NBER WORKING PAPER SERIES

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Working Paper 33054
http://www.nber.org/papers/w33054

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2024, Revised October 2024

We thank Hunt Allcott, Luigi Pistaferri, Uta Schönberg, Chris Taber, and various seminar participants for their helpful comments and Chenyan Gong for outstanding research assistance. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 33054
October 2024, Revised October 2024
JEL No. D12, D90, E24, I23, L82, L86, Z13

ABSTRACT

Concerns over the excessive use of mobile phones, especially among youths and young adults, are growing. We present, to our knowledge, the first estimates of both behavioral spillover and contextual peer effects, as well as the first comprehensive evidence of how own and peers' mobile app usage affects academic performance, physical health, and labor market outcomes. Our analysis leverages administrative data from a Chinese university of three cohorts of students over up to four years merged with mobile phone records, random roommate assignments, and a policy shock that affects peers' peers. App usage is contagious: a one s.d. increase in roommates' in-college app usage raises own app usage by 5.8% on average, with substantial heterogeneity across students. High app usage is detrimental to all outcomes we measure. 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 exerts both direct effects (e.g., noise and disruptions) and indirect effects (via behavioral spillovers) on GPAs and wages, resulting in a total negative impact of over half the size of the own usage effect. Extending China's minors' game restriction of three hours per week to college students would boost their initial wages by 0.9%. Using high-frequency GPS data, we identify one underlying mechanism: high app usage crowds out time in study halls and increases late arrivals at and absences from lectures.

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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. In a 2018 China survey, 77.5% of college students admitted to playing mobile games during class (with 35% doing so frequently);[2] a 2019 UK study found that 39% of young adults reported smartphone addiction (Sohn et al., 2021). In the U.S., over 70% of high school teachers in a 2023 survey identified phone distractions as a significant issue in the classroom (Lin et al., 2024). In a 2023 OECD study, 65% of students reported being distracted by their own usage of digital devices during Maths lessons, while 59% reported distractions from other students' use of digital devices in those lessons (OECD, 2023). That is, digital distractions can be detrimental to *not only* individuals themselves *but also* their peers.

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

Despite the widespread concerns about app overuse and government policy responses, little is known (rigorously) about the long-term implications of app usage for individuals' and their peers' human capital development and for the aggregate labor market. Following three cohorts of college students for up to four years, we take a step forward to address this issue and present, to our knowledge, the first comprehensive evidence of how app usage by individuals and their peers affects academic performance, physical well-being, and early career outcomes.

[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] Sources: `https://www.chinadaily.com.cn/a/201801/10/WS5a55539ea3102e5b17371b6f.html`.

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

Empirical investigations on how own and peer app usage affect human capital accumulation face three key challenges. First, researchers lack suitable data that links phone usage with outcome measures. We overcome this obstacle by merging two unique datasets: the first from a leading Chinese cellular service provider that contains comprehensive mobile phone records of all subscribers in a populous Chinese province, and the second from a university in the same province that contains administrative records of students' demographic and academic backgrounds, in-college performances, and job market outcomes upon graduation for several cohorts.

The second challenge involves the typical complications encountered in empirical estimation of peer effects, e.g., correlated effects (exposure to a common group environment) (Manski, 1993; Bramoulle et al., 2020). We recover peer effects in two steps. First, by leveraging the university's random dorm room assignment policy and focusing on a narrowly defined peer group — roommates, we provide causal estimates of the "reduced-form" peer effects that are functions of both behavioral spillover effects and contextual peer effects. Second, we disentangle these two types of peer effects using quasi-experimental policy variations as a result of the 2019 minors' game restriction policy that impacted peers' peers (Bramoulle et al., 2009; De Giorgi et al., 2020; Evtushenko and Kleinberg, 2021; Barwick et al., 2023).

The third challenge arises from the endogeneity of mobile app usage. Factors such as unobserved ability and attitudes, stress from school, and extracurricular activities could influence both app usage and academic and labor market outcomes. To address this, we use two sets of instruments. The first exploits the 2019 China's minors' game restriction mentioned earlier, which directly impacted 8% of our sample students but indirectly affected all of them through their underage friends.[4] Event studies confirm the 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 first set of instruments for app usage. The

[4] Gaming often occurs in social groups. 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.

second set of instruments exploits the launch of the blockbuster game "Yuanshen" midway through our sample period. 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 whenever possible.

Our analyses yield five 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, the latter of which is modest and statistically insignificant. That is, peer influence in app usage is primarily driven by peers' actions rather than their characteristics. Despite the extensive literature on peer effects, this analysis provides, to our knowledge, the first empirical estimates that distinguish between behavioral spillover effects and contextual peer effects.

Second, mobile app usage negatively affects GPAs. Different from the existing literature, we allow roommates' app usage to affect academic outcomes *both* indirectly via behavioral spillovers *and* directly. The direct effect may arise because roommates' game-playing disrupts the study environment in the dorm or because roommates' app usage crowds out time spent in group studies and hence decreases positive peer influences. 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, a one s.d. increase in roommates' app usage directly lowers a student's GPA by 20.6% of a s.d. Combining the direct and the indirect (via behavioral spillover) peer effects, 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 size of the own usage effect.

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

Fourth, 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).

Fifth, there is considerable heterogeneity in peer effects and the effects of app usage on outcomes. Students from wealthier families and those who were heavier app users before college experience much stronger peer behavioral spillover effects. These students also suffer more severe negative impacts from app usage on their GPAs, though not more negative impacts on wage outcomes. The latter finding could be driven by labor market connections by wealthy families (Kramarz and Skans, 2014) as well as student traits valued by employers that are correlated with app usage, which help mitigate the wage effect.

Finally, we present two sets of evidence to shed light on the mechanisms underlying these findings. 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 that allow us to precisely measure the extensive-margin time allocation. We find that app usage reduces (increases) students' time spent in study halls (dorms) and increases late arrivals at and absences from lectures. The second set of evidence comes from our online 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 to account for peer effects and examine the consequences of app usage on academic achievements and physical health over multi-year periods and on early labor market outcomes.

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). We exploit the same type of exogenous variation and combine it with additional quasi-random policy variations and a panel data structure to separate behavioral spillover effects from contextual peer effects. We further demonstrate that peers' phone usage exerts both indirect effects (through behavioral spillovers) and direct effects on individuals' outcomes. To the extent that app usage crowds out study time, our analysis also relates to studies on students' effort choices in the presence of peer effects (Calvó-Armengol et al.,

[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, and 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.

[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), Burks et al. (2015), Dustmann et al. (2016), Booij et al. (2017), Feld and Zölitz (2017), and Blumenstock et al. (2023) 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.

2009; Fruehwirth, 2013; De Giorgi and Pellizzari, 2014; Tincani, 2018; Conley et al., 2024).

The rest of the paper proceeds as follows. Section 2 provides institutional background and describes the data. Section 3 separately identifies behavioral spillover effects and contextual peer effects. Section 4 analyzes the effects of app usage on GPA and labor market outcomes. Section 5 conducts robustness checks and examines effect heterogeneity. Section 6 investigates the underlying mechanisms. Section 7 concludes. The appendices contain more details and additional analyses.

2 Institutional Background and Data Description

2.1 Background Information

Mobile Apps and Game Restriction Policy An average smartphone user spends over 3 hours per day on mobile apps. Of the 1.81 million apps in the Apple App Store, over 20% were game apps. In 2023, game app usage accounted for approximately 11% 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 (13 million users) and one of the most popular globally (over 100 million users); the majority of its users are under age 25.[8]

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

[7] See `https://backlinko.com/smartphone-usage-statistics` for phone time, and `https://www.statista.com/statistics/1465726/global-daily-time-spent-mobile-usage/` for game app usage.

[8] See `https://www.sgpjbg.com/hyshuju/ef7ee7929c8f2a7fea2484a591c025d3.html`.

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 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 dorms. Dorm rooms are equipped with multiple bunk beds and workstations, sized at approximately 50-70 square feet per student. As is typical in Chinese universities, each dorm room accommodates 4 to 8 students, with 4 being the most common arrangement (Figure B.1).

Upon enrollment, Freshmen within each major are randomly divided into 5 adminis-

[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).

trative 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-major units, we find no correlation between roommates in their pre-college app usage, CEE scores, demographics, and socioeconomic backgrounds. (Table B.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 two primary datasets linked via individuals' National ID: administrative records for 2018-2020 freshmen cohorts at the university and detailed phone usage data from a dominant telecommunication service provider in the same province for 2018-2021. These datasets allow us to examine peer effects in app usage and evaluate the impact of app usage on academic and labor market outcomes. For further analysis, we incorporate geocoded location data from mobile phone GPS systems as well as field surveys. Throughout our analysis, we exclude the spring semester of 2020 for all cohorts, as students were off campus due to COVID-19.

