive-margin time allocation on day d (e.g., whether late for class). To account for temporal variation, we include week-of-sample and day-of-week fixed effects.[35]

Table 7 displays the estimates. Following the release of Yuanshen, an average student arrives at the study hall 18.2 minutes later and returns to the dorm 23.4 minutes earlier than they did before the game's release.[36] After the implementation of the minors' game restriction policy, students with the average number of minor friends arrive at study halls 17.4 minutes earlier and return to the dorm 19.8 minutes later. Similarly, Yuanshen leads to a higher probability of at least 10 minutes late for major-required courses and a higher chance of being absent; the minors' game restriction has the opposite effect.

These findings are further confirmed in event studies. Figure 5 demonstrates that the release of Yuanshen negatively affects all observed dimensions of time allocation, including the time of first arrival at the study hall, the time of last return to the dorm, duration at the study hall, duration at the dorm, lateness to classes, and absences from classes. The effect is immediate and *intensifies* over time, consistent with the game's growing popularity on campus. In contrast, Figure 6 shows that the minors' game restriction policy improves

[35]We additionally control for interactions between week-of-year and pre-college app usage to capture seasonal patterns. Results are robust to excluding these interactions.

[36]The effect of Yuanshen = 0.067 (Column 1) $\times$ 4.53 (mean of own pre-college app use in log) $\times$ 60 minutes = 18.2 minutes.

all measures of time allocation. Its impact is most pronounced in the months following the policy's introduction, but gradually diminishes as the number of underage pre-college friends declines over time.

5.2 Effect of App Usage on Sleep

Sleep may represent another channel through which app usage affects academic performance. To assess the impact of app usage on sleep patterns, we estimate OLS regressions controlling for student fixed effects, class-by-semester fixed effects, week-of-sample and day-of-week fixed effects, and interactions between college-entrance-exam scores and semester linear trends.[37] The analysis excludes weekends and the February 2024 winter break to focus on regular school days. We define late sleep as falling asleep after midnight and late wake-up as waking after 9 a.m. We do not conduct the IV analyses, as our instruments (the release of Yuanshen and the implementation of the minors' game restriction policy) predate the sleep data.

Table 8 suggests that nighttime app usage (between 9 p.m. and 3 a.m.) significantly reduces sleep duration and increases the likelihood of late sleep and late wake-up. Specifically, a one standard deviation increase in total nighttime app usage is associated with a reduction in sleep duration by roughly 30 minutes (7% of the mean), a 34 percentage point increase in the probability of sleeping late, and a 4.5 percentage point increase in the probability of waking up late.

Interestingly, daytime app usage (between 8 a.m. when a normal school day begins and 9 p.m.) is also associated with adverse sleep outcomes. A one standard deviation increase in daytime total app usage is linked to a reduction in sleep duration by roughly 7.2 minutes (1.8% of the mean) and a 3.7 percentage point increase in the probability of late wake-up, though it has no significant effect on sleeping late.

These findings indicate that heavy app usage, whether during the day or at night, and especially at night, can disrupt students' sleep schedules and may be a pathway through

[37] We also control for interactions between week-of-year indicators and pre-college app usage, though results are robust without these interactions.

which mobile app usage affects academic and health outcomes. One limitation of the sleep data is that it does not overlap with the 2018-2021 GPA or wage data. Therefore, we are unable to directly examine the relationship between sleep patterns and academic or labor market outcomes and leave this for future analysis.

5.3 Survey Evidence

Lastly, Table C.7 presents suggestive evidence from field surveys.[38] Panel A correlates app usage with personal traits. Students with higher degrees of openness and extraversion tend to allocate more time to mobile apps.

Panel B shows a significant negative correlation between app usage and self-reported physical health, echoing findings in Section 4.1. Furthermore, individuals with higher app usage are more likely to report high levels of stress. Given that heavy app users tend to be more extraverted and open (Panel A), traits that are typically associated with lower levels of stress (Schneider et al. (2012)), this finding suggests that there may be a direct link between app usage and stress, which likely has contributed to poor health, academic performance, and labor market outcomes.

Panel C analyzes the relationship between app usage and job search behaviors. Heavier app users are less likely to have obtained any professional certificate by graduation, another measure of in-college achievement valued by employers. In addition, heavier app users tend to submit fewer job applications, suggesting that reduced job search efforts may partly explain the negative impact of app usage on job market outcomes, as shown in Section 4.2. In addition, heavier app users report lower satisfaction with the job offers they receive.

Finally, Panel D reports how app usage correlates with students' views on games and their relationships with roommates. Perhaps surprisingly, heavier app users are *more* likely to acknowledge the addictive nature of apps and games, suggesting a self-control issue rather than a lack of awareness. They also report having better relationships with their roommates

[38] We do not use IVs due to the small sample size and lack of statistical power. The survey sample is reweighted to match the population average of the rural/urban status and parental wealth.

and being more likely to follow roommates' advice regarding post-graduation choices, which could serve as a direct channel through which peers affect individuals' labor market outcomes.

6 Conclusion

Leveraging unique datasets that link students' administrative records with detailed mobile phone usage data, we investigate the effects of app usage on college students' academic performances, physical health, and labor market outcomes. We find economically and statistically significant negative consequences of app usage, not only for individuals but also for their peers.

There are several fruitful directions for future research. The first is to delve deeper into the underlying mechanisms, beyond the broad patterns of time allocation and suggestive evidence of job search behaviors, through which digital distractions influence own and peers' outcomes. The second is to go beyond individual-level outcomes and study how digital distractions may affect the aggregate economy through their effects on workplace productivity and firm-worker sorting.

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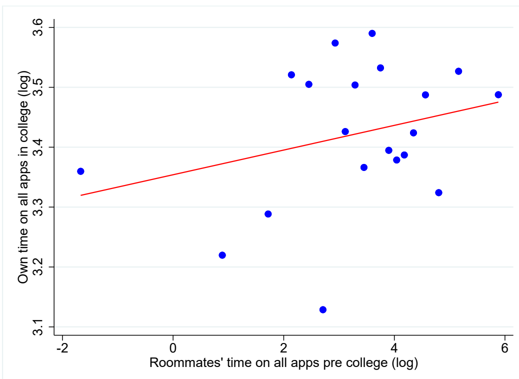
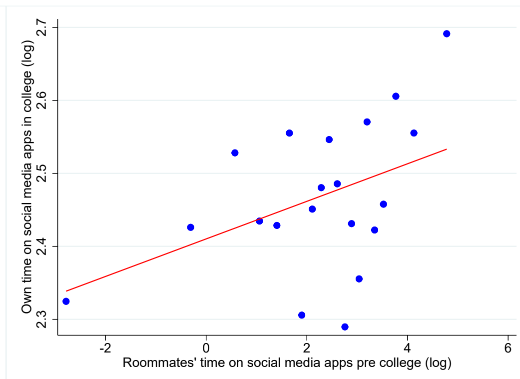
Figure 1: Reduced-form peer effect of mobile app usage

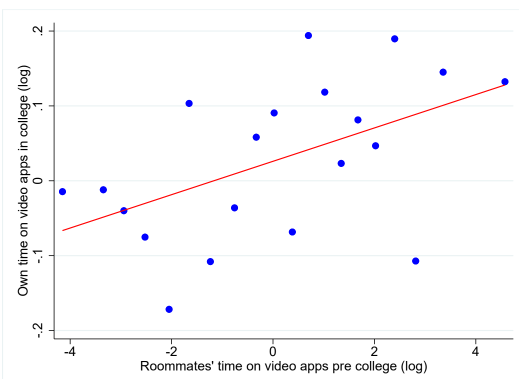
(a) Total app time



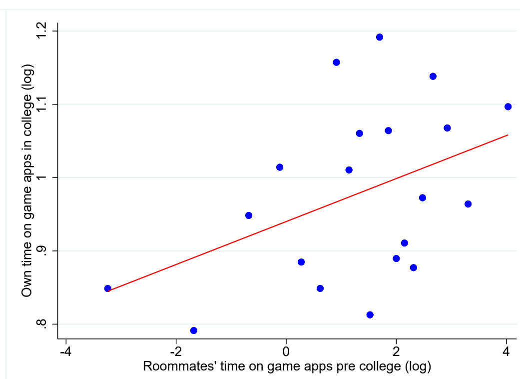
(b) Social media



(c) Video



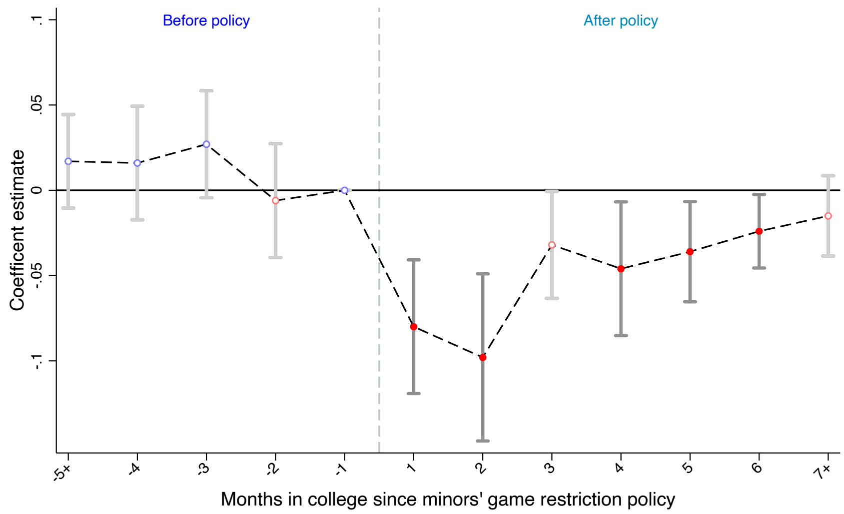
(d) Game



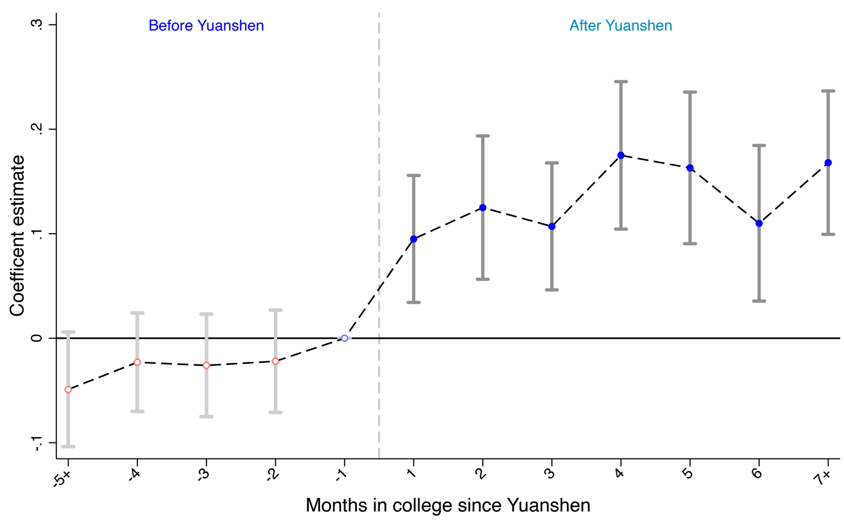
Notes: These graphs present the residualized relationship between students' mobile app usage (in logarithm) during college and their roommates' pre-college app usage (in logarithm), both for all apps and separately for social media, video, and game apps. All graphs control for month-of-sample, class-by-gender, and dorm-size fixed effects. "Class" is a triplet of cohort, major, and administrative unit and consists of 20-50 students. The solid line represents the linear fit estimated from the underlying microdata using OLS.

Figure 2: Effect of minors' game restriction policy and Yuanshen on game usage

(a) Effect of minors' game restriction policy on game app time



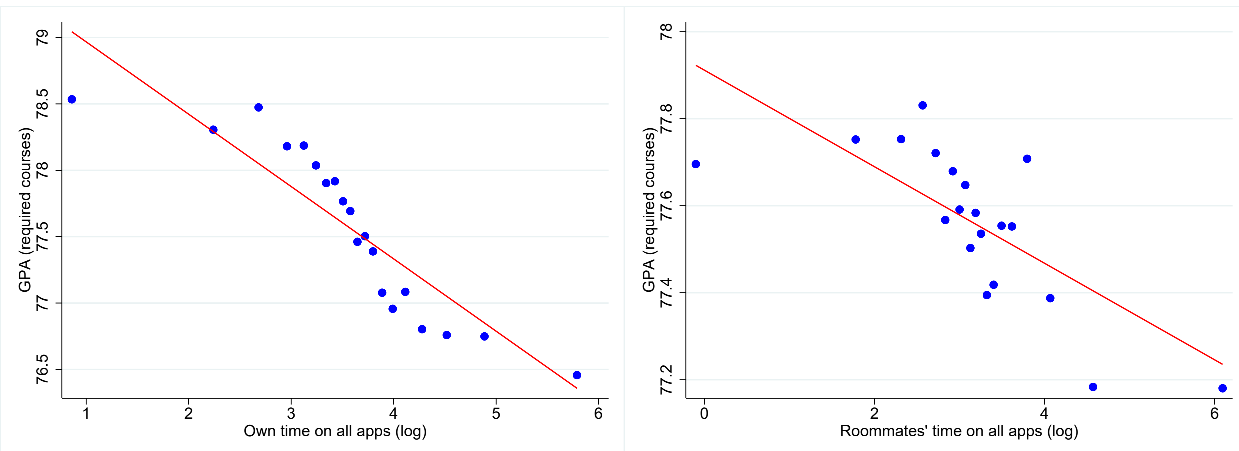
(b) Effect of Yuanshen on game app time



Notes: These graphs present the event study coefficients for the interaction between minors' game restriction policy × the number of underage pre-college friends (Panel A) and coefficients for the interaction between Yuanshen × pre-college game app usage (Panel B), showing the impact of the two shocks on game app time. The coefficient for one month prior to each shock is normalized to zero. The dots are point estimates, the grey lines represent the 95% confidence intervals, and solid dots / dark grey lines denote significance at the 5% level.

Figure 3: Effect of mobile app usage on GPA

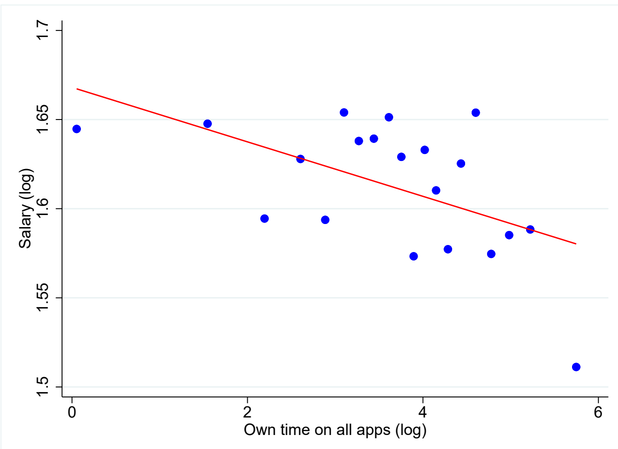
(a) GPA v.s. own mobile app usage (b) GPA v.s. roommates' mobile app usage



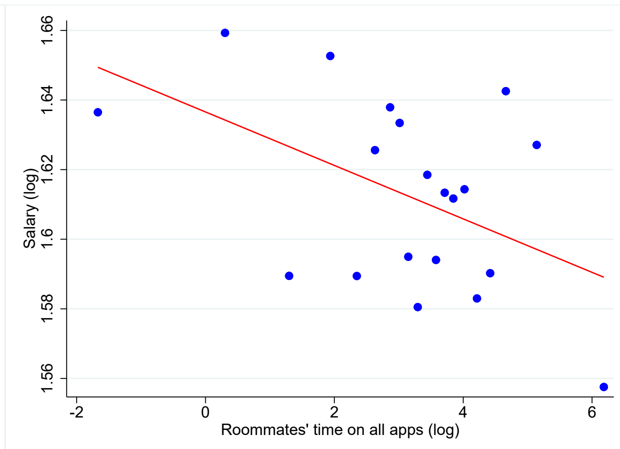
Notes: These graphs present the residualized relationship between GPA and app usage during college, for students' own app usage (in logarithms) in Panel (a) and roommates' app usage (in logarithms) in Panel (b). All graphs control for student fixed effects and class-semester fixed effects, where a class is a triplet of cohort, major, and administrative unit and consists of 20-50 students. The solid line represents the linear fit estimated from the underlying microdata using OLS.

Figure 4: Effect of mobile app usage on wage

(a) GPA v.s. own mobile app usage



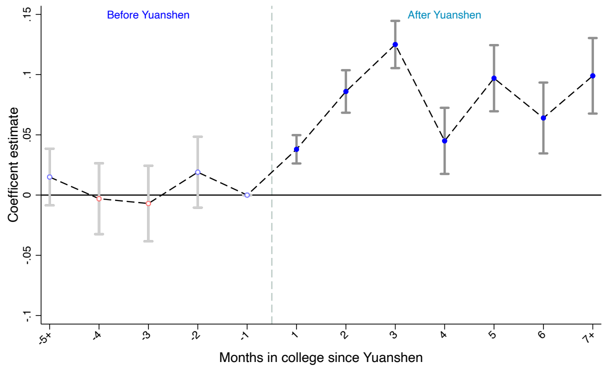
(b) GPA v.s. roommates' mobile app usage



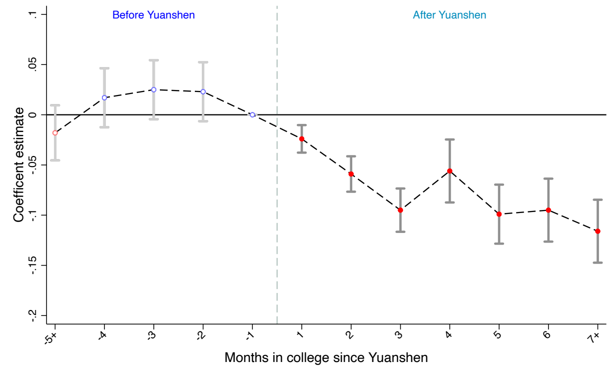
Notes: These graphs present the residualized relationship between wage upon graduation and own app usage (in logarithm) during college (Panel a) and that between wage and average roommates' app time (in logarithm) during college (Panel b). We control for class-by-gender, hometown, and dorm-size fixed effects in both graphs. The solid line represents the linear fit estimated from the underlying microdata using OLS.

Figure 5: Effect of Yuanshen on on-time performance

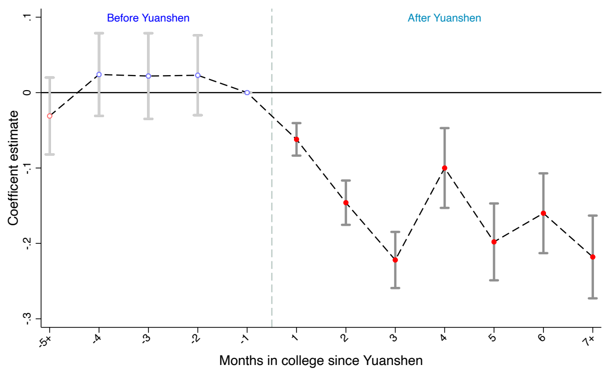
(a) Time of first arrival at study hall



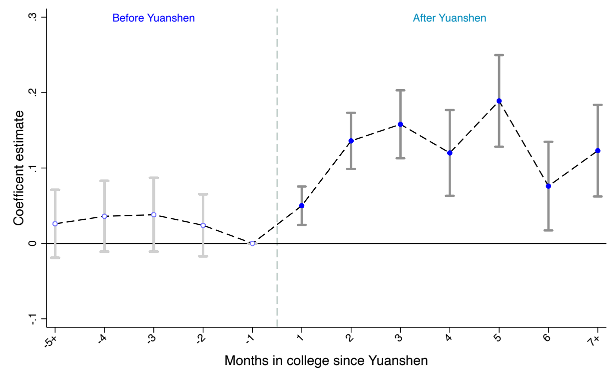
(b) Time of last return to dorm



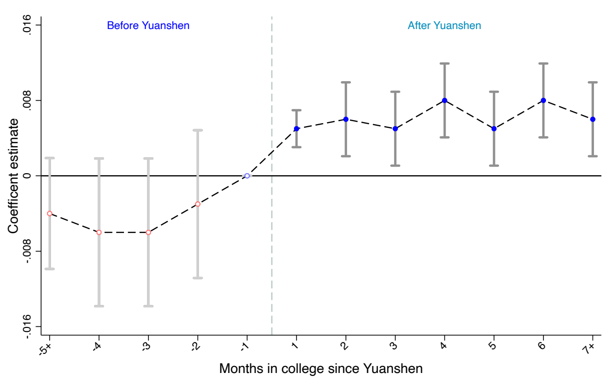
(c) Duration at study hall



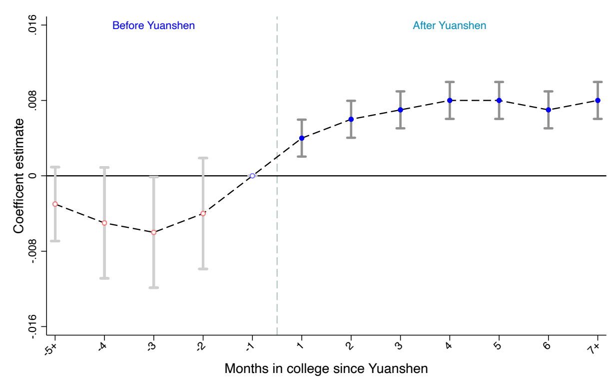
(d) Duration at dorm



(e) Lateness for classes



(f) Absence from classes

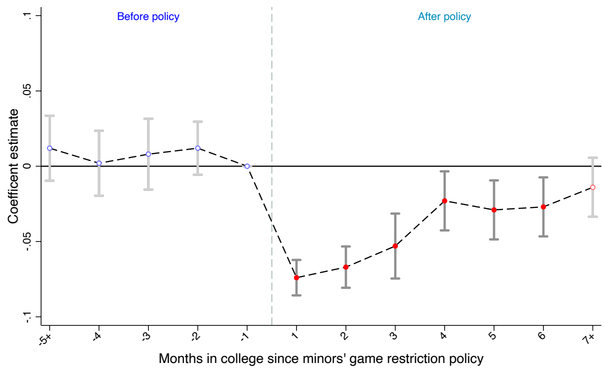


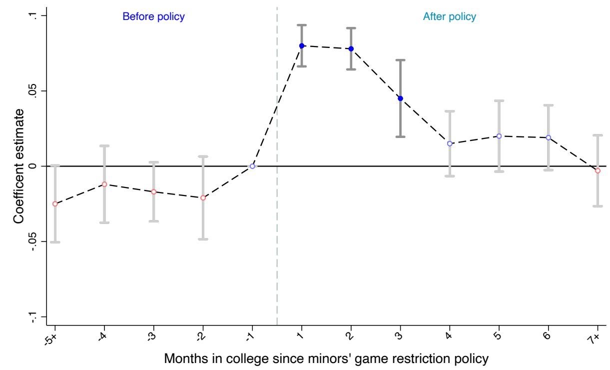
Notes: These graphs display the event study coefficients for the interaction between Yuanshen $\times$ own pre-college app usage (in logarithm), showing the impact of the Yuanshen shock on on-time performance metrics. The dependent variables in Panels (a)-(f) are: time of first arrival at the study hall (in hourly format), time of last return to the dorm (in hourly format), duration at the study hall in hours, duration at the dorm in hours, lateness by at least ten minutes for major-required classes, and absences from major-required classes, respectively. The coefficient for one month prior to the Yuanshen shock is normalized to zero. The dots are point estimates, the grey lines represent the 95% confidence intervals, and solid dots / dark grey lines denote significance at the 5% level.