2.2.1 Data for Main Analysis

Administrative Student Records Our 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;[11] 2) admission records, containing each

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

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.[12]

Phone Usage Data Our phone usage data, provided by one of the largest wireless carriers in China, covers all 71 million users in the same province from 2018 to 2021 (representing a 75% market share). For each user, we observe monthly usage time for every app with at least 500 users. Following the app classifications by the Android and Apple App Stores, we group mobile apps into six categories: social media, video, games, news, shopping, and others. Out of 7,479 students, we successfully matched 6,430 to their phone usage data; the remaining students were not users of this cellular carrier.[13] We exclude app usage data in 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,[14] 2) had never been enrolled in i's college 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. Due to the ID requirement for mobile phone registrations, we know the exact age of students and their friends over time.

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

[13]To maximize sample size, we calculated the average characteristics and phone usage of all roommates in each dorm room based on matched students. Excluding unmatched roommates should not bias our estimates because roommate assignments (which are random) are orthogonal to students' choice of cellular providers. Results remain similar when dorms with unmatched students are excluded.

[14]Not all high school students have mobile phones, but almost everyone obtains a mobile phone by the end of high school.

2.2.2 Supplementary Data

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 coverage areas by cell towers: 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.

Field Surveys We conducted two rounds of online surveys (see Table B.2 for a summary and Appendix C for questionnaires). These surveys were administered by the university's 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, with a response rate of 24%. We merged the survey data with administrative records using student IDs.

On the downside, the survey 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 reflect the distribution of observables in the full student sample. On the upside, the quality of our surveys is quite high: respondents' self-reported answers align well with the administrative records. Moreover, the survey complements well the main datasets with additional information on: 1) personality (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) (Goldberg, 1993); 2) physical and mental health; 3) professional certification, job search processes, and satisfaction with job offers; 4) views on game playing; and 5) interactions among roommates.

2.3 Summary Statistics

Demographics, Grades, Jobs, and App Usage Table 1 presents summary statistics for the 6,430 students in our main sample. Compared to an average university in China (2021 China Education Statistical Yearbook), Panel A shows that students at this university are less likely to be female (42% in our sample vs. 53% in the national college student population) and 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).[15] Throughout the paper, all monetary values are measured in 2023 RMB. On average, students have four underage pre-college friends.

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, 9.9 hours on news, 9.3 hours on shopping, and 5.8 hours on the remaining "other" category. Notably, time spent on educational apps in the "other" category is modest at 1.2 hours per month.

Our analyses below focus on the total app, game app, and game+video app usage, though the results are generally consistent with other app categories (except for shopping apps). A potential concern may be app usage on other devices, which we do not observe. With due caveats remaining, two pieces of evidence may alleviate this concern. First, according to a 2019 report by Aurora, 80.8% of game players play on mobile devices.[16] Second, app usage is likely positively correlated across devices. Based on the data from the China Family Panel

[15] The exchange rate in 2023 is ¥7.07 per USD.
[16] See https://news.futunn.com/en/post/4733764.

Study (wave 2018), the correlation between smartphone and computer use is around 0.46.

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

Panel D reports job market outcomes for the 2022 and 2023 graduating cohorts. Of these graduates, 14% were admitted to some post-graduate programs 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 B.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 Spent at Different Locations Panel E in Table 1 offers a glimpse into where students spend their time on a typical weekday during the semester. On average, students arrive at study halls at 10:56 am and return to their dorms at 5:49 pm. 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.

3 Peer Effects on App Usage

Our first set of analyses examines peer effects on app usage. First, by leveraging the random roommate assignment, we provide causal estimates of the reduced-form peer effects in app usage.[17] Then, we quantify the behavioral spillover effects by exploiting quasi-experimental policy variations that influence the behavior of peers' peers differentially across students and time. These two sets of estimates allow us to separately recover behavioral spillover and

[17]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.

contextual peer effects.

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.

3.1 Reduced-Form Estimates

Consistent with anecdotal evidence, there is a strong correlation of app usage among roommates, as shown in Figure B.3, which are residualized scatter plots of individuals' and their roommates' monthly mobile app usage during college, controlling for month-of-sample and individual fixed effects.

While suggestive, these correlations do not directly speak to peer effects (Manski, 1993). To proceed, 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 x_i, roommates' app usage y_{jt}, and roommates' characteristics x_j. Specifically, we focus on one pre-determined characteristic (pre-college app usage), while suppressing other characteristics that we account for in the analysis. Let N_i, of size $|N_i|$, denote the set of individual i's roommates. We have:

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

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 (1) can be written in matrix notations:

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

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

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

where the reduced-form coefficients $\mathbf{\Theta}_\gamma$ are functions of the behavioral spillover effect β, contextual peer effect δ, the roommate network $\mathbf{G}$, and individual effect γ.

Causal Estimate of Reduced-form Peer Effects The random assignment of roommates implies that the "peer network" $\mathbf{G}$ is orthogonal to residual ε, allowing us to consistently estimate Equation (2) via the following OLS:

$$
y_{it} = \theta_\alpha + \theta_{\gamma_1} x_i + \theta_{\gamma_2}\frac{1}{|N_i|}\sum_{j\in N_i} x_j + \mathbf{z}'_{it}\rho + \eta_{cg} + \eta_m + \eta_t + \varepsilon_{it}, \qquad (3)
$$

where x_i is pre-college app usage and vector $\mathbf{z}_{it}$ includes 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).

Table 2 displays the estimates. Standard errors are clustered at the class level to allow for potential temporal correlations. Column (1) shows the result for total app usage, Columns (2)-(6) present the estimates for each major app category separately. The estimated effects of own pre-college app usage are of very similar magnitudes and significant in all columns. The effects of roommates' pre-college app usage are similar and significant in all columns except for Column (6), which examines shopping app usage. Take Column (1) as an example. If student A's total app usage before college is twice that of student B, our estimate suggests that student A would use apps 19% more frequently than student B during college, ceteris paribus. The coefficient of roommates' pre-college mobile app usage is 0.035 (significant at the 1% level), which implies that being assigned to roommates' whose pre-college app usage is one s.d. higher increases a student's in-college app usage by 4.1%. Note that the reduced-form estimate of peer effect is 18.4% of the own effect, suggesting that peer effects are economically significant. These patterns can also be seen more vividly in Figure 1, which are residualized scatter plots of students' *in-college* usage against roommates' *pre-college* app usage, controlling for class-by-gender, dorm-size, and month-of-sample fixed effects.

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.

3.2 Separating behavioral spillover effects from contextual effects

Having established the existence of peer effects, we now disentangle behavioral spillover effects (contagion) and contextual peer effects by leveraging the panel data structure and the minors' game restriction policy implemented midway through the sample period (Section 2.1). This policy had a minimal direct impact on students in our sample (8% of students were under 18 when the policy started), but it indirectly affected students through their under-age pre-college friends (defined in Section 2.2.1). Specifically, we estimate the following equation via 2SLS:

$$y_{it} = \eta_i + \beta \frac{1}{|N_i|} \sum_{j \in N_i} y_{jt} + \epsilon_{it} \tag{4}$$

where η_i is a student fixed effect that absorbs both own and roommates' (time-invariant) characteristics, including pre-college usage. To address concerns about endogeneity and reverse causality associated with roommates' in-college app usage y_{jt}, we construct an instrument for y_{jt} by interacting the timing of the restriction policy with the evolving number of minors among roommates' pre-college friends. This instrument is uncorrelated with the residual by construction (as roommates are randomly assigned and their pre-college friends do not overlap with individual i's friends) but affects roommates' usage (as shown below in Section 5.1). This approach creates a shift-share instrument, where the indirect effects of the policy are likely stronger for roommates with more (pre-college) friends under 18.

Causal Estimates of behavioral spillover effects Panel A of Table 3 presents IV estimates of the behavioral spillover effect (contagion) of roommates' app usage. 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. To the extent that the strength of friends' influences may vary with the strength of friendship, our preferred specification – Columns (4) to (6) – employs 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.

Panel B of Table 3 reports the first stage results. Students with more under-age pre-college friends tend to spend more time playing games, but the effect is halved after the minors' game restriction policy.

Recovering Contextual Effect Recall that the reduced-form estimates (Θ_γ) in Equation (2) are functions of both behavioral spillover effects (β) and contextual peer effects (δ): $\mathbf{\Theta}_\gamma = (\mathbf{I} - \beta\mathbf{G})^{-1}(\gamma\mathbf{I} + \delta\mathbf{G})$. Using the estimates on behavioral spillover effects from Table 3, we can now recover contextual peer effects from estimates in Table 2. Table 4 reports the estimated contextual peer effects and behavior effects, with standard errors for the former derived via the Delta method.

Relative to behavioral spillover effects, contextual peer effects are much smaller and statistically insignificant. These findings suggest that in the context of mobile app usage, peer (observable and unobservable) characteristics do not appear to have a meaningful influence on individual behavior. Instead, it is the direct actions of peers — whether and how frequently they use the app — that drive peer influences. The limited role of contextual peer effects could be due to the situational and spontaneous nature of mobile app usage, where peer behaviors provide more immediate social cues than static peer attributes. Despite the extensive literature on peer effects, our analysis provides, to our knowledge, the first set of empirical estimates that distinguishes between behavioral spillover effects and contextual peer effects.