Figure 6: Effect of minors' game restriction policy on on-time performance

(a) Time of first arrival at study hall

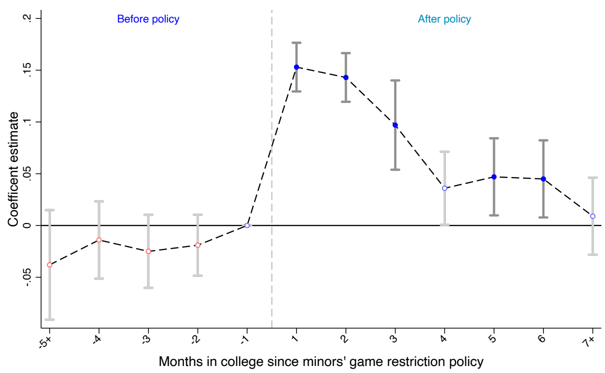
(b) Time of last return to dorm

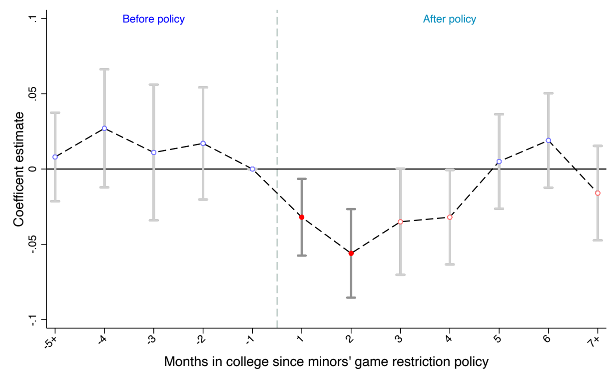




(c) Duration at study hall

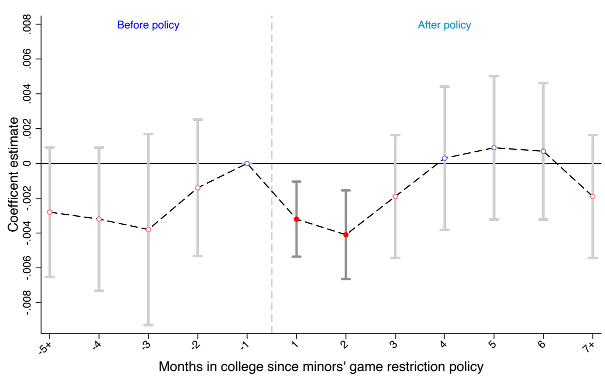
(d) Duration at dorm

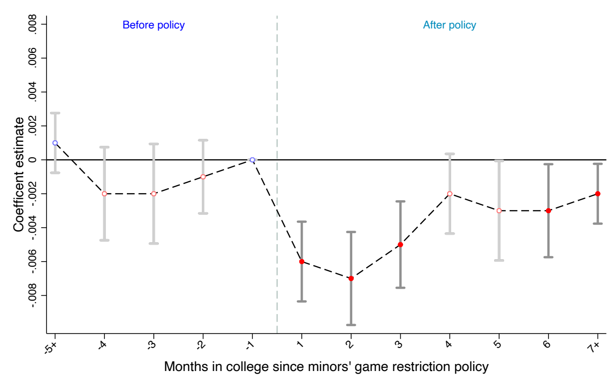




(e) Lateness for classes

(f) Absences from classes





Notes: These graphs present the event study coefficients for the interaction between minors' restriction policy × own minor friends, showing the impact of the minors' game restriction policy shock on on-time performance metrics. The dependent variables in Panels (a)-(f): time of first arrival at the study hall (in hourly format), time of last return to the dorm (in hourly format), duration at the study hall in hours, duration at the dorm in hours, lateness by at least ten minutes for major-required classes, and absences from major-required classes, respectively. The coefficient for one month prior to the policy shock is normalized to zero. The dots are point estimates, the grey lines represent the 95% confidence intervals, and solid dots / dark grey lines denote significance at the 5% level.

Table 1: Summary statistics

Variable	Observations	Mean	Std. Dev.
Panel A: Demographic characteristics (cohorts 2018-2020)			
Female	6,430	0.42	0.49
Age (years)	6,430	19.64	1.14
Rural residency	6,430	0.40	0.35
Social science track	6,430	0.25	0.43
CEE scores	6,430	505.61	30.95
Housing price (million RMB)	6,430	5.70	11.52
No. of pre-college friends under 18	6,430	4.18	4.55
Panel B: Monthly mobile app time in hours (cohorts 2018-2020)			
Total app time	104,307	92.9	108.5
Social media	104,307	33.4	37.9
Video	104,307	22.4	50.2
Games	104,307	12.1	16.6
Other	104,307	25.0	45.3
Panel C: Academic performance (cohorts 2018-2020)			
GPA (Required courses)	15,508	77.56	6.29
GPA (all courses)	15,508	77.69	6.6
GPA (required major courses)	15,508	78.49	7.48
GPA (PE)	12,288	80.53	8.24
Panel D: Job outcomes (cohorts 2018-2019)			
Admitted to post-graduate programs	3,783	0.14	0.34
Unemployed	3,783	0.07	0.25
Monthly wage (RMB)	2,812	5,376.93	2098.17
Panel E: College performance (cohorts 2018-2020)			
Time of first-time arrival at the study hall (in hourly format)	1,357,527	10.56	2.45
Time of last-time arrival at dorm (in hourly format)	1,412,824	17.49	2.62
Late at least 10 minutes for major-required classes	1,488,711	0.25	0.43
Absence from major-required classes	1,488,711	0.09	0.29
Duration at study hall (in hours)	1,357,527	6.88	4.25
Duration at dorm (in hours)	1,412,824	14.60	4.56

Notes: Panel A presents demographic data for the 2018-2020 cohorts. Each observation is a student. *Rural residency* indicates students from rural areas, *Social science track* indicates those who chose the social science track in high school, *CEE scores* refers to college entrance exam scores, *Housing price* is the average listed housing prices of the neighborhood (similar to a census tract in the U.S.) where students lived before college, adjusted to 2023 RMB. *No. of pre-college friends under 18* is the number of one's pre-college friends under 18. Panel B shows monthly mobile app usage in hours by category. Each observation is a student-year-month from September 2018 to June 2021, excluding January-June 2020 due to COVID-19 and winter and summer breaks (February, July, and August). The "other" category includes apps in news, shopping, finance, education, music, photos, tools, travel, health, food, and unclassified apps. Panel C summarizes GPA data on a 0-100 scale for the 2018-2020 cohorts. Each observation is a student-semester. The spring 2020 semester is excluded for all cohorts, as students were off campus due to COVID-19. Panel D shows job status for the 2018-2019 cohorts who graduated in June 2022 and June 2023. Each observation is a student. *Admitted to post-graduate programs* is an indicator for post-graduate admissions, *Unemployed* indicates students without a job one month after graduation, and *Wage* denotes the initial wage upon graduation. Panel E presents summary statistics of on-time performance. Each observation denotes a student-day from September 2018 to June 2021, excluding vacations and weekends.

Table 2: Causal estimates of reduced-form peer effects in mobile app usage

Variable: All in log(hours)	(1) Total app time	(2) Social media	(3) Video	(4) Game
Own *pre* total app time	0.190***			
	(0.012)			
Roommates' *pre* total app time	0.035***			
	(0.011)			
Own *pre* social media		0.191***		
		(0.012)		
Roommates' *pre* social media		0.029***		
		(0.011)		
Own *pre* video			0.207***	
			(0.011)	
Roommates' *pre* video			0.026**	
			(0.010)	
Own *pre* game				0.217***
				(0.013)
Roommates' *pre* game				0.036***
				(0.012)
Age	0.024	0.033	0.000	-0.005
	(0.025)	(0.024)	(0.033)	(0.029)
Rural residency	-0.079	-0.075	-0.000	-0.074
	(0.057)	(0.057)	(0.063)	(0.066)
Social science track	0.064	0.090	-0.035	-0.009
	(0.110)	(0.102)	(0.123)	(0.114)
CEE scores	-0.001	-0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Housing prices	0.050***	0.038***	0.036***	0.027***
	(0.002)	(0.002)	(0.003)	(0.002)
Roommates' age	-0.032**	-0.035**	-0.017	-0.026*
	(0.015)	(0.014)	(0.019)	(0.015)
Roommates' rural residency	-0.014	0.005	-0.045	0.011
	(0.059)	(0.056)	(0.057)	(0.063)
Roommates' social science track	-0.051	-0.057	-0.054	-0.035
	(0.054)	(0.052)	(0.061)	(0.056)
Roommates' CEE scores	0.001**	0.001***	0.001	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Roommates' housing prices	-0.002	-0.001	-0.004**	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	104,307	104,307	104,307	104,307
R-squared	0.12	0.11	0.14	0.11
Month-of-sample FE	Yes	Yes	Yes	Yes
Class-gender FE	Yes	Yes	Yes	Yes
Dorm-size FE	Yes	Yes	Yes	Yes

Notes: This table reports the causal estimates of reduced-form peer effects via Equation (2). Each observation is a student-year-month. The dependent variable in Columns (1)-(4) is own app usage in college in log hours, and the explanatory variables are students' and average roommates' pre-college app usage in log hours. All regressions control for class-by-gender, dorm-size, and month-of-sample fixed effects. 'Class' is a triplet of cohort, major, and administrative unit and consists of 20-50 students. Standard errors are clustered at the class level and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: IV estimates of behavioral peer effects in mobile app usage

Variable: All in log(hours)	(1) Total app time	(2) Game	(3) Game+Video	(4) Total app time	(5) Game	(6) Game+Video
Panel A: IV model						
Average roommates' time						
in log(hours) spent on:						
Total apps	0.038			0.050*		
	(0.028)			(0.030)		
Game apps		0.071**			0.078**	
		(0.030)			(0.034)	
Game + Video apps			0.051*			0.056
			(0.030)			(0.036)
Kleibergen-Paap rk Wald F stat.	34.1	31.2	32.3	34.5	31.8	33.0
p-value for Hansen J.	0.64	0.13	0.23	0.56	0.12	0.23
Observations	104,307	104,307	104,307	104,307	104,307	104,307
R-squared	0.54	0.52	0.53	0.54	0.52	0.53
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: First stage						
Average roommates'						
After game policy *	-0.032***	-0.034***	-0.037***			
No. of friends under 18	(0.008)	(0.007)	(0.007)			
No. of friends under 18	0.061***	0.063***	0.075***			
	(0.011)	(0.009)	(0.010)			
After game policy *				-0.041***	-0.041***	-0.048***
No. of *weighted* friends under 18				(0.010)	(0.009)	(0.010)
No. of *weighted* friends under 18				0.094***	0.092***	0.107***
				(0.015)	(0.015)	(0.015)
Observations	104,307	104,307	104,307	104,307	104,307	104,307
R-squared	0.52	0.50	0.51	0.52	0.50	0.50
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel A reports the IV estimates of the behavioral peer effect, where we regress students' monthly app usage in college (in logarithm) on their roommates' app usage in college (in logarithm) via Equation (3). Each observation denotes a student-year-month, excluding February, July, and August when students are on winter/summer vacations. The instruments in Columns (1)-(3) are the interaction between the minors' game restriction policy and the number of roommates' pre-college friends under 18. The instruments in Columns (4)-(6) are similar, except that the number of pre-college friends under 18 is weighted by phone call frequency before college. Panel B presents the first-stage results. All regressions control for student and month-of-sample fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Behavioral peer effect vs. contextual peer effect

	(1) **Contagion effect**	(2) **Contextual effect**
Roommates' total app time	0.050*	0.024
	(0.030)	(0.032)
Roommates' game	0.078**	0.017
	(0.034)	(0.034)
Roommates' game + video	0.056	0.013
	(0.036)	(0.029)

Notes: This table recovers both behavioral peer effects (contagion) and contextual effects. Column (1) reproduces the behavioral peer effect estimates in Columns (4)-(6) of Table 3. Column (2) reports contextual effects recovered from Equation (B.2), with standard errors calculated by the Delta method. The small and insignificant contextual effect estimates indicate that peer effects in the context of app usage are dominated by behavioral effects, with peer characteristics (contextual effect) playing a minor role. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: OLS and IV estimates of the effect of mobile app usage on academic performance

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA (required courses)			PE scores		
OLS model						
Variables: log(hours)						
Own total app time	-0.546***			-1.577***		
	(0.036)			(0.082)		
Roommates' total app time	-0.112***			-0.049		
	(0.024)			(0.055)		
Own game		-0.616***			-1.631***	
		(0.030)			(0.067)	
Roommates' game		-0.166***			-0.070	
		(0.028)			(0.072)	
Own game + video			-0.533***			-1.537***
			(0.028)			(0.061)
Roommates' game + video			-0.139***			-0.033
			(0.024)			(0.058)
Observations	15,508	15,508	15,508	12,288	12,288	12,288
R-squared	0.80	0.81	0.81	0.70	0.70	0.70
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-semester FE	Yes	Yes	Yes	Yes	Yes	Yes
CEE scores×semester linear trend	Yes	Yes	Yes	Yes	Yes	Yes
IV model						
Own total app time	-0.613***			-2.350***		
	(0.214)			(0.854)		
Roommates' total app time	-0.349**			0.140		
	(0.155)			(0.325)		
Own game		-0.816***			-2.463***	
		(0.226)			(0.789)	
Roommates' game		-0.343*			0.279	
		(0.181)			(0.413)	
Own game + video			-0.681***			-1.804***
			(0.185)			(0.574)
Roommates' game + video			-0.359**			0.145
			(0.160)			(0.360)
Kleibergen-Paap rk Wald F stat.	16.9	14.3	19.6	9.4	8.1	14.4
P-value for Hansen J	0.29	0.55	0.52	0.67	0.88	0.65
Observations	15,508	15,508	15,508	12,288	12,288	12,288
R-squared	0.80	0.81	0.80	0.67	0.65	0.68
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-semester FE	Yes	Yes	Yes	Yes	Yes	Yes
CEE scores×semester linear trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the OLS (panel A) and IV (panel B) estimates of how mobile app usage (in logarithms) affects GPA for required courses and physical health (measured by grades in physical education). Each observation is a student-semester cell, excluding the spring of 2020 for all cohorts. Yuanshen was released in September 2020, and the minors' game restriction policy was first implemented in November 2019. There are two endogenous regressors: own app usage and roommates' app usage, with four IVs: the interaction between Yuanshen and own vs. roommates' pre-college app usage, and the interaction between the minors' restriction policy and the number of own vs. roommates' pre-college friends under 18. All regressions control for student and class-by-semester fixed effects and the interaction between students' CEE scores and a semester linear trend. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: OLS and IV estimates of the effect of mobile app usage on wages