4 Effects on Academic and Labor Market Outcomes

4.1 App Usage and Academic Performance

We now examine the effects of both own and peers' app usage on academic outcomes. Peers' app usage may affect students' academic performance *indirectly* through the contagion effect. It may also *directly* affect one's performance: for example, roommates' game-playing could disrupt the study environment (a non-trivial fraction of students in our surveys reported being disturbed by roommates' gaming in the dorm, see Section 6.2), or it could reduce positive peer influences by crowding out time and effort spent in group studies.

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

$$\text{GPA}_{is} = \alpha_1 \text{Phone}_{is} + \alpha_2 \frac{1}{|N_i|} \sum_{j \in N_i} \text{Phone}_{js} + \alpha_3 \text{CEE}_i \times \eta_s + \eta_i + \eta_{cs} + \epsilon_{is} \tag{5}$$

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 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 Table B.3 reports the OLS estimates. 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.[18] The corresponding magnitudes by app categories range from 17.5% s.d. (shopping) to 36.3% s.d. (games). The association between peers' app usage and academic outcomes is economically significant, ranging from one-fifth to one-third the size of the individuals' own effect. These patterns can also be seen in the residualized plots in Figure 2. To conserve space, in the remaining analysis, we focus on all apps, games, and game+video apps because the instruments are more relevant to game usage, although results are similar for other app categories (except for a weaker result for shopping apps).

IV Estimates The estimates of α_1 and α_2 in Equation (5) 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, is the interaction between the timing of minors' game restriction policy and the (evolving) number of pre-college minor friends. However, as shown in the event study in Section 5.1, the policy's effect dissipates after approximately six months (due to the drop in the number of minor friends as students age).

As a second set of IVs, we leverage 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

[18] The effect of one s.d. increase in total app usage = [0.546 (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%.

are more affected by the release of Yuanshen compared to light pre-college gamers.[19] The assumption is that, conditional on student fixed effects, the inter-temporal variation in unobserved factors affecting GPAs (the residual in Equation (5)) is orthogonal to the introduction date of Yuanshen. Similarly, we use the interaction of Yuanshen with roommates' pre-college app usage to instrument for roommates' in-college usage.[20]

Columns (1)-(3) in Table 5 present the IV results on the effects of mobile app usage (total apps, gaming apps, and game + video apps) on GPAs in required courses. Students' own app usage has a strong negative impact on GPAs, with all coefficients statistically significant at the 1% level. Specifically, 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.[21] Additionally, a one s.d increase in roommates' app usage *directly* lowers the student's GPA by 0.408 points, or 20.6% s.d. Our analyses in Section 3.2 uncovers the behavioral spillover effects of roommates' app usage: a one s.d. roommates' app usage *increases* 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% 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 1.119-point reduction in GPAs, or 56.6% s.d. The direct effect of roommates'

[19] 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.

[20] The first stage uses the following specification:

$$\begin{aligned} y_{is} &= \lambda_1 \mathrm{YS}_s \times \mathrm{PrePhone}_i + \lambda_2 \mathrm{YS}_s \times \frac{1}{|N_i|}\sum_{j\in N_i} \mathrm{PrePhone}_j + \lambda_3 \mathrm{Policy}_s \times \mathrm{Minor}_{is} \\ &+ \lambda_4 \mathrm{Policy}_s \times \frac{1}{|N_i|}\sum_{j\in N_i} \mathrm{Minor}_{js} + \lambda_5 \mathrm{Minor}_{is} + \lambda_6 \frac{1}{|N_i|}\sum_{j\in N_i} \mathrm{Minor}_{js} \\ &+ \mathrm{CEE} \times \eta_s + \eta_i + \eta_{cs} + \epsilon_{is} \end{aligned} \tag{6}$$

where y_{is} is app usage in semester s and (with slight abuse of notation) CEE $\times\ \eta_s$ is CEE scores interacted with a linear semester trend.

[21] 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.

game usage is similar to that of total app usage. Relative to IV estimates, OLS estimates in Table B.3 are biased toward zero. This may arise from, for example, a bad health shock that lowers both GPA and app usage.

Columns (4)-(6) examine the effect of app usage on physical education, a required course in the university.[22] 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). However, we do not find direct effects of roommates' app usage on PE scores. On the one hand, this is quite reasonable: although roommates' game-playing creates noise and disrupts students' concentration on studying, such disturbances are less relevant for physical activities. On the other hand, it is plausible that roommates' app usage can directly affect PE scores if it crowds out peers' positive influence (e.g. via team sports). Our estimate suggests that the latter effect is weak.

4.2 App Usage and Labor Market Outcomes

Figure 3 indicates that wages upon graduation are negatively associated with both individuals' and roommates' mobile app usage. Now, we examine this relationship formally. Since labor market outcomes are measured only once for each student, we cannot use the panel data technique. Instead, we exploit the cross-cohort variation in the exposure to Yuanshen and the cross-sectional variation in the number of own and roommates' underage pre-college friends. Specifically, we estimate the following equation:

$$y_i = \gamma_1 \text{Phone}_i + \gamma_2 \frac{1}{|N_i|} \sum_{j \in N_i} \text{Phone}_j + X_i' \gamma_X + \eta_{cg} + \eta_m + \hat{\eta}_i + \varepsilon_i, \tag{7}$$

where y_i represents individual i's post-college labor market outcome, such as the (log) initial wage upon graduation.[23] Phone_i (Phone_j) is individual i's (roommates') average app usage

[22]We lose 3220 obs for this analysis due to missing data for the 2018 cohort in some departments.

[23]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.

during college, X_i is a vector of characteristics (age, rural residency, social science/science track in high school, CEE scores, housing prices, and hometown fixed effects), along with both own and roommates' pre-college app usage.[24] Variables η_{cg} and η_m denote class-gender and dorm-size fixed effects, respectively. Finally, to capture unobserved ability that is correlated with job placement outcomes, we control for the estimated student fixed effect $\hat{\eta}_i$ from the GPA Equation (5).

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.[25]

Table 6 presents results for wage outcomes. Columns (1)-(3) report the effects on (log) wages from all apps, games, and game+video apps; Columns (4)-(6) examine app effects on obtaining a top-quartile wage within a cohort-major; Columns (7)-(9) assess app effects on obtaining a bottom-quartile wage. According to Column (1), doubling 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.[26] This detrimental effect is also reflected in the increased probability of being in the bottom quartile of the 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 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

[24] We include hometown fixed effects in wage regressions to capture potential "birthplace" effects as some students return to their home counties to work.

[25] We use Equation (6) to predict mobile app usage for all apps, game apps, and game+video apps and then average across all semesters. Table B.4 reports OLS estimates, which are similar to IV estimates, suggesting that our rich set of controls is probably adequate at capturing potential confounding factors.

[26] 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%.

s.d.

Policy Implications: Game Time Restriction We perform a back-of-the-envelope calculation of what would happen if China's minors' game restriction policy that caps gaming time to 3 hours per week were imposed on college students. This policy cap would directly result in a one-third reduction in average monthly gaming time, from 12.1 hours to eight hours. Taking into consideration the behavioral spillover effects via Equation (2) at around 0.078 (Table 4), students' gaming time would further drop to 7.68 hours. We then multiply this magnitude by the sum of coefficients on students' and roommates' game usage in the wage regression (Table 6). Our calculation suggests that a cap of 3 hours per week would increase post-graduation wages by 0.9%, or 4.8% of the within-cohort-major s.d. The effect size is non-trivial — about half the wage premium associated with an additional year of work experience in developing countries (Lagakos et al., 2019).[27]

5 Robustness and Heterogeneity

5.1 Robustness Analysis

Validating IVs We use two sets of shift-share type of instruments: 1) the interaction of Yuanshen and pre-college app usage, and 2) the interaction of the minors' game restriction policy and the number of underage pre-college friends. We conduct two event studies in Figure B.4 to validate these IVs. Reassuringly, there is no pre-trend in either event study. After the release of Yuanshen, the increase in app usage depends significantly on one's pre-college app usage; moreover, such differential impacts persist and strengthen over time (Panel (a)). Upon the introduction of the minors' game restriction, students with more underage pre-college friends reduced app usage significantly more than those with fewer

[27] Lagakos et al. (2019) documents that a one-year experience premium — changes in wage as a result of one additional year of working experience — is 1.3%-2% for developing countries like Brazil, Chile, and Mexico.

underage friends; however, this effect became insignificant after 7 months as these second-degree friends aged out of the policy's targeted population (Panel (b)). These patterns suggest that these two shocks generate exogenous variations in students' app usage that are unlikely driven by other confounding factors (which are captured by time series fixed effects.)

Peer Effects Table B.5 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 own (roommates') pre-college usage weakens over time, which is perhaps not surprising. Table B.6 replicates the analysis on behavioral spillover effects (Table 3), but uses the predicted roommate usage derived from the first stage as a single instrumental variable. This leads to higher F-statistics, but the estimates are qualitatively and quantitatively similar to those in the baseline specifications, with all contagion effects being precisely estimated.

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 B.7: 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).[28]

Second, 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 B.8 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.

Third, another concern relates to the fact that GPA is largely based on students' perfor-

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

mance in final exams, and hence, the effect of app usage on GPAs could be driven mostly by time allocation during the exam month. We provide two sets of evidence that go against this "exam-month" hypothesis. First, Figure B.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. In addition, their game app usage peaks in the second month and declines moderately in the last two months of the semester. Overall, there is no evidence that app usage in the exam month differs substantially from other months. Second, we revisit the peer effect analysis and find no evidence that peer effects differ in the exam month from other months (Table B.9).

Lastly, we explore alternative instrument variables in Table B.10. Results are robust if we use only the Yuanshen shift-share IV, only the minors' game restriction interaction IV, or the optimal instruments incorporating machine learning techniques as proposed by Chen et al. (2023).

5.2 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 B.11 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 B.11, we find systematic and significant differences only by family wealth and by pre-college app usage when we examine heterogeneity in peer effects and the effects of app usage on outcomes across student groups. Table 7 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 (3)-(4)). 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 6) 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 6.2, heavy users exhibit higher degrees of openness and extraversion.[29]

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

6 Evidence on Underlying Mechanisms

We use two supplementary sources of information — high-frequency location data and field surveys — to shed light on the mechanisms underlying our findings.

6.1 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). Our GPS data allow us to precisely measure the former. We exploit the same quasi-random variations used in our GPA analyses to estimate the following equation:

$$\begin{aligned} y_{id} &= \lambda_1 \mathrm{YS}_d \times \mathrm{PrePhone}_i + \lambda_2 \mathrm{YS}_d \times \frac{1}{|N_i|} \sum_{j \in N_i} \mathrm{PrePhone}_j + \lambda_3 \mathrm{Policy}_d \times \mathrm{Minor}_{id} \\ &+ \lambda_4 \mathrm{Policy}_d \times \frac{1}{|N_i|} \sum_{j \in N_i} \mathrm{Minor}_{jd} + \lambda_5 \mathrm{Minor}_{id} + \lambda_6 \frac{1}{|N_i|} \sum_{j \in N_i} \mathrm{Minor}_{jd} \\ &+ \eta_i + \eta_{cs} + \eta_{t(d)} + \epsilon_{id}, \end{aligned} \tag{8}$$

where y_{id} represents student i's (extensive-margin) time allocation on a specific day d. The variables YS_d and Policy_d are dummy variables for the Yuanshen shock and the minors' game restriction shock, while Minor_{id} is the evolving number of i's underage pre-college friends. We include an extensive set of fixed effects: student fixed effects η_i (to account for persistent habits), class-semester fixed effects η_{cs} (to account for shocks that affect the entire class), and week-of-sample and day-of-week fixed effects $\eta_{t(d)}$ (to account for seasonality).

Table 8 displays the estimates. Following the release of Yuanshen, an average student arrives at the study hall 17.7 minutes later and returns to the dorm 24.5 minutes earlier than they did before the game's release.[30] After the implementation of the minors' game restriction policy, students with the average number of minor friends arrive at study halls

[30] The effect of Yuanshen = 0.065 (Column 1) × 4.53 (mean of own pre-college app use in log) × 60 minutes = 17.7 minutes.

16.1 minutes earlier and return to the dorm 18.8 minutes later. Similarly, Yuanshen leads to a higher probability of arriving at least 10 minutes late at major-required courses and a higher chance of being absent; the minors' game restriction has the opposite effects.

These findings are further confirmed in event studies. Figure 4 demonstrates that Yuanshen has a significant effect on every time allocation outcome immediately after its release, and its effect *intensifies* over time, reflecting the gradual penetration of the game on campus. Figure 5 shows that the effect of the minors' game restriction policy is pronounced in the months after its introduction but weakens afterward as the number of underage pre-college friends declines over time.

6.2 Survey Evidence

Our field surveys provide further suggestive evidence.[31] We present the main findings in Table 9. Panel A correlates app usage with personal traits. Students with higher degrees of openness and extraversion tend to allocate more time to mobile apps. Such correlations point to the literature's concern on how to interpret peer effects: is it peers' traits or actions that affect one's behavior? Our analysis in Section 3.2 contributes to this literature by disentangling behavioral spillover effects and contextual peer effects and demonstrates that behavioral spillover effects are the main driver of peer effects in this context.

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

[31]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.

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

7 Conclusion

Leveraging unique datasets of students' administrative records merged with detailed phone records, 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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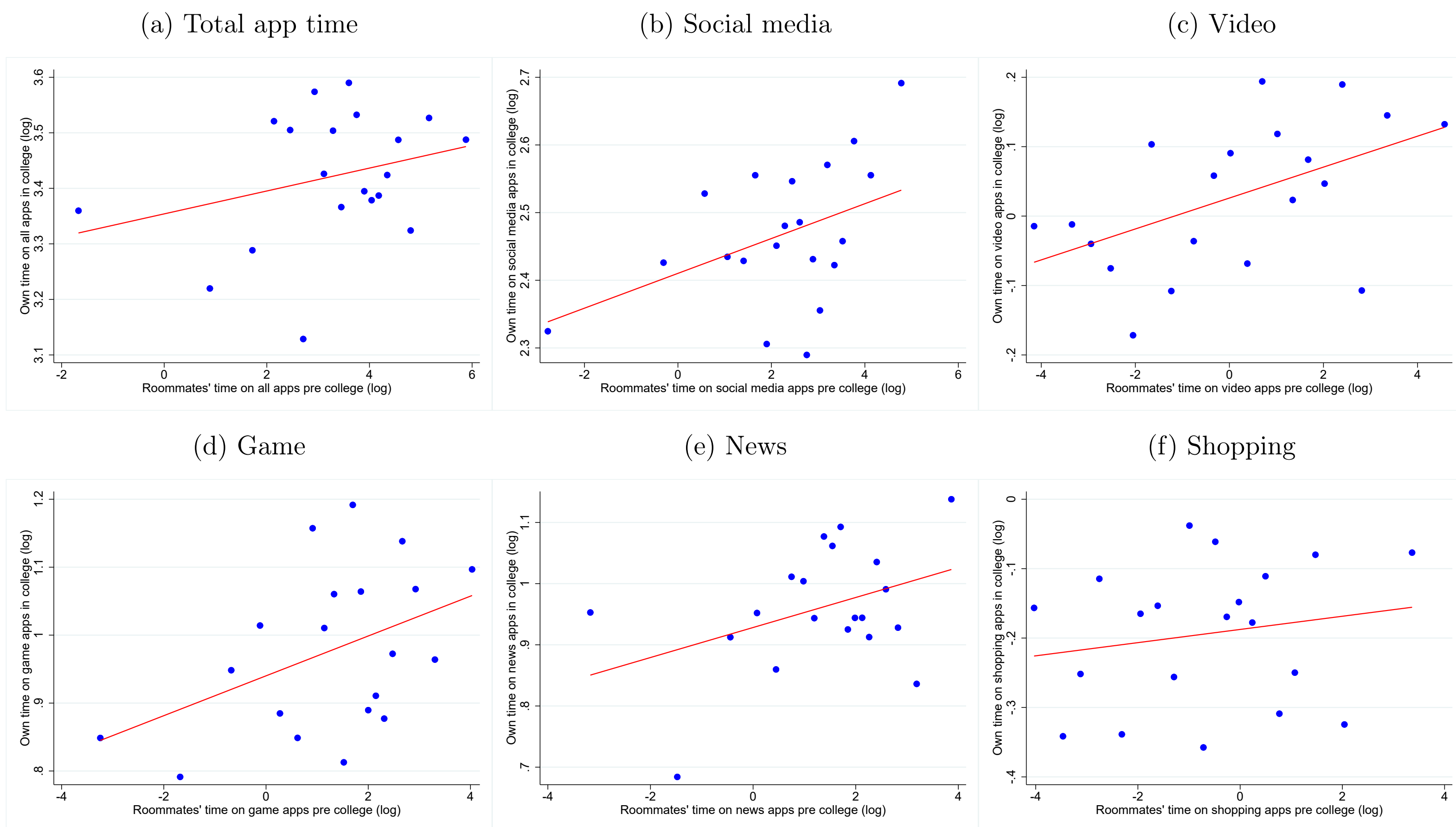
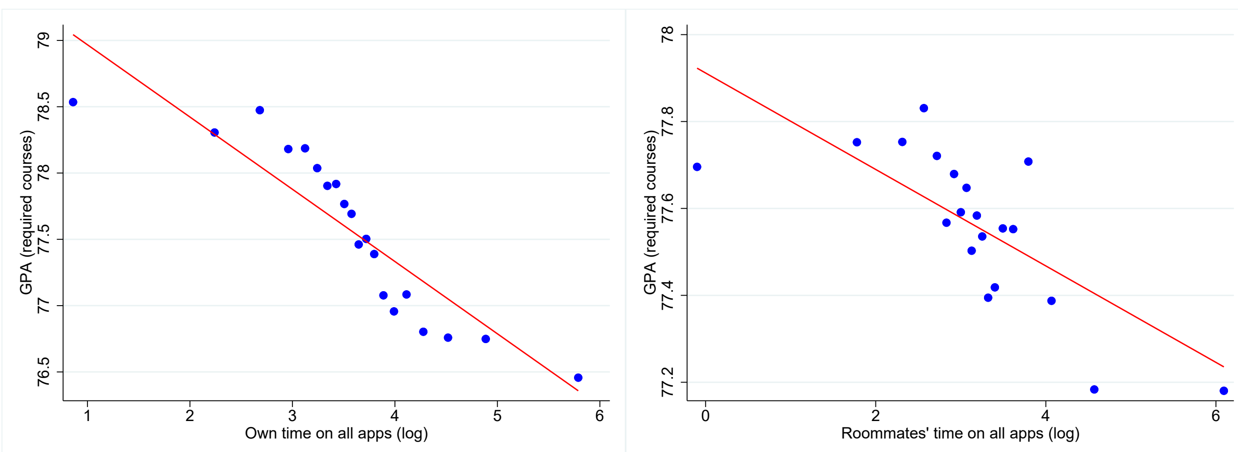
Figure 1: Reduced-form peer effect of mobile app usage