Variable	(1)	(2)	(3)	(4)	(5)	(6)
			Wage (in log)			
		OLS model			IV model	
Variables: log(hours)						
Own total app time	-0.015***			-0.020***		
	(0.005)			(0.006)		
Roommates' total app time	-0.008*			-0.008*		
	(0.004)			(0.005)		
Own game		-0.015***			-0.015***	
		(0.003)			(0.003)	
Roommates' game		-0.008			-0.010*	
		(0.005)			(0.005)	
Own game + video			-0.014***			-0.015**
			(0.003)			(0.004)
Roommates' game + video			-0.008*			-0.009*
			(0.004)			(0.005)
Ability proxy	0.006**	0.006**	0.006**	0.006**	0.006**	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Kleibergen-Paap rk Wald F stat.	-	-	-	317.3	4,625.3	1,904.0
Observations	2,812	2,812	2,812	2,812	2,812	2,812
R-squared	0.23	0.23	0.23	0.23	0.23	0.23
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hometown FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-gender FE	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-size FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the effect of in-college app usage (in logarithm) on wages (in log) upon graduation via Equation (6). The sample contains the 2018 and 2019 cohorts who graduated in June 2022 and June 2023. Columns (1)-(3) and (4)-(6) display OLS and IV estimates, respectively. Each observation denotes a student. We use the predicted mobile app use in college, derived from Equation (5) and averaged across all semesters, as instruments. "Ability proxy" refers to IV estimates of student fixed effects $\hat{\eta}_i$ in Equation (4). It captures time-invariant, unobserved characteristics that systematically influence GPA, such as innate ability or talent, motivation or work ethic, family background or socioeconomic status, and stable personality traits. These time-invariant characteristics are also likely to influence labor market outcomes. All regressions control for own and average roommate's pre-college app usage and characteristics (age at college enrollment, rural residency, social science track in high school, CEE scores, parents' housing prices), and hometown, class-by-gender, and dorm-size fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Effect of Yuanshen and minors' game restriction policy on on-time performance

	(1) Time of first arrival at study hall	(2) Time of last return to dorm	(3) Duration at study hall	(4) Duration at dorm	(5) Being late at least 10 minutes	(6) Absent from major-required classes
Yuanshen * own *pre* college all app usage (in log)	0.067***	-0.086***	-0.152***	0.085***	0.010***	0.012***
	(0.008)	(0.008)	(0.015)	(0.013)	(0.002)	(0.002)
Yuanshen * Roommates' *pre* college all app usage (in log)	0.016**	-0.011	-0.027*	0.024	0.001	0.003*
	(0.008)	(0.009)	(0.015)	(0.017)	(0.002)	(0.002)
Minors' game policy * own friends under 18	-0.064***	0.073***	0.137***	-0.054***	-0.002	-0.007***
	(0.006)	(0.007)	(0.012)	(0.009)	(0.001)	(0.001)
Minors' game policy * Roommates' friends under 18	-0.010**	-0.000	0.010	-0.005	-0.001	-0.004***
	(0.004)	(0.004)	(0.007)	(0.008)	(0.001)	(0.001)
Own friends under 18	-0.022**	0.022*	0.044**	0.002	-0.010***	-0.011***
	(0.009)	(0.011)	(0.019)	(0.017)	(0.003)	(0.003)
Roommates' friends under 18	0.012**	-0.007	-0.019*	-0.013	-0.002	-0.001
	(0.005)	(0.005)	(0.010)	(0.008)	(0.001)	(0.001)
Observations	1,357,527	1,412,824	1,357,527	1,412,824	1,488,711	1,488,711
R-squared	0.33	0.32	0.39	0.14	0.23	0.20
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-semester FE	Yes	Yes	Yes	Yes	Yes	Yes
CEE scores×semester linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-year FE× pre-college app usage	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the effect of Yuanshen and minors' game restriction policy on students' on-time performance in college. Each observation denotes a student-day from September 2018 to June 2021, excluding weekends, holidays, and summer/winter breaks. The time of first arrival at the study hall and last return to the dorm is recorded by the hour (the average arrival time at the study hall is 10.56 a.m. or 10:34 a.m.). Time spent at the study hall and in the dorm is measured in hours. Yuanshen was released in September 2020, and the minors' game restriction policy was first implemented in November 2019. All regressions control for student, class-by-semester, week-of-sample, day-of-week fixed effects, the interaction between CEE scores and a semester linear trend, and the interaction between week-of-year indicators and individual's pre-college app usage. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: Effect of app usage on sleep patterns

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sleep duration (hours)			Slept late (=1)			Woke-up late (=1)		
Variables: own usage in log(hours)									
Total app time at night	-0.199***			0.132***			0.018***		
	(0.003)			(0.001)			(0.001)		
Total app time at daytime	-0.029***			0.000			0.009***		
	(0.002)			(0.000)			(0.000)		
Gaming time at night		-0.258***			0.170***			0.022***	
		(0.005)			(0.001)			(0.001)	
Gaming time at daytime		-0.037***			0.000			0.012***	
		(0.003)			(0.000)			(0.001)	
Game + video night usage			-0.236***			0.156***			0.021***
			(0.004)			(0.001)			(0.001)
Game + video daytime usage			-0.034***			0.000			0.011***
			(0.003)			(0.000)			(0.001)
Observations	254,155	254,155	254,155	254,155	254,155	254,155	254,155	254,155	254,155
R-squared	0.15	0.14	0.14	0.21	0.24	0.25	0.16	0.16	0.16
Student FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class-semester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEE scores× semester linear trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-year FE× pre-college app usage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table examines the effect of app usage (in logarithms) on sleep patterns for the 2020 cohort from November 1st, 2023 to June 30th, 2024, except for weekends and the winter break (Feb 2024). Each observation denotes a student-day. The dependent variables are sleep duration in hours, an indicator for sleeping late, and an indicator for waking up late. All regressions control for student, week-of-sample, day-of-week, class-by-semester fixed effects, the interaction between college-entrance-exam scores and a semester linear trend, and the interaction between week-of-year indicators and an individual's pre-college app usage. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendices. For Online Publication Only

A Data construction

Parental wealth measure To construct an estimate of students' parental wealth, we use the housing price of the residential property where they stayed the summer before college. Specifically, we use a phone's GPS system to track locations and define a student's home location as the location where they spent at least 5 hours a day between 10 pm and 7 am for at least 25 days per month in the summer before entering college. We then collect the 2018 housing price for the geocoded locations from Soufun.com, a major online real estate brokerage intermediary and rental service provider in China that collects housing listing and transaction information for residential properties (Deng et al., 2015).

On-time performance measure To construct a measure of students' on-time performance, we first organized and structured the course timetable data (including start and end times) for 2,103 specialized courses across 56 majors over six semesters from 2018 to 2021 at the university. Then, using geocoded location information (in longitude and latitude) collected by mobile devices at 5-minute intervals, we constructed daily movement trajectories for each student. This allows us to construct several time allocation measures, including whether a student is more than 10 minutes late to a class and whether a student is absent from the class on a given day.

Sleep measure For the 2020 cohort (2,153 students), we also observe detailed hourly app usage data from November 1, 2023, to June 30, 2024 (the other cohorts had graduated by then). We implement the following algorithm to define sleep and wake-up time. For each student, we identify sleep onset as the first hour in a consecutive 3-hour window after 9 p.m. during which total app usage falls below 10% of the student's average daily usage over the previous month. Wake-up time is defined as the first hour in a consecutive 3-hour window after 6 a.m. when app usage exceeds 50% of the average daily usage. If no such low-usage window occurs by 3 a.m., the sleep start time is coded as missing, indicating the student likely did not sleep through the night. Similarly, if no high-usage window is found by 6 p.m., the wake-up time is also coded as missing.

Summary statistics for key variables are presented in Table C.3, where we exclude weekends and the winter break in February 2024 to focus on regular school days. As shown, a typical student falls asleep after 11 p.m. and wakes up before 7 a.m., averaging 6.8 hours of sleep per night. In approximately 15% of all student-day observations, the student's sleep onset time was later than midnight, while in about 16% of cases, the wake-up time was later than 9 a.m. Between 9 p.m. and 3 a.m., students spent an average of 1 hour using mobile apps, including 15 minutes (0.25 hours) on game apps.

Personality measures We employ the same measurement scales as those utilized in the China Family Panel Studies (CFPS) to assess human personality traits.[39] This scale, rooted in the widely accepted framework of psychology known as the Five-Factor Model (Conscientiousness, Extraversion, Openness, Neuroticism, and Agreeableness), evaluates each dimension with three items. Following the approach of Wu and Gu (2020), we exclude four negatively worded items (leaving 11 items, as shown in the questionnaire in Appendix D), while retaining the original 1-5 scoring system to evaluate the personality scale using the surveys administered by the university.[40] We calculate each Big-5 dimension score by averaging the scores of all corresponding questions.

B Theoretical framework for peer effect estimation

We follow the literature (Bramoulle et al., 2020) and hypothesize that an individual's in-college app usage in month t, y_{it}, is affected by his pre-determined characteristics, roommates' app usage y_{jt}, and roommates' characteristics. Specifically, we focus on one pre-determined characteristic x_i: pre-college app usage, while suppressing other characteristics for notation simplicity (we account for other attributes in the analysis). Let N_i, of size $|N_i|$, denote the set of individual i's roommates. We have:

$$y_{it} = \alpha + \gamma x_i + \beta \frac{1}{|N_i|} \sum_{j \in N_i} y_{jt} + \delta \frac{1}{|N_i|} \sum_{j \in N_i} x_j + \epsilon_{it}, \tag{B.1}$$

where γ is the individual effect, β is the behavioral spillover effect (contagion), and δ measures the contextual effect. Let $\mathbf{G}$ denote the interaction matrix (the roommate network): $g_{ij} = \frac{1}{|N_i|}$ if $j \in N_i$ and $g_{ij} = 0$ otherwise. Equation (B.1) can be written in matrix notations:

$$\mathbf{y} = \alpha \mathbf{1} + \gamma \mathbf{x} + \beta \mathbf{G} \mathbf{y} + \delta \mathbf{G} \mathbf{x} + \epsilon$$

[39]CFPS is a nationally representative survey in China conducted by the China Social Survey Center of Peking University.

[40]According to Wu and Gu (2020), the inclusion of both positively and negatively worded items may diminish the internal consistency of the scale.

If the matrix $\mathbf{I} - \beta\mathbf{G}$ is invertible, this system of equations is equivalent to the following reduced-form equation:

$$\begin{aligned} \mathbf{y} &= \frac{\alpha}{1-\beta}\mathbf{1} + (\mathbf{I} - \beta\mathbf{G})^{-1}(\gamma\mathbf{I} + \delta\mathbf{G})\mathbf{x} + (\mathbf{I} - \beta\mathbf{G})^{-1}\epsilon \\ &= \theta_\alpha\mathbf{1} + \mathbf{\Theta}_\gamma\mathbf{x} + \varepsilon, \end{aligned} \tag{B.2}$$

where the reduced-form coefficients $\mathbf{\Theta}_\gamma = (\mathbf{I}-\beta\mathbf{G})^{-1}(\gamma\mathbf{I}+\delta\mathbf{G})$ are functions of the behavioral spillover effect β, contextual peer effect δ, the roommate network $\mathbf{G}$, and individual effect γ.

C Robustness and heterogeneity

C.1 Robustness analysis

Peer effects Table C.8 replicates the reduced-form analysis for peer effects (Table 2) separately for each year in college. The correlation between students' in-college usage and their roommates' pre-college usage weakens over time, which is perhaps not surprising.

Placebo test and IV validity Our analyses exploit two exogenous shocks – Yuanshen and the Minors' game restriction policy – to construct instruments for endogenous app usage. Since these shocks specifically target/affect game apps, one might expect their impact on non-game apps to be limited. We conduct a placebo test and replicate the first stage for shopping apps and news apps, two categories that have low correlations with game apps (0.34 and 0.23, respectively). For comparison, we also replicate the first stage for social media and video apps, which are more closely related to game app usage, with correlations of 0.83 (between social media and game) and 0.71 (between video and game).

Table C.4 reports the results. Panel A presents the first-stage estimates using the minors' game restriction policy interacted with the (evolving) number of (pre-college) minor friends. Panel B reports the first stage results using the Yuanshen shock interacted with pre-college usage of the corresponding app category (e.g., pre-college news app usage for predicting current news app usage). As expected, there is a strong and significant first stage for social media and video apps, the two categories that are closely related to games, but NOT for news or shopping apps.

ITT event study To further validate the instruments we use, we conduct an ITT event-study and report the coefficients for the interaction between the minors' game restriction policy and the average number of *roommates*' underage pre-college friends in Figure C.4. Students whose roommates had more underage friends experienced larger reductions in game app usage following the policy's implementation, compared to those whose roommates had fewer underage friends. Consistent with Figure 2 in the main text, the effect was immediate and sizable upon policy introduction, gradually attenuated over time, and became statistically insignificant approximately three months later, as these second-degree peers aged out of the policy's targeted age group.

We do not conduct an ITT event study for the effects on app usage by month as a function of roommates' exposure to Yuanshen shock, as its introduction directly affects both students' own usage and their peers' usage. This overlap makes it unsuitable for isolating peer effects. For the same reason, we do not use the Yuanshen shock to estimate peer contagion effects in Section 3.2 of the main text.

Effects on academic performance We have conducted a battery of robustness analyses regarding the effect of app usage on academic performance. First, we examine alternative GPA measures in Table C.9: overall GPA and GPA for major-specific required courses. The results are similar to those in the baseline that examines GPA for all required courses (Table 5).[41]

Second, we examine the overall effect of app usage on cumulative college GPA using between-student variations. The overall impact of own app usage and peer app usage on cumulative GPA is similar to that estimated using student-semester level data, as shown in Table C.10 below. This similarity arises likely due to the large number of controls in place of student fixed effects — own and average roommate's pre-college app usage and characteristics (including age at college enrollment, rural residency, social science track in high school, CEE scores, and parents' housing prices) as well as class-by-gender and dorm-size fixed effects — which does a good job capturing time-invariant factors absorbed by student fixed effects.

Third, one might worry about course selections. How students choose elective courses can be correlated with their app usage and affect not only their GPA in electives (easy vs. hard courses) but also GPA in required courses (due to effort crowd-out and/or cross-course complementarity). Table C.11 examines the number of selected courses, the fraction of selected electives that are new courses, and the difficulty level of selected electives (measured by the previous cohort's grades). There is no evidence that app usage affects these outcomes, ruling out course selection as a confounding factor.

Fourth, another concern relates to the fact that GPA is largely based on students' performance in final exams, and hence, the effect of app usage on GPAs could be driven mostly by

[41] Required courses that are not related to majors differ across fields but often include math, English, political study, etc.

time allocation during the exam month. Figure C.5 presents app usage by month across four groups of students defined by their pre-college usage from high to low. The monthly trends in usage are parallel across groups. All groups of students spend less time on total apps during the first month of a semester, after which usage stabilizes. Their game app usage peaks in the second month and declines moderately in the last two months of the semester, but there is no strong evidence that students either cram or sharply reduce their game-app usage in the final month.

Lastly, we explore alternative instrument variables in Table C.12. Results are robust if we use only the Yuanshen shift-share IV and only the minors' game restriction interaction IV.

Effects of social media apps The analyses in the main text focus on gaming apps (or game+video apps) because the instruments we have are most appropriate for these apps. Given the popularity of social media apps, which accounts for about a third of total app usage, here we examine the impact of social media apps on student outcomes.

Using the IV specification (Equation 4), Column (1) of Table C.13 shows that both students' own and their roommates' social media app usage significantly reduce GPA, with all coefficients statistically significant at the 1% level. Column (2) examines impacts on physical education performance: while students' own social media usage negatively affects PE scores, we find no significant direct effect from roommates' usage. Finally, applying Equation (6), Column (3) shows that doubling one's social media usage during college is associated with a 2% reduction in wages upon graduation, though the effect of roommates' usage on wages is insignificant. Overall, the effect of social media app usage on academic and labor market outcomes is comparable to that of game app usage.

C.2 Heterogeneity

As shown in Table 1, app usage differs widely across students: the s.d. of monthly hours (108.5) is larger than the mean (92.9). Table C.14 examines monthly usage by student characteristics. The patterns are consistent across all app categories. First, app usage differs substantially by family wealth: students whose family wealth is above the median spend twice as much time as students in the other half of the family wealth distribution (120 vs. 60.3 hours per month). Second, as expected, students with heavy (above median) pre-college app usage continue to spend more time on apps in college than light users. Third, only small differences exist between students grouped by gender, science vs social science track, urban vs. rural status, or high vs. low CEE scores.

Echoing findings in Table C.14, we find systematic and significant differences only by family wealth and by pre-college app usage when we examine effect heterogeneity. Table C.15 reports the analyses on peer effects, GPA, and wage separately for students from wealthy vs. less wealthy families (Columns (1)-(2)) and heavy vs. light pre-college users (Columns (4)-(5)). Each panel and column represents a regression.

Panel A reveals that students from wealthier families and those who were heavy app users before college are more susceptible to behavioral spillover effects. For wealthier students (heavy pre-college users), the estimate is 0.114 (0.113) and statistically significant, compared to 0.048 (0.03) for less wealthy students (light users). Panel B shows that wealthy students experience a much stronger negative effect on their GPAs from playing apps (the coefficient estimate is -0.781) relative to less wealthy students (-0.47). Roommates' app usage is also more detrimental to GPAs for wealthy students (-0.333 and significant) than for less wealthy students (-0.139 and insignificant). In contrast, while heavy pre-college users experience stronger negative effects from their own app usage, their GPAs are less directly affected by their roommates' app usage compared to light pre-college users. This probably reflects the fact that heavy users spend less time studying (see Section 5) and hence are less influenced by noise and disruptions in the dorm.

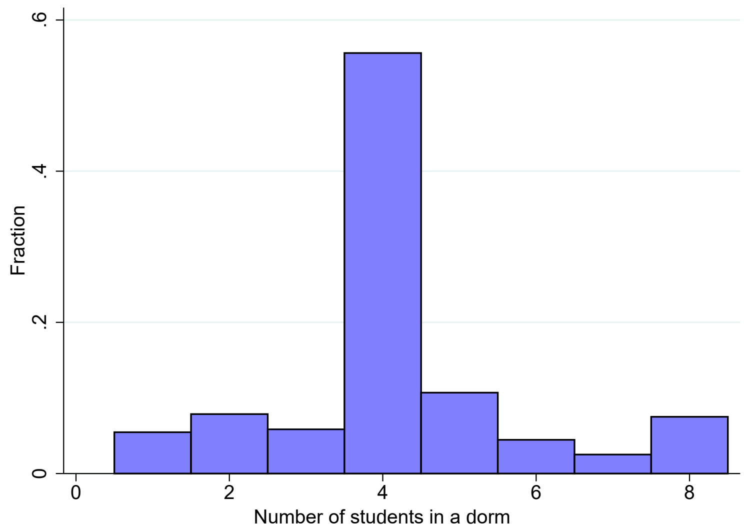
In contrast, Panel C indicates that app usage has similar effects on wages, *regardless* of students' family wealth or pre-college usage. One possible explanation is the correlation between family wealth and job market connections (Kramarz and Skans, 2014). Another reason might be that app usage and/or family wealth are correlated with students' traits that are valued by employers. As we show in 5.3, heavy users exhibit higher degrees of openness and extraversion.[42]

Finally, columns (3) and (6) test whether the heterogeneous estimates differ significantly across groups. The effect of own game-app usage on GPA is substantially different and statistically significant at the 5% level between wealthy and less wealthy students, as well as between students with heavy and light pre-college app usage. The remaining differences are not statistically significant, partially driven by the noisier estimates when the sample is split in estimation.

[42]Unfortunately, we could not directly investigate the relationship between personal traits and job market outcomes due to limited data on personal traits from the student surveys.

C.3 Figures and tables

Figure C.1: Distribution of the number of students in a dorm



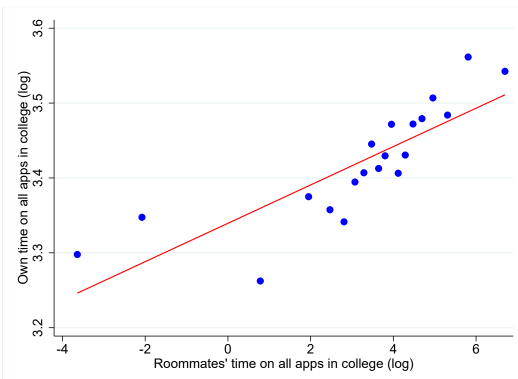
Notes: This graph displays the distribution of dormitory sizes, measured by the number of students per dorm, at the university in our study.

Figure C.2: Distribution of wages upon graduation

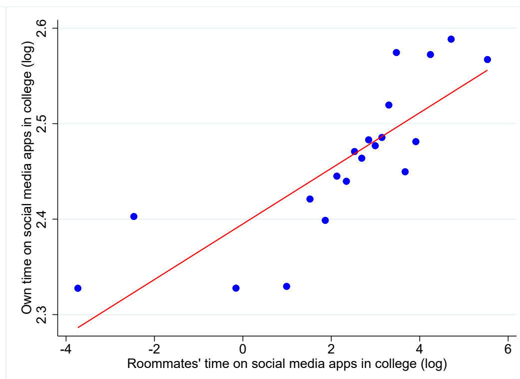
Notes: This graph shows the distribution of monthly wages upon graduation for the 2018 and 2019 cohorts in our sample.

Figure C.3: Contemporaneous correlation in mobile app usage

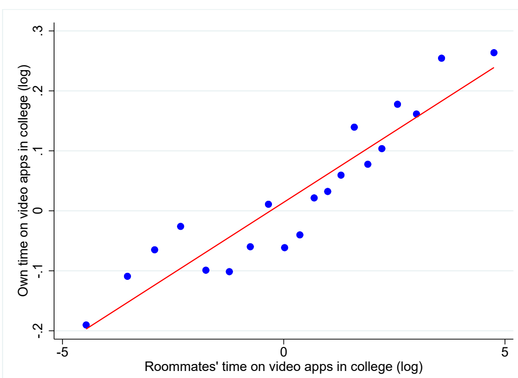
(a) Total app time



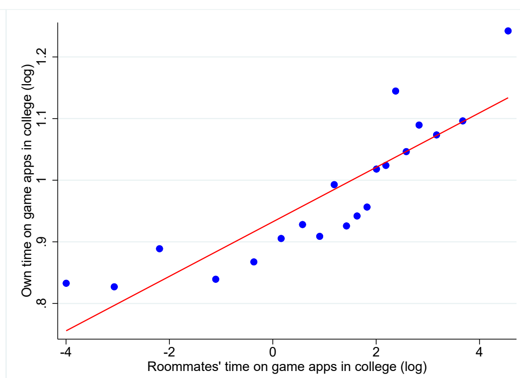
(b) Social media



(c) Video

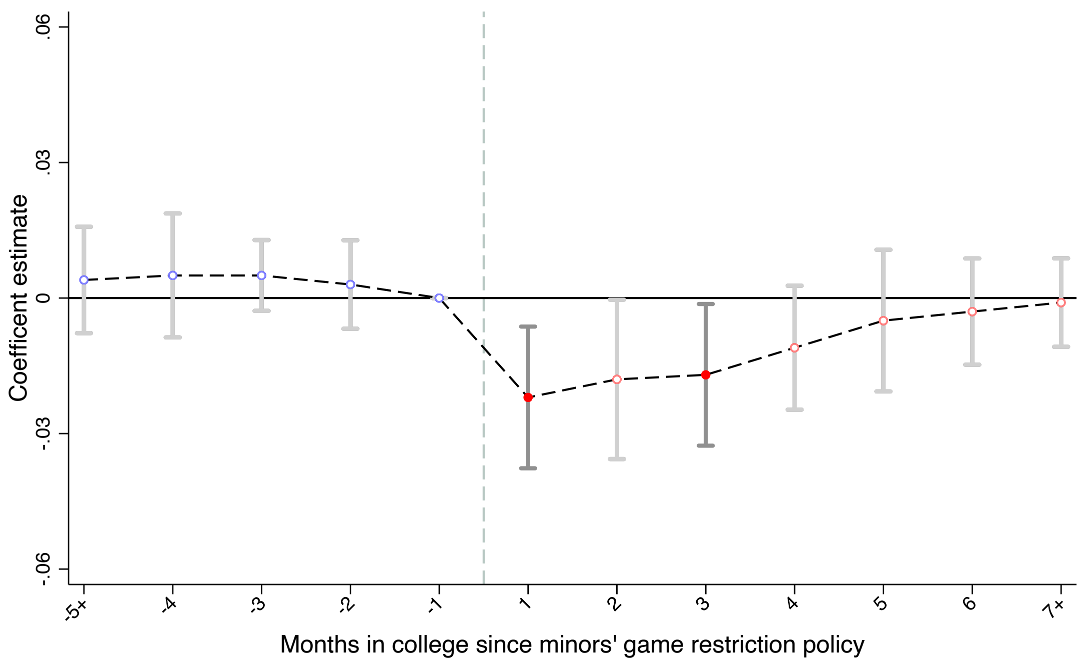


(d) Game



Notes: These graphs present the residualized binscatter plots between own and average roommate's monthly mobile app time (in logarithm) in college. The solid line shows the linear fit estimated on the underlying microdata using OLS. The correlation between own and roommates' app usage (which corresponds to an OLS estimate of the behavioral peer effect) is 0.025, 0.031, 0.037, and 0.039 for total app, social media, video, and game app usage, respectively, and all significant at the 1% level.