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 five major app categories. We control for month-of-sample, class-by-gender, and dorm-size fixed effects in every graph. "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 mobile app usage on GPA

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

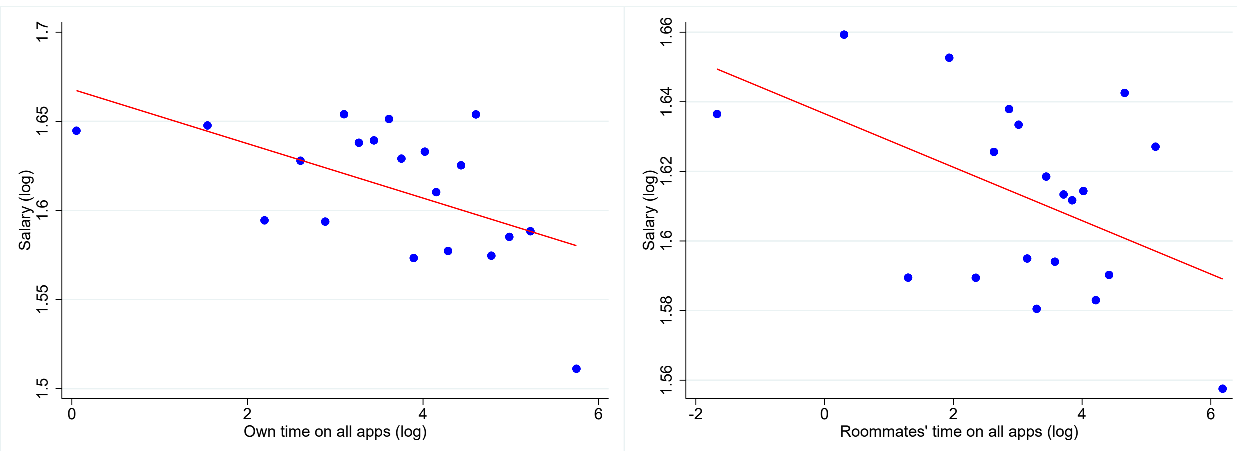


Notes: These graphs present the residualized relationship between GPA and own app usage (in logarithm) during college (Panel a) and that between GPA and average roommates' app time (in logarithm) during college (Panel b). We control for class-semester (with class a triplet of cohort, major, and administrative unit, consisting of 20-50 students) and student fixed effects in each graph. The solid line represents the linear fit estimated from the underlying microdata using OLS.

Figure 3: Effect of mobile app usage on wage

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

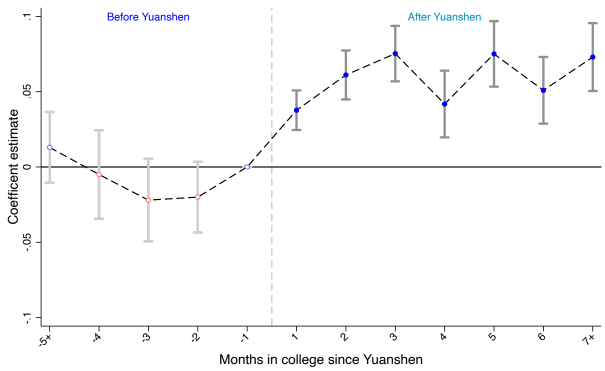
(b) GPA v.s. roommates' mobile app usage



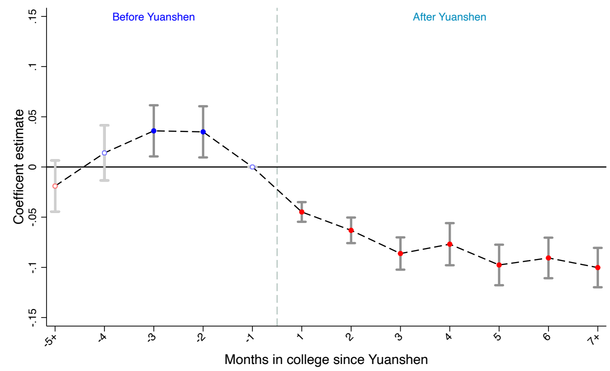
Notes: These graphs present the residualized relationship between wage upon graduation and own app usage (in logarithm) during college (Panel a) and that between wage and average roommates' app time (in logarithm) during college (Panel b). We control for class-by-gender, hometown, and dorm-size fixed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

Figure 4: Effect of Yuanshen on on-time performance

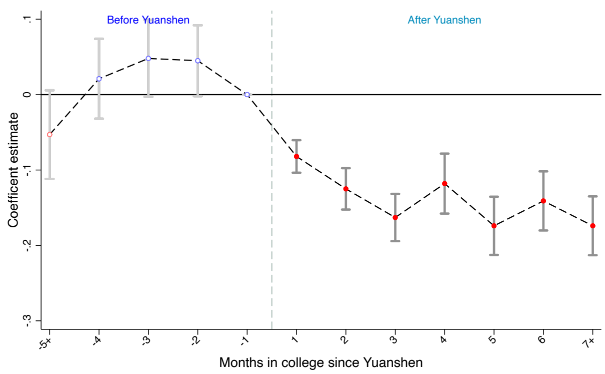
(a) Time of first arrival at study hall



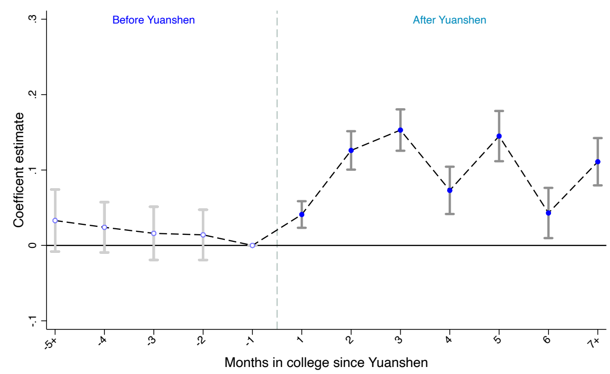
(b) Time of last return to dorm



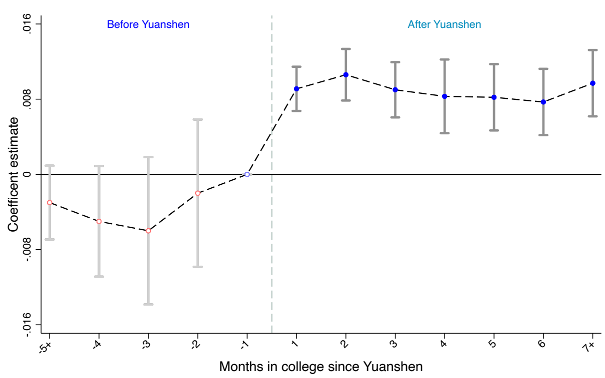
(c) Duration at study hall



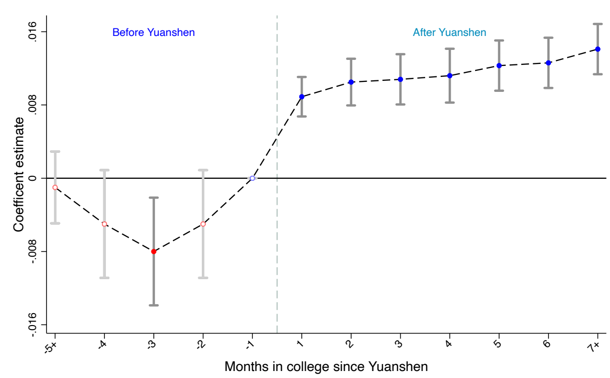
(d) Duration at dorm



(e) Lateness for classes



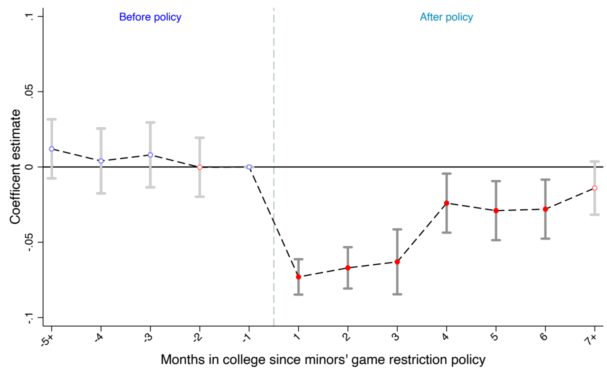
(f) Absence from classes



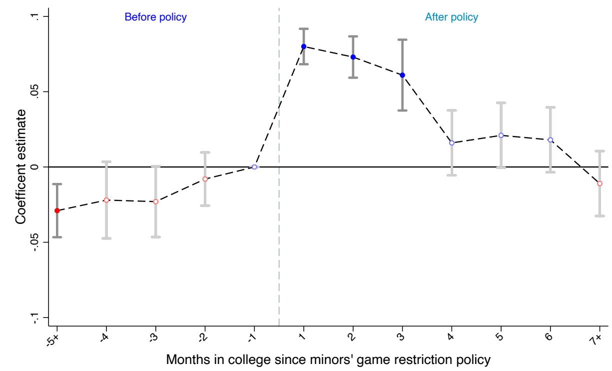
Notes: These graphs display the event study coefficients for the interaction between Yuanshen $\times$ own pre-college app usage (in logarithm), showing the impact of the Yuanshen shock on on-time performance metrics. The dependent variables in Panels (a)-(f) are: time of first arrival at the study hall (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, and the solid grey lines represent the 95% confidence intervals.

Figure 5: Effect of minors' game restriction policy on on-time performance

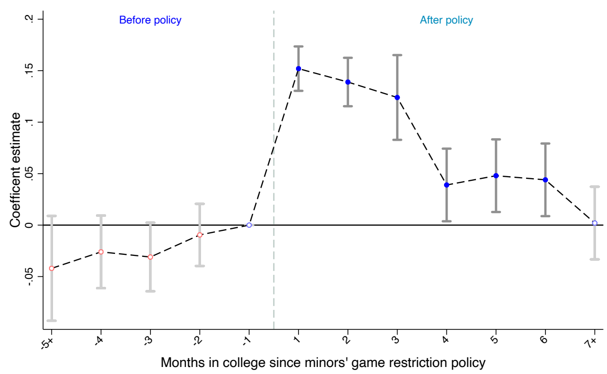
(a) Time of first arrival at study hall



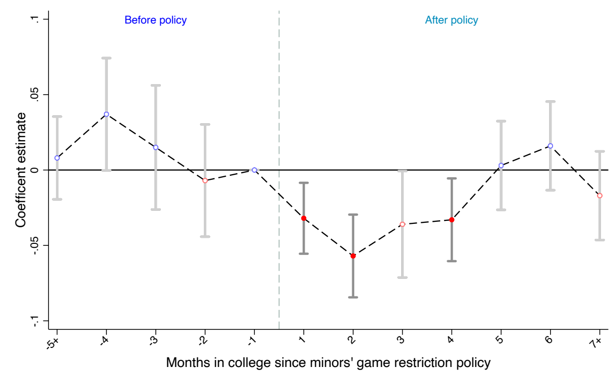
(b) Time of last return to dorm



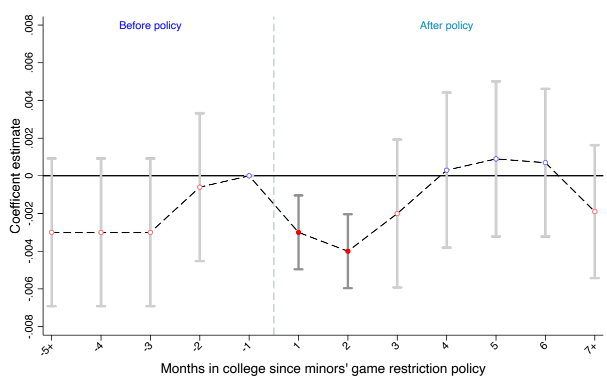
(c) Duration at study hall



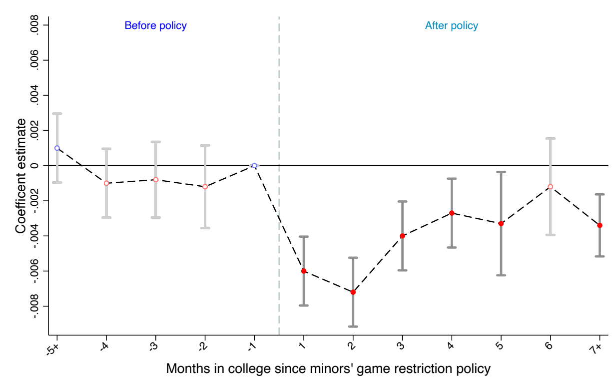
(d) Duration at dorm



(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, and the solid grey lines represent the 95% confidence intervals.

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
News	104,307	9.9	13.5
Shopping	104,307	9.3	26.3
Others	104,307	5.8	9.0
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 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 jobs 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	(5) News	(6) Shopping
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)		
Own *pre* news					0.186***	
					(0.014)	
Roommates' *pre* news					0.030**	
					(0.012)	
Own *pre* shopping						0.167***
						(0.009)
Roommates' *pre* shopping						0.006
						(0.009)
Age	0.024	0.033	0.000	-0.005	-0.004	0.033
	(0.025)	(0.024)	(0.033)	(0.029)	(0.029)	(0.022)
Rural residency	-0.079	-0.075	-0.000	-0.074	-0.105*	-0.116***
	(0.057)	(0.057)	(0.063)	(0.066)	(0.059)	(0.042)
Social science track	0.064	0.090	-0.035	-0.009	0.030	0.282***
	(0.110)	(0.102)	(0.123)	(0.114)	(0.114)	(0.077)
CEE scores	-0.001	-0.001	0.001	0.000	0.000	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Housing prices	0.050***	0.038***	0.036***	0.027***	0.027***	0.103***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Roommates' age	-0.032**	-0.035**	-0.017	-0.026*	-0.025*	-0.050***
	(0.015)	(0.014)	(0.019)	(0.015)	(0.015)	(0.015)
Roommates' rural residency	-0.014	0.005	-0.045	0.011	0.018	0.005
	(0.059)	(0.056)	(0.057)	(0.063)	(0.052)	(0.044)
Roommates' social science track	-0.051	-0.057	-0.054	-0.035	-0.052	-0.083*
	(0.054)	(0.052)	(0.061)	(0.056)	(0.052)	(0.047)
Roommates' CEE scores	0.001**	0.001***	0.001	0.001*	0.001*	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Roommates' housing prices	-0.002	-0.001	-0.004**	-0.006***	-0.004*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	104,307	104,307	104,307	104,307	104,307	104,307
R-squared	0.12	0.11	0.14	0.11	0.11	0.32
Month-of-sample 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 reports the causal estimates of reduced-form peer effects via Equation (3). Each observation is a student-year-month. The dependent variable in Columns (1)-(8) is own app usage in college (in logarithm), and the explanatory variables are students' and average roommates' pre-college app usage (in logarithm). 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 spillover effects (*Contagion*) 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 spillover (contagion) effect, where we regress students' monthly app usage in college (in logarithm) on their roommates' app usage in college (in logarithm) via Equation (4). 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: Contagion effect vs. contextual 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 reports both behavioral spillover effects (contagion) and contextual effects. Column (1) reproduces the contagion effect estimates in columns (4)-(6) in Table 3. Column (2) reports contextual effects recovered from Equation (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 spillover effects, with peer characteristics (contextual effect) playing a minor role. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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

IV model	(1)	(2)	(3)	(4)	(5)	(6)
	GPA (required courses)			PE scores		
Variables: log(hours)						
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 IV estimates of how mobile app usage (in logarithm) affects GPA for required courses and physical health (measured by grades in physical education, a required course). Each observation is a student-semester cell, excluding the spring of 2020 for all cohorts. Yuanshen was released in September 2020. The minors' game restriction policy was initiated in November 2019. Each of the two endogenous regressors (own app usage and roommates' app usage) has two IVs: the interaction between Yuanshen and pre-college app usage and the interaction between the minors' restriction policy and the number of (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: IV estimates of the effect of mobile app usage on wages