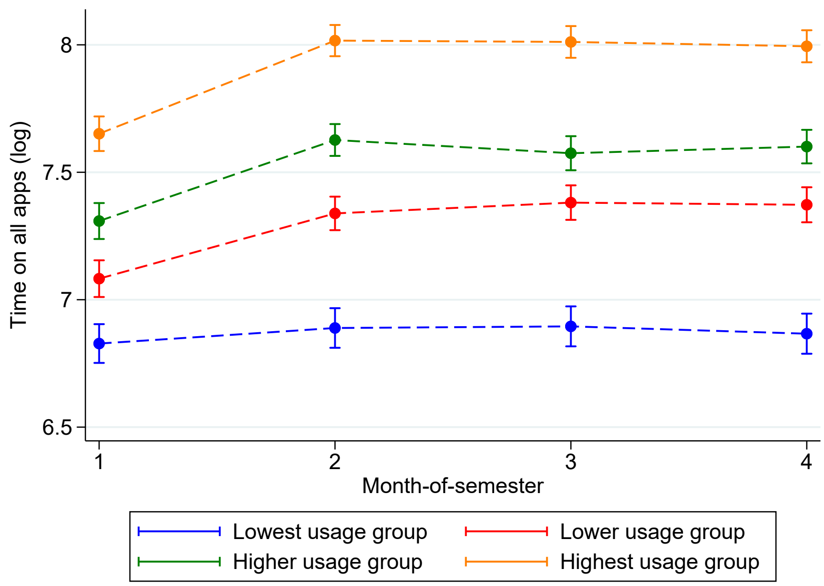
Figure C.4: Effect of the game restriction policy on own game app usage by roommates' underage friend exposure



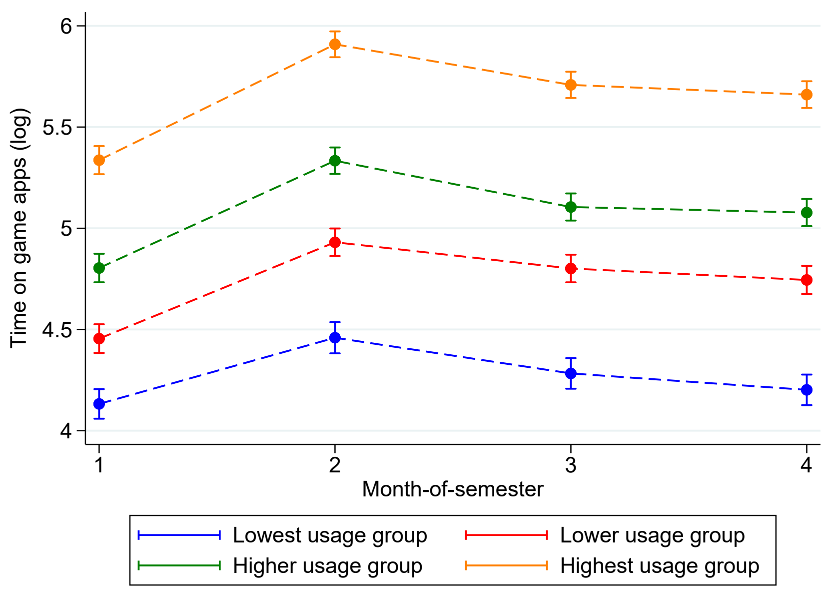
Notes: This figure is similar to Panel (A) of Figure 2 in the main text, except that it presents the event study coefficients for the interaction between minors' game restriction policy × the number of *roommates'* underage pre-college friends (the ITT event study coefficients). The coefficient for one month prior to each shock is normalized to zero. The dots are point estimates, the grey lines represent the 95% confidence intervals, and solid dots / dark grey lines denote significance at the 5% level.

Figure C.5: App usage across months within a semester

(a) Total app time



(b) Game app time



Notes: This graph shows total and game app usage across months within a semester. On the x-axis, the marks 1-4 denote the first, second, third, and final month of a semester, respectively. We split students into four equal-sized groups based on their pre-college app time. Total app usage appears reasonably stable across months within a semester (after the first month), with no strong evidence that students either cram or sharply reduce their game-app usage in the final month.

Table C.1: Balance tests — correlations between individuals' and their roommates' pre-college characteristics

Variable: log(hours)	(1) *Pre* total app time	(2) *Pre* social media	(3) *Pre* video	(4) *Pre* game	(5) Age	(6) Rural Residency	(7) Social science track	(8) CEE scores	(9) Housing prices
Average roommates' (log(hours)):									
Pre total app time	-0.014								
	(0.028)								
Pre social media		0.007							
		(0.029)							
Pre video			-0.003						
			(0.021)						
Pre game				-0.008					
				(0.026)					
Age					0.005				
					(0.005)				
Rural residency						0.010			
						(0.036)			
Social science track							0.012		
							(0.034)		
CEE scores								0.001	
								(0.000)	
Housing prices									0.030
									(0.022)
Observations	6,340	6,340	6,340	6,340	6,340	6,340	6,340	6,340	6,340
R-squared	0.05	0.05	0.04	0.06	0.22	0.31	0.59	0.80	0.14
Class-gender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the correlations between individuals' and their roommates' pre-college characteristics. Each observation denotes a student cell. The dependent and explanatory variables in Columns (1)-(9) are students' characteristics before college and their average roommate's characteristics before college. In each regression, we control class-by-gender and dorm-size fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.2: Summary statistics of the survey sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Demographics and personal traits					
Rural residency (=1)	1,798	0.65	0.48	0	1
The only child (=1)	1,798	0.22	0.41	0	1
Father with junior school or below (=1)	1,798	0.55	0.50	0	1
Mother with junior school or below (=1)	1,798	0.67	0.47	0	1
Openness	1,108	2.30	0.70	1	3
Conscientiousness	1,108	2.36	0.72	1	3
Extraversion	1,108	2.19	0.71	1	3
Agreeableness	1,108	2.34	0.89	1	3
Neuroticism	1,108	2.28	0.73	1	3
Panel B: Physical and mental health					
Physical health level	690	3.14	0.88	1	5
Mental health level	690	3.10	0.98	1	5
Pressure level	690	3.32	1.10	1	5
Panel C: Certification status and job search behaviors					
Having obtained no professional certificates (=1)	690	0.13	0.34	0	1
No. of job applications submitted	513	17.55	36.66	0	150
No. of interviews	513	2.50	1.96	0	16
No. of offers	513	0.69	1.13	0	7
Offer satisfaction level	513	2.18	0.72	1	4
Panel D: Views on games and relationships with roommates (=1)					
Playing games is addictive	1,798	0.52	0.37	0	1
Playing games is disturbing in dorms	1,798	0.18	0.39	0	1
Playing games adversely affects academic performance	1,798	0.14	0.34	0	1
Ever being invited by roommates	1,798	0.92	0.30	0	1
Accept roommates' invitations	1,328	0.65	0.45	0	1
Good relationships with roommates	1,798	0.88	0.32	0	1
Following roommates' job suggestions	690	0.34	0.47	0	1
Following roommates' post-graduate study suggestions	690	0.35	0.48	0	1

Notes: This table reports the summary statistics for the surveyed students. Panel A shows student demographics and personal traits. Panel B contains self-reported physical and mental health status. Panel C presents certification status and job search behaviors. Panel D shows students' views on playing games and their relationships with roommates. There are 690 and 1,108 participants in the 2022 and 2023 surveys, respectively. The 2022 survey includes students from the 2018 cohort only. The 2023 survey includes 513 and 595 students from the 2019 and 2020 cohort, respectively. Not all questions were asked in both surveys, which explains the differences in the number of observations across rows. Questions regarding personal traits in Panel A were specific to the 2023 survey wave, while questions about health status in Panel B, certification status in Panel C, and the importance of roommates' suggestions in Panel D were exclusive to the 2022 wave. Questions about job search behaviors applied only to the 2019 cohort in the 2023 survey wave. All remaining questions were included in both survey waves. See Appendix D for the full questionnaires. We lose 470 observations for the question "*Accept roommates' invitations*", as it is contingent upon students having been invited by their roommates to play games.

Table C.3: Summary statistics for variables related to the sleep analysis

Variable	Observations	Mean	Std. Dev.
Sample: cohort 2020			
Sleep duration (hours)	296,971	6.81	1.92
Sleep onset time (in hourly format)	296,971	23.88	0.87
Wake-up time (in hourly format)	296,971	6.60	1.65
Slept late (=1)	296,971	0.15	0.35
Woke-up late (=1)	296,971	0.16	0.37
Duration of total app usage between 8 a.m.-9 p.m. (hours)	296,971	2.15	4.13
Duration of game+video app usage between 8 a.m.-9 p.m. (hours)	296,971	0.79	2.62
Duration of game app usage between 8 a.m.-9 p.m. (hours)	296,971	0.53	2.07
Duration of total app usage between 9 p.m.-3 a.m. (hours)	296,971	1.01	2.58
Duration of game+video app usage between 9 p.m.-3 a.m. (hours)	296,971	0.67	2.13
Duration of game app usage between 9 p.m.-3 a.m. (hours)	296,971	0.25	1.91

Notes: This table reports summary statistics on daily app usage and sleep patterns. Each observation represents a student-date between November 1st, 2023, and June 30th, 2024, excluding weekends and the winter vacation (February 2024). Sleep onset times are recorded using a 24-hour scale that recodes times past midnight: for example, 0:00 a.m., 1:00 a.m., 2:00 a.m., and 3:00 a.m. are recoded as 24:00, 25:00, 26:00, and 27:00, respectively. Sleep onset is coded as missing if no low-usage window occurs by 3:00 a.m. The average sleep onset time is 23.88. The indicator variable *Slept late* equals 1 if sleep onset occurs after 24:00 (i.e., after midnight), and *Woke-up* late equals 1 if wake-up time is after 9:00 a.m.