Variable	(1)	(2) Wage (in log)	(3)	(4)	(5) Top 25% Wage (=1)	(6)	(7)	(8) Bottom 25% Wage (=1)	(9)
Variables: log(hours)									
Own total app time	-0.020***			-0.005			0.038***		
	(0.006)			(0.006)			(0.006)		
Roommates' total app time	-0.008*			-0.008*			0.006		
	(0.005)			(0.005)			(0.006)		
Own game		-0.015***			-0.005			0.031***	
		(0.003)			(0.004)			(0.004)	
Roommates' game		-0.010*			-0.009			0.010	
		(0.005)			(0.006)			(0.007)	
Own game + video			-0.015***			-0.010**			0.027***
			(0.004)			(0.004)			(0.004)
Roommates' game + video			-0.009*			-0.007			0.008
			(0.005)			(0.005)			(0.007)
Ability proxy	0.006**	0.006**	0.006**	0.005*	0.005*	0.005*	-0.007**	-0.007**	-0.007**
	(0.002)	(0.002)	(0.002)	(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	317.3	4,625.3	1,904.0
Observations	2,812	2,812	2,812	2,812	2,812	2,812	2,812	2,812	2,812
R-squared	0.23	0.23	0.23	0.21	0.21	0.21	0.20	0.21	0.21
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hometown FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 shows the effect of in-college app usage (in logarithm) on wages via Equation (7). Each observation denotes a student. The sample contains the 2018 and 2019 cohorts who graduated in June 2022 and June 2023. The dependent variables in Columns (1)-(9) are wages upon graduation (in logarithm), an indicator for wages in the top quartile, and an indicator for wages in the bottom quartile. We employ the predicted mobile app use in college as instruments via Equation (6). All regressions control for own and average roommate's pre-college app usage and characteristics (including age, rural residency, social science track in high school, CEE scores, and housing prices) and hometown, class-by-gender, and dorm-size fixed effects. Ability proxy refers to estimated student fixed effects $\hat{\eta}_i$ in Equation (5). 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: Heterogeneous effects

	(1)	(2)	(3)	(4)
	Family wealth		Pre-college game app usage	
Sample	Above median	Below median	Above median	Below median
Variables: log(hours)		**Panel A: Own game time (in log)**		
Roommates' game time	0.114**	0.048	0.113**	0.030
	(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***	-0.711***	-0.538***
	(0.039)	(0.050)	(0.040)	(0.046)
Roommates' game time	-0.333***	-0.139	-0.184**	-0.280***
	(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***	-0.016**	-0.011*
	(0.007)	(0.005)	(0.006)	(0.006)
Roommates' game time	-0.006	-0.008	-0.008	-0.011
	(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 presents heterogeneity for peer effects, effect of app usage on major-required GPA, and effect of app usage on wages in Panels A, B, and C, respectively. Columns (1)-(2) split the sample by the median value of housing prices. Columns (3)-(4) split the sample by the median value of pre-college game app usage. 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, 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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: 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)	0.065***	-0.090***	-0.155***	0.081***	0.010***	0.013***
	(0.008)	(0.007)	(0.014)	(0.011)	(0.002)	(0.002)
Yuanshen * Roommates' *pre* college all app usage (in log)	0.017**	-0.010	-0.027*	0.025	0.001	0.003*
	(0.007)	(0.009)	(0.015)	(0.017)	(0.002)	(0.002)
Minors' game policy * own friends under 18	-0.064***	0.075***	0.138***	-0.051***	-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**	-0.001	0.010	-0.005	-0.001	-0.004***
	(0.004)	(0.004)	(0.007)	(0.008)	(0.001)	(0.001)
Own friends under 18	-0.023**	0.023**	0.047**	0.002	-0.009***	-0.011***
	(0.009)	(0.011)	(0.019)	(0.015)	(0.003)	(0.003)
Roommates' friends under 18	0.012**	-0.007	-0.019*	-0.013	-0.001	-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

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 AM or 10:34 AM). 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 initiated in November 2019. All regressions control for student, class-by-semester, week-of-sample, day-of-week fixed effects, and the interaction between 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 9: 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*
Extraversion	0.082*	0.106**	0.106**
Conscientiousness	0.040	0.055	0.055
Agreeableness	0.044	0.059	0.059
Neuroticism	-0.011	-0.019	-0.025
Panel B: Physical and mental health			
Physical health level	-0.197**	-0.221**	-0.217**
Mental health level	-0.030	-0.003	-0.002
Pressure level	0.162**	0.172**	0.165**
Panel C: Certification status and job search efforts			
Having obtained no professional certificate (=1)	0.077	0.089*	0.120**
No. of job applications submitted	-0.207**	-0.180**	-0.195**
No. of interviews	0.064	0.014	0.041
No. of offers	0.078	0.085	0.082
Offer satisfaction level	-0.125*	-0.125*	-0.145*
Panel D: Views on games and relationships with roommates (=1)			
Playing games is addictive	0.080**	0.116**	0.110**
Playing games adversely affects academic performance	0.008	0.028	0.015
Interested in playing games with roommates	0.038	0.045	0.036
Accept roommates' invitations	0.017	0.038	0.042
Playing games is disturbing in dorms	-0.025	-0.010	-0.002
Good relationships with roommates	0.054*	0.058*	0.043
Following roommates' job suggestions	0.055	0.068**	0.070**
Following roommates' post-graduate study suggestions	-0.036	0.061*	0.051

Notes: This table describes the pairwise correlations between mobile app usage and survey responses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendices. For Online Publication Only

A Data Construction

To construct an estimate of students' parental wealth, we use the housing price of the residential property they stayed at 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).

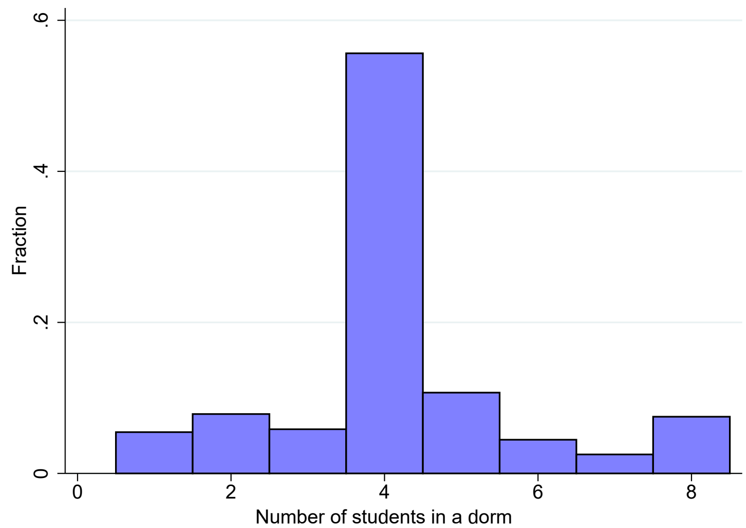
We employ the same measurement scales as those utilized in the China Family Panel Studies (CFPS) to assess human personality traits. CFPS is a nationally representative survey in China conducted by the China Social Survey Center of Peking University. This scale, rooted in the widely accepted framework 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 B), while retaining the original 1-5 scoring system to evaluate the personality scale in our survey.[32] By taking the average of scores for all questions by dimension, we derive the score for each Big-5 dimension.

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. By matching the two sets of information, we created two indicators: whether a student was more than 10 minutes late to a class and whether a student was absent from the class.

B Figures and Tables

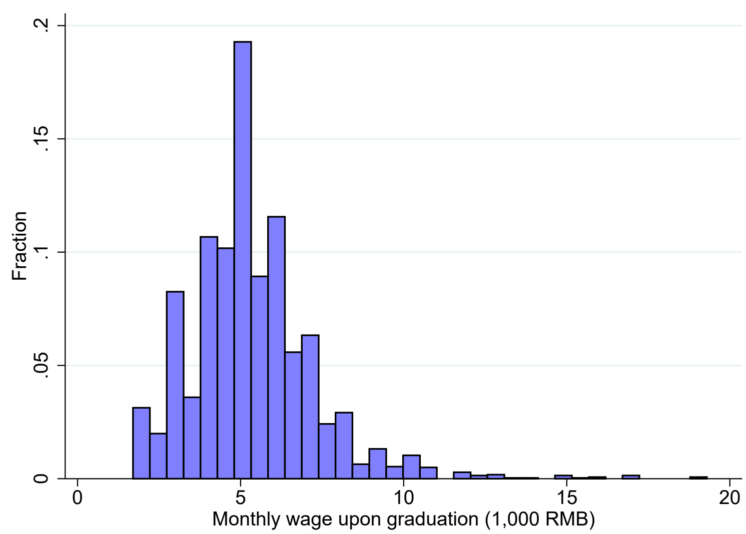
[32] According to Wu and Gu (2020), the inclusion of both positively and negatively worded items may diminish the internal consistency of the scale.