Table C.4: First-stage estimates on other app categories: a placebo test

Variable: All in log(hours)	(1) Social media	(2) Video	(3) News	(4) Shopping
Panel A: Minors' game restriction shock				
After game policy *	-0.045***	-0.067***	-0.019	-0.007
No. of *weighted* friends under 18	(0.010)	(0.011)	(0.015)	(0.014)
No. of *weighted* friends under 18	0.099***	0.136***	0.100***	0.120***
	(0.015)	(0.017)	(0.015)	(0.017)
Observations	104,307	104,307	104,307	104,307
R-squared	0.55	0.50	0.54	0.59
Student FE	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes
Panel B: Yuanshen shock				
Yuanshen * own *pre*	0.123***	0.133***	0.014	-0.018
college app usage (in log)	(0.014)	(0.016)	(0.013)	(0.014)
Observations	104,307	104,307	104,307	104,307
R-squared	0.52	0.54	0.54	0.59
Student FE	Yes	Yes	Yes	Yes
Month-of-sample FE	Yes	Yes	Yes	Yes

Notes: This table presents the first-stage results on other app categories. Yuanshen and the minors' game restriction policy affect social media and video app usage, two categories closely related to gaming apps, but have no effect on shopping or news apps, as expected. All regressions control for student and month-of-sample fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.5: Effect of mobile app usage on the probability of having top and bottom quartile wages

Variable	(1)	(2)	(3)	(4)	(5)	(6)
		Top 25% Wage (=1)			Bottom 25% Wage (=1)	
Panel A: OLS model						
Variables: log(hours)						
Own total app time	-0.010**			0.026***		
	(0.005)			(0.005)		
Roommates' total app time	-0.007			0.006		
	(0.004)			(0.006)		
Own game		-0.007*			0.029***	
		(0.004)			(0.004)	
Roommates' game		-0.006			0.009	
		(0.005)			(0.007)	
Own game + video			-0.009**			0.026***
			(0.004)			(0.004)
Roommates' game + video			-0.005			0.007
			(0.005)			(0.006)
Ability proxy	0.005*	0.005*	0.005*	-0.007**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	2,812	2,812	2,812	2,812	2,812	2,812
R-squared	0.21	0.21	0.21	0.20	0.21	0.21
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hometown FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-gender FE	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-size FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: IV model						
Own total app time	-0.005			0.038***		
	(0.006)			(0.006)		
Roommates' total app time	-0.008*			0.006		
	(0.005)			(0.006)		
Own game		-0.005			0.031***	
		(0.004)			(0.004)	
Roommates' game		-0.009			0.010	
		(0.006)			(0.007)	
Own game + video			-0.010**			0.027***
			(0.004)			(0.004)
Roommates' game + video			-0.007			0.008
			(0.005)			(0.007)
Ability proxy	0.005*	0.005*	0.005*	-0.007**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Kleibergen-Paap rk Wald F stat.	317.3	4,625.3	1,904.0	317.3	4,625.3	1,904.0
Observations	2,812	2,812	2,812	2,812	2,812	2,812
R-squared	0.21	0.21	0.21	0.20	0.21	0.21
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hometown FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-gender FE	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-size FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the effect of in-college app usage (in logarithms) on the likelihood of earning a wage in the top or bottom quantile upon graduation for the 2018 and 2019 cohorts. Each observation denotes a student. Panels A and B display the OLS and IV estimates, respectively. The dependent variables in Columns (1)–(3) and (4)–(6) are indicators for earning a wage in the top and bottom quartiles of the distribution, respectively. Ability proxy refers to the IV estimate $\hat{\eta}_i$ from Equation (4). It captures time-invariant, unobserved characteristics that systematically influence GPA, such as innate ability or talent, motivation or work ethic, family background or socioeconomic status, and stable personality traits. These time-invariant characteristics are also likely to influence labor market outcomes. All regressions control for own and average roommate's pre-college app usage and characteristics (including age at college enrollment, rural residency, social science track in high school, CEE scores, and parents' housing prices), and hometown, class-by-gender, and dorm-size fixed effects. In panel B, we use the predicted mobile app use in college, derived from Equation (5) and averaged across all semesters, as instruments. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.6: Effect of mobile app usage on wages through the GPA channel

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Wage (in log)					
Variables: log(hours)						
Own total app time	-0.019***	-0.015**				
	(0.006)	(0.006)				
Roommates' total app time	-0.007	-0.004				
	(0.004)	(0.004)				
Own game			-0.015***	-0.010***		
			(0.004)	(0.004)		
Roommates' game			-0.009*	-0.008		
			(0.005)	(0.005)		
Own game + video					-0.011***	-0.007*
					(0.004)	(0.004)
Roommates' game + video					-0.008*	-0.007
					(0.005)	(0.005)
Cumulative GPA		0.006**		0.006**		0.006**
		(0.002)		(0.002)		(0.002)
Kleibergen-Paap rk Wald F stat.	315.1	303.4	4662.2	3826.6	1805.6	1723.3
Observations	2,812	2,812	2,812	2,812	2,812	2,812
R-squared	0.22	0.23	0.23	0.23	0.22	0.22
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hometown FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-gender FE	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-size FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table replicates the IV estimates in Table 6 in the main text, except that it drops the ability proxy and adds cumulative GPA in Columns (2), (4), and (6). All regressions control for own and average roommate's pre-college app usage and characteristics (including age at college enrollment, rural residency, social science track in high school, CEE scores, and parents' housing prices), and hometown, class-by-gender, and dorm-size fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.7: Correlations between mobile app usage and survey responses

Variables: log(hours)	Own total app time	Own game	Own game + video
Panel A: Personal traits (Big five)			
Openness	0.076*	0.085*	0.078*
	(526)	(526)	(526)
Extraversion	0.082*	0.106**	0.106**
	(526)	(526)	(526)
Conscientiousness	0.040	0.055	0.055
	(526)	(526)	(526)
Agreeableness	0.044	0.059	0.059
	(526)	(526)	(526)
Neuroticism	-0.011	-0.019	-0.025
	(526)	(526)	(526)
Panel B: Physical and mental health			
Physical health level	-0.197***	-0.221***	-0.217***
	(624)	(624)	(624)
Mental health level	-0.030	-0.003	-0.002
	(624)	(624)	(624)
Pressure level	0.162***	0.172***	0.165***
	(624)	(624)	(624)
Panel C: Certification status and job search efforts			
Having obtained no professional certificate (=1)	0.077*	0.089**	0.120***
	(624)	(624)	(624)
No. of job applications submitted	-0.207***	-0.180***	-0.195***
	(267)	(267)	(267)
No. of interviews	0.064	0.014	0.041
	(267)	(267)	(267)
No. of offers	0.078	0.085	0.082
	(267)	(267)	(267)
Offer satisfaction level	-0.125**	-0.125**	-0.145**
	(267)	(267)	(267)
Panel D: Views on games and relationships with roommates (=1)			
Playing games is addictive	0.080***	0.116***	0.110***
	(1150)	(1150)	(1150)
Playing games adversely affects academic performance	0.008	0.028	0.015
	(1150)	(1150)	(1150)
Interested in playing games with roommates	0.038	0.045	0.036
	(1150)	(1150)	(1150)
Accept roommates' invitations	0.017	0.038	0.042
	(952)	(952)	(952)
Playing games is disturbing in dorms	-0.025	-0.010	-0.002
	(1150)	(1150)	(1150)
Good relationships with roommates	0.054*	0.058**	0.043
	(1150)	(1150)	(1150)
Following roommates' job suggestions	0.055	0.068*	0.070*
	(624)	(624)	(624)
Following roommates' post-graduate study suggestions	-0.036	0.061	0.051
	(624)	(624)	(624)

Notes: This table describes the pairwise correlations between mobile app usage and survey responses. The number of observations is reported in parentheses below the estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.8: Dynamic reduced-form peer effects in mobile app usage

Variables: log(hours)	(1) Total app time	(2) Social media	(3) Video	(4) Game
Own *pre* total app time (FY)	0.228***			
	(0.014)			
Roommates' *pre* total app time (FY)	0.040***			
	(0.013)			
Own *pre* total app time (SY)	0.159***			
	(0.021)			
Roommates' *pre* total app time (SY)	0.032*			
	(0.016)			
Own *pre* total app time (TY)	0.136***			
	(0.019)			
Roommates' *pre* total app time (TY)	0.030			
	(0.023)			
Own *pre* social media (FY)		0.231***		
		(0.014)		
Roommates' *pre* social media (FY)		0.033**		
		(0.013)		
Own *pre* social media (SY)		0.158***		
		(0.021)		
Roommates' *pre* social media (SY)		0.032**		
		(0.015)		
Own *pre* social media (TY)		0.135***		
		(0.018)		
Roommates' *pre* social media (TY)		0.014		
		(0.023)		
Own *pre* video (FY)			0.230***	
			(0.015)	
Roommates' *pre* video (FY)			0.036***	
			(0.012)	
Own *pre* video (SY)			0.189***	
			(0.014)	
Roommates' *pre* video (SY)			0.019	
			(0.016)	
Own *pre* video (TY)			0.162***	
			(0.022)	
Roommates' *pre* video (TY)			0.004	
			(0.018)	
Own *pre* game (FY)				0.249***
				(0.014)
Roommates' *pre* game (FY)				0.032**
				(0.014)
Own *pre* game (SY)				0.186***
				(0.023)
Roommates' *pre* game (SY)				0.044**
				(0.017)
Own *pre* game (TY)				0.166***
				(0.020)
Roommates' *pre* game (TY)				0.022
				(0.028)

Notes: This table shows the reduced-form peer effect in mobile app usage (in logarithm) by academic year. FY, SY, and TY are short for the first year, second year, and third year at college, respectively. Each year in college is a separate regression. All regressions control for students' and their roommates' age, rural residency, social science track, CEE scores, housing prices, and class-by-gender, dorm-size, and month-of-sample fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.9: The effect of app usage on other GPA measures

	(1)	(2)	(3)	(4)	(5)	(6)
IV model		Overall GPA			Major required-course GPA	
Variables: log(hours)						
Own total app time	-0.766**			-0.670***		
	(0.313)			(0.249)		
Roommates' total app time	-0.368**			-0.401***		
	(0.140)			(0.147)		
Own game		-0.995***			-0.827***	
		(0.348)			(0.241)	
Roommates' game		-0.349**			-0.425**	
		(0.159)			(-0.177)	
Own game + video			-0.855***			-0.703***
			(0.298)			(0.209)
Roommates' game + video			-0.389***			-0.430***
			(0.142)			(0.159)
Kleibergen-Paap rk Wald F stat.	16.9	14.3	19.6	16.9	14.3	19.6
P-value for Hansen J	0.07	0.25	0.17	0.51	0.84	0.74
Observations	15,508	15,508	15,508	15,508	15,508	15,508
R-squared	0.75	0.75	0.75	0.78	0.78	0.78
Controls and FEs	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows IV estimates of the effect of app usage on other GPA measures. The instruments include Yuanshen shock (interacted with pre-college app usage) and minors' game restriction policy (interacted with pre-college underage friends). All regressions control for the interactions between individuals' CEE scores and a linear semester trend and student and class-semester fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.10: Effect of mobile app usage on cumulative GPA

	(1)	(2)	(3)
IV model	Cumulative GPA (required courses)		
Variables: log(hours)			
Own total app time	-0.596***		
	(0.105)		
Roommates' total app time	-0.064		
	(0.059)		
Own game usage		-0.700***	
		(0.064)	
Roommates' game usage		-0.105	
		(0.068)	
Own game + video usage			-0.617***
			(0.051)
Roommates' game + video usage			-0.116*
			(0.064)
Kleibergen-Paap rk Wald F stat.	350.0	5446.4	2405.3
Observations	6,430	6,430	6,430
R-squared	0.23	0.24	0.23
Controls	Yes	Yes	Yes
Class-gender FE	Yes	Yes	Yes
Dorm-size FE	Yes	Yes	Yes

Notes: This table presents the IV estimates of the effects of mobile app usage (logarithmic) on cumulative GPA using between-student variations. Each observation represents a student. All regressions control for own and average roommate's pre-college app usage and characteristics (including age at college enrollment, rural residency, social science track in high school, CEE scores, and housing prices) as well as class-by-gender and dorm-size fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.11: The effect of app usage on course selections

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		No. of selected courses			New course ratio (%)			Hard course ratio (%)			Course difficulty	
Variables: log(hours)												
Own total app time	0.006			1.246			-1.141			-0.006		
	(0.044)			(1.087)			(1.071)			(0.020)		
Roommates' total app time	-0.013			0.079			0.386			0.004		
	(0.026)			(0.872)			(0.769)			(0.014)		
Own game		0.014			0.968			-1.215			-0.024	
		(0.043)			(1.022)			(1.095)			(0.022)	
Roommates' game		-0.007			0.091			0.601			0.003	
		(0.030)			(1.053)			(0.971)			(0.019)	
Own game + video			-0.012			1.241			-0.844			-0.008
			(0.040)			(0.888)			(1.001)			(0.018)
Roommates' game + video			-0.011			0.147			0.536			0.002
			(0.028)			(0.970			(0.862)			(0.016)
Kleibergen-Paap rk Wald F stat.	11.2	9.3	10.8	11.2	9.3	10.8	10.8	9.2	10.8	10.8	9.2	10.8
P-value for Hansen J	0.45	0.77	0.71	0.61	0.76	0.76	0.99	0.99	0.94	0.82	0.99	0.86
Observations	11,924	11,924	11,924	11,924	11,924	11,924	11,355	11,355	11,355	11,355	11,355	11,355
R-squared	0.90	0.90	0.90	0.66	0.66	0.66	0.78	0.78	0.78	0.75	0.75	0.75
Controls and FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows IV estimates of the effect of app usage on course selections. Students in their freshman year are excluded as they do not have selected courses. We categorize all courses within a cohort-major into five groups based on their difficulty levels, measured by the previous year's average final scores. Difficulty ranges from 1 to 5, from the easiest to the hardest. *Hard course ratio* is the fraction of courses with a difficulty level of five among all selected courses. All regressions control for the interactions between individuals' CEE scores and a linear semester trend and student and class-semester fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.12: Alternative IV estimates of the effect of app usage on GPAs

	(1)	(2)	(3)	(4)	(5)	(6)
IV model	GPA (required courses)					
	Yuanshen IV			Game restriction policy IV		
Variables: log(hours)						
Own total app time	-0.595**			-0.856***		
	(0.247)			(0.305)		
Roommates' total app time	-0.523*			-0.307*		
	(0.310)			(0.168)		
Own game		-0.836***			-0.884***	
		(0.276)			(0.305)	
Roommates' game		-0.307*			-0.324*	
		(0.170)			(0.195)	
Own game + video			-0.654***			-0.912***
			(0.227)			(0.267)
Roommates' game + video			-0.435*			-0.313***
			(0.226)			(0.181)
Kleibergen-Paap rk Wald F stat.	12.8	10.7	17.3	14.7	11.5	15.5
Observations	15,508	15,508	15,508	15,508	15,508	15,508
R-squared	0.80	0.81	0.80	0.80	0.81	0.80
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-semester FE	Yes	Yes	Yes	Yes	Yes	Yes
CEE scores×semester linear trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table considers alternative IVs for the GPA analyses. We use Yuanshen shock interacted with pre-college app usage as IVs in Columns (1)-(3) and minors' game restriction policy interacted with the (evolving) number of minor friends as IVs in Columns (4)-(6). Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.13: Effects of social media app usage

Variables: log(hours)	(1) GPA (required courses)	(2) PE scores	(3) Wage (in log)
Own social media	-0.731***	-2.544***	-0.020***
	(0.234)	(0.989)	(0.006)
R's social media	-0.370**	0.163	-0.008
	(0.168)	(0.367)	(0.005)
Kleibergen-Paap rk Wald F stat.	19.0	7.8	329.9
P-value for Hansen J.	0.51	0.71	-
Observations	15,508	12,288	2,812
R-squared	0.80	0.66	0.23
All controls and FE	Yes	Yes	Yes

Notes: This table shows the effect of social media app usage on GPA for required courses (Column 1), physical health (measured by grades in physical education, Column 2), and wage in logarithms (Column 3). The specifications in Columns (1)-(2) and Column (3) are Equations (4) and (6) in the main text, respectively. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.14: Time allocation on mobile app categories by student characteristics

App category (in hours)	(1) Rich family	(2) Poor family	(3) Heavy game users	(4) Light game users	(5) Urban	(6) Rural
Total app time	120.0	60.3	107.8	77.5	94.4	88.3
Social media	41.6	23.4	38.8	27.8	33.7	32.5
Video	27.9	15.9	26.7	18.2	23.1	20.2
Games	14.2	9.3	14.7	9.3	12.4	11.1
Observations	51,656	52,651	51,877	52,430	26,430	77,877
	(7) Female	(8) Male	(9) Science track	(10) Social science track	(11) CEE scores above median	(12) CEE scores below median
Total app time	94.4	92.0	92.1	95.5	89.7	95.3
Social media	33.7	33.1	33.2	34.2	32.6	34.0
Video	20.9	23.3	22.1	22.9	21.2	23.3
Games	11.4	12.5	11.9	12.4	11.5	12.5
Observations	39,152	65,155	79,145	25,162	45,323	58,984

Notes: This table summarizes monthly time spent on mobile apps (in hours) by student characteristics. Each observation denotes a student-year-month cell. Our sample consists of 6,430 students in cohorts 2018-2020, with a sample period ranging from September 2018 to June 2021. The period from January 2020 to June 2020 is excluded for all cohorts as students did not return to campus due to COVID-19. We exclude winter and summer breaks (February, July, and August). Family wealth is measured by the average listed housing prices in the neighborhood where students lived before college. 'Rich (poor) family' denotes students with above-median (below-median) family wealth. 'Heavy (light) game users' denotes students with above-median (below-median) pre-college app usage.

Table C.15: Heterogeneity by family wealth and pre-college app usage

	(1)	(2)	(3)	(4)	(5)	(6)
	Family wealth		p-value	Pre-college game app usage		p-value
Sample	Above median	Below median	for (1)-(2)	Above median	Below median	for (3)-(4)
Variables: log(hours)			**Panel A: Own game time (in log)**			
Roommates' game time	0.114**	0.048	0.43	0.113**	0.030	0.19
	(0.055)	(0.054)		(0.048)	(0.043)	
Observations	57,866	46,441		57,850	46,457	
All controls and FEs	Yes	Yes		Yes	Yes	
Variables: log(hours)			**Panel B: Major-required GPA**			
Own game time	-0.781***	-0.470***	0.00	-0.711***	-0.538***	0.01
	(0.039)	(0.050)		(0.040)	(0.046)	
Roommates' game time	-0.333***	-0.139	0.15	-0.184**	-0.280***	0.43
	(0.094)	(0.093)		(0.086)	(0.097)	
Observations	7,945	7,563		7,766	7,742	
All controls and FEs	Yes	Yes		Yes	Yes	
Variables: log(hours)			**Panel C: Wage (in log)**			
Own game time	-0.014**	-0.015***	0.86	-0.016**	-0.011*	0.58
	(0.007)	(0.005)		(0.006)	(0.006)	
Roommates' game time	-0.006	-0.008	0.81	-0.008	-0.011	0.71
	(0.009)	(0.007)		(0.007)	(0.007)	
Observations	1,629	1,183		1,687	1,125	
All controls and FEs	Yes	Yes		Yes	Yes	

Notes: This table examines heterogeneity by family wealth and pre-college app usage in terms of peer effects, the effect of app usage on major-required GPA, and the effect of app usage on wages in Panels A, B, and C, respectively. Columns (1)-(2) split the sample at the median of parents' housing prices. Columns (4)-(5) split the sample at the median of pre-college game app usage. Columns (3) and (6) report the p-values for the difference in coefficients between Columns (1)-(2) and (4)-(5). In Panel A, we control for student and month-of-sample fixed effects. In Panel B, we control for student and class-semester fixed effects and the interaction between students' CEE scores and a semester linear trend. In Panel C, we control for own and average roommate's pre-college app usage and characteristics (including age at college enrollment, rural residency, social science track in high school, CEE scores, and housing prices) and hometown, class-by-gender, and dorm-size fixed effects. Standard errors are clustered at the class level (where a class is a triplet of cohort, major, and administrative unit) and reported in parentheses under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D Survey questionnaires

The online surveys we have access to were distributed via a WeChat application in June 2022 (focusing on the 2018 cohort) and March 2023 (targeting the 2019-2020 cohorts). Due to different university staff administering the questionnaires each year, some questions varied between the two survey waves, although both waves share many similarities. Below is the English version of the survey questions.[43]

Questionnaires for the Field Surveys

> Dear Student,
>
> Thank you for participating in this annual survey. Its purpose is to understand your campus life and career development, enabling the university to provide more targeted services and activities that better meet your needs.
>
> Participation is entirely **voluntary**. The information you provide will be protected in accordance with applicable laws and the university's regulations. There are no right or wrong answers; please respond honestly based on your situation. You may exit the survey at any time, and any information provided before exiting will not be collected or used.
>
> If you understand and agree to participate, please click the Agree button below to proceed to the questionnaire.
>
> Thank you for your participation!

[Wave 1 & 2, Demographics] What grade are you in college now? [Single choice question]

- Freshman
- Sophomore
- Junior
- Senior

[Wave 1 & 2, Demographics] What is your current household registration status (if you are a student collective household, please choose the original household registration status)? [Single-choice question]

- Rural household registration
- Urban household registration

[43]The order of the survey questions below aligns with the flow of the related topics in the main text, rather than the actual sequence in the survey.

- Unclear

[Wave 1 & 2, Demographics] How many siblings do you have (if you are the only child, please choose 0)? [Single-choice question]

- 0
- 1
- 2
- 3
- 4
- Other, please specify

[Wave 1 & 2, Demographics] What is the highest level of education your father has completed? [Single-choice question]

- Junior high school and below
- High school
- University
- Postgraduate or above
- Not sure

[Wave 1 & 2, Demographics] What is the highest level of education your mother has completed? [Single-choice question]

- Junior high school and below
- High school
- University
- Postgraduate or above
- Not sure

[Wave 2 only, Big Five] In this section, you will see several different phrases and sentences. Please use the response options to indicate how accurately each phrase or sentence describes you.

- Serious at work
- Talkative

- Creative
- Easily worried
- Tolerant
- Outgoing and sociable
- Appreciates art and aesthetic experience
- Easily nervous
- Efficient
- Considerate of others
- Rich imagination

Answer options for each question above are the same as follows:

- Very Inaccurate
- Moderately Inaccurate
- Moderately Accurate
- Very Accurate

[Wave 1 only, Health] Overall, how would you rate your current physical health? [Single Choice]

- Very good
- Quite good
- Average
- Not so good
- Very poor

[Wave 1 only, Health] Overall, how would you rate your current mental health? [Single Choice]

- Very good
- Quite good
- Average
- Not so good

- Very poor

[Wave 1 only, Health] Overall, how would you rate the stress you've experienced this semester? [Single choice]

- Very stressful
- Moderately stressful
- Average
- Moderately stress-free
- Completely stress-free

[Wave 1 only, Certification status] Which of the following skills certificates have you obtained? [Multiple Choice]

- Foreign Language (e.g., English CET-4/CET-6, TOEFL, etc.)
- Computer (e.g., Computer Level 2, etc.)
- Professional Qualification Certificate (e.g., Accounting Certificate, Judicial Certificate, Teacher Qualification Certificate, etc.)
- Sports (e.g., Provincial Athlete, Referee Certificate, etc.)
- Art and Fine Arts (e.g., Grading Certificate, etc.)
- Other, please specify

[Wave 1 & 2, Job search] What is your current (or planned) graduation destination? [Single choice question]

- Employment (including entrepreneurship, civil service, etc.)
- Further study (postgraduate)
- Joining the military
- Participating in non-governmental or non-profit organizations (NGOs, etc.)
- Taking a gap year to decide
- Unsure/Undecided
- Other, please specify

[Wave 2 only, Job search] What are your main job search channels? [Multiple choice question]

- Participate in social recruitment (submitting resumes)
- School recommendation to cooperative units
- Family/friend recommendation to related units
- Other, please specify

[Wave 2 only, Job search] Have you received any "internal referrals or guaranteed offers" before participating in social recruitment? [Single choice question]

- Yes
- No

[Wave 2 only, Job search] Up to now, how many resumes have you sent out? [Single choice question]

- 0
- 1-10
- 11-30
- 31-50
- 51-70
- 71-100
- over 100

[Wave 2 only, Job search] Up to now, how many interview notices have you received? [Single choice question]

- 0
- 1-5
- 6-10
- 11-20
- 21-30
- over 30

[Wave 2 only, Job search] Up to now, how many job offers (including verbal job offers) have you received? [Single choice question]

- 0
- 1-5
- 6-10
- 11-20
- 21-30
- over 30

[Wave 2 only, Job search] Are you satisfied with your current job offer results? [Single choice question]

- Very satisfied
- Basically satisfied
- Not very satisfied
- Extremely unsatisfied

[Waves 1 & 2, Views on games] Do you agree or disagree that playing video games will harm your academic performance? [Single-choice question]

- Strongly agree
- Somewhat agree
- Neutral
- Disagree

[Wave 1 & 2, Views on games] What is your attitude when you see your roommate(s) playing video games? [Single-choice question]

- Interested
- Indifferent
- Resistant or repulsed

[Wave 1 & 2, Relationships with roommates] Have your roommate(s) ever invited you to play video games together? [Single-choice question]

- Often
- Occasionally
- Never

[Wave 1 & 2, Relationships with roommates] What is your attitude towards your roommate(s)' invitation to play video games together? [Single-choice question]

- Willing to join
- Unwilling to join, but find it hard to refuse
- Refuse

[Wave 1 & 2, Relationships with roommates] Do you think your roommate(s) playing video games in the dormitory disturbs your dormitory life? [Single-choice question]

- Very disturbing
- Somewhat disturbing
- Occasionally disturbing
- Not disturbing at all
- Don't care

[Wave 1 & 2, Relationships with roommates] How would you rate your relationship with your "video-gaming roommate(s)"? [Single-choice question]

- Very good
- Good
- Average
- Not very close
- If possible, I would like to change my "video-gaming roommate(s)" to someone who does not play video games.

[Wave 1 only, Relationships with roommates] Did you follow your roommate(s)' advice about your job search? [Single Choice]

- Fully followed

- Partially followed
- Not followed at all

[Wave 1 only, Relationships with roommates] Did you follow your roommate(s)' advice about your further studies? [Single Choice]

- Fully followed
- Partially followed
- Not followed at all

[Wave 1 & 2, Identifier] fill in your student ID: [Fill in the blanks]