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



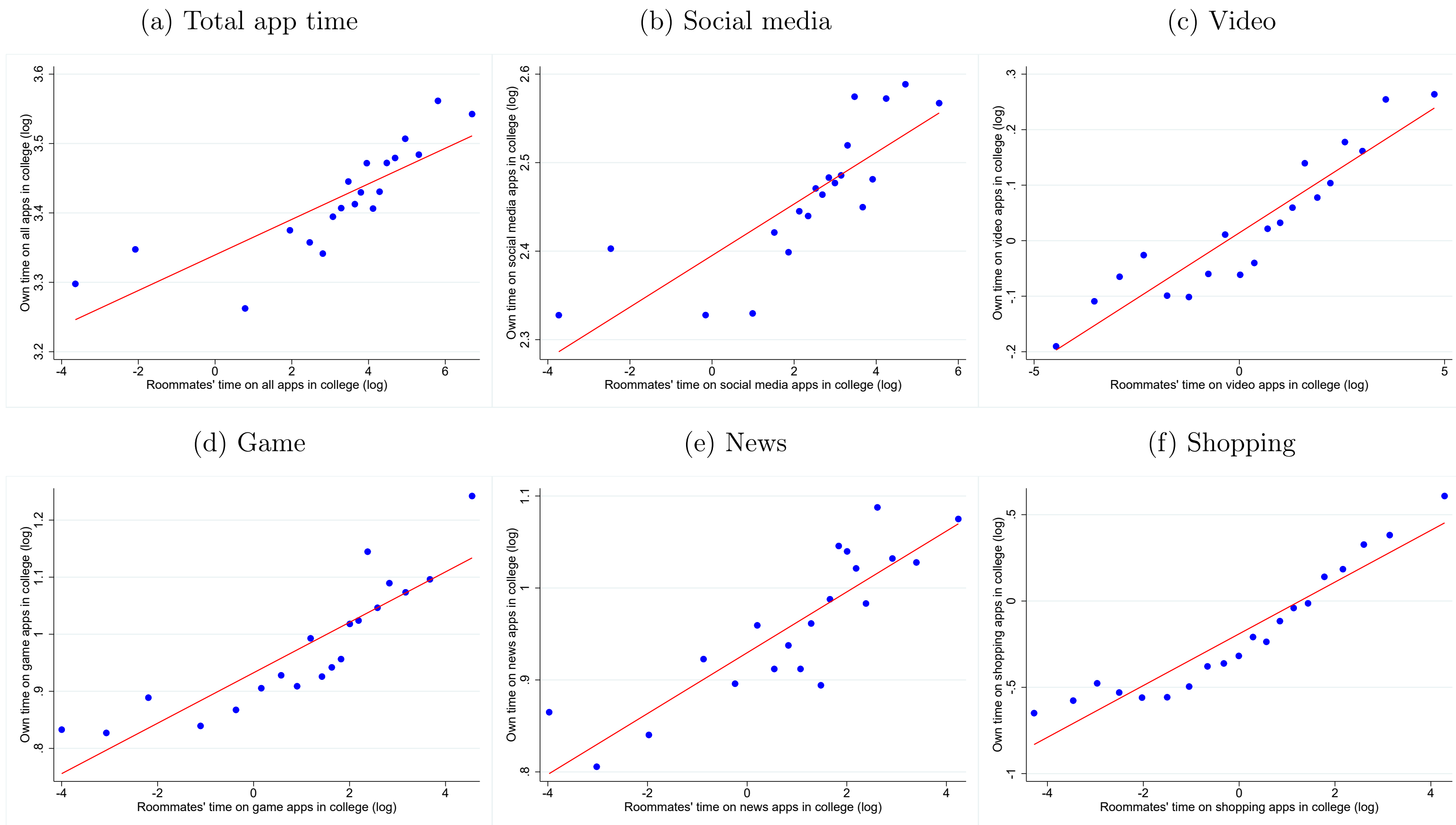
Notes: This graph shows the distribution of the number of students in a dorm.

Figure B.2: Distribution of wages upon graduation



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

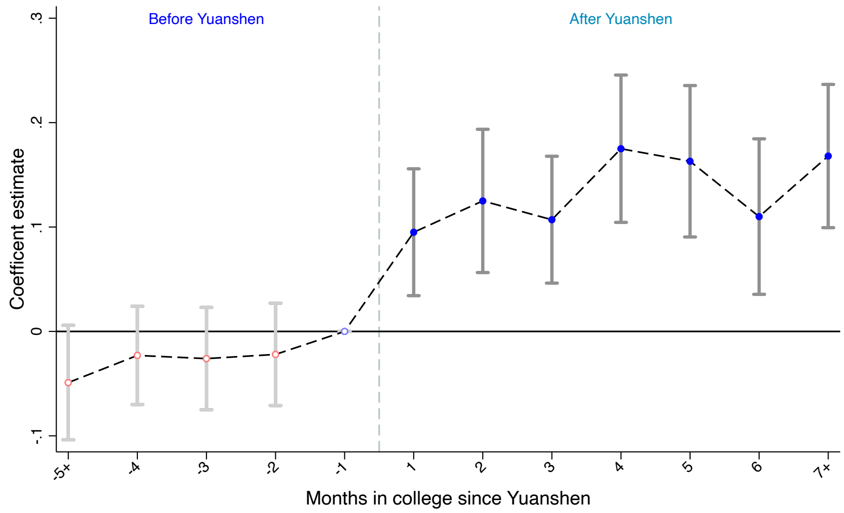
Figure B.3: Contemporaneous correlation in mobile app usage



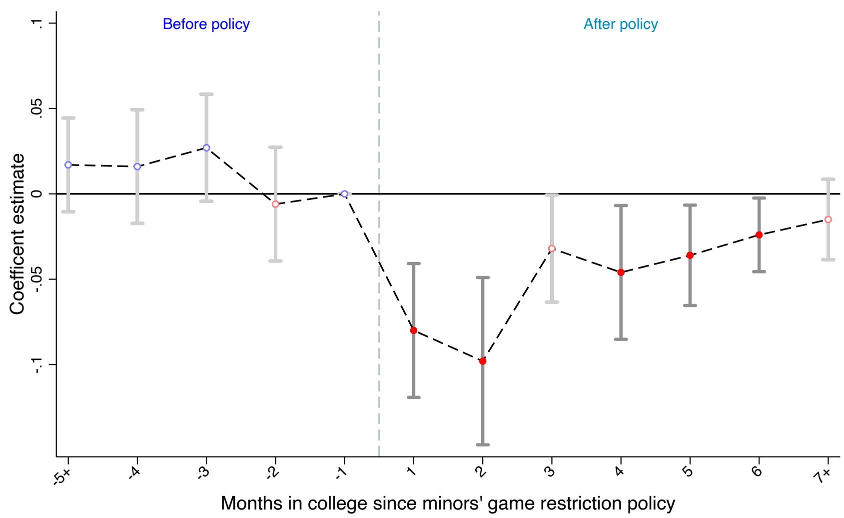
Notes: These graphs present the residualized relationship between own and average roommate's monthly mobile app time (in logarithm) at college. Take Panel (A) as an example. To construct the binned scatter plot, we first residualize individuals' and their roommates' mobile time at college, partialing out month-of-sample and individual fixed effects. We then divide x-variable residuals into twenty equal-sized groups and plot the means of the y-variable residuals within each bin against the mean value of x-variable residuals within each bin. Finally, we add the unconditional mean of the y variable in the estimation sample to facilitate the interpretation of the scale. The solid line shows the linear fit estimated on the underlying microdata using OLS.

Figure B.4: Effect of Yuanshen and minors' game restriction policy on game app time

(a) Effect of Yuanshen on game app time



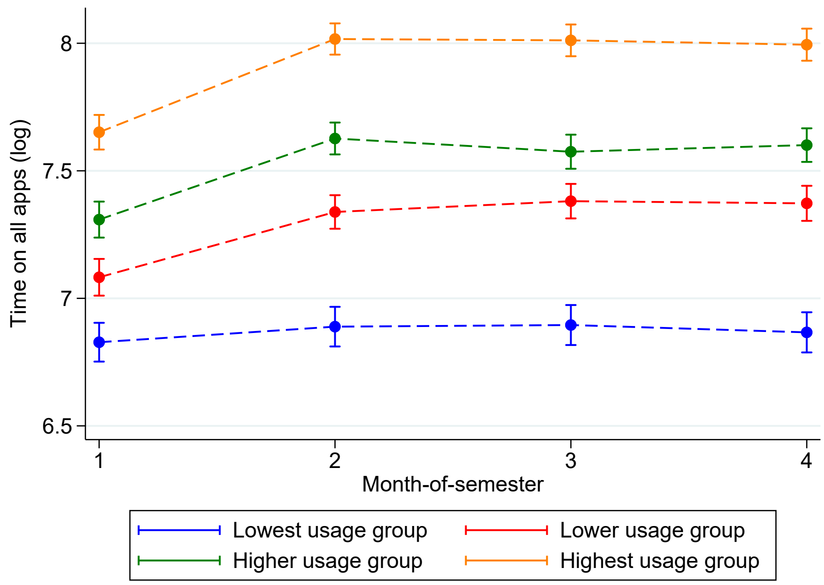
(b) Effect of minors' game restriction policy on game app time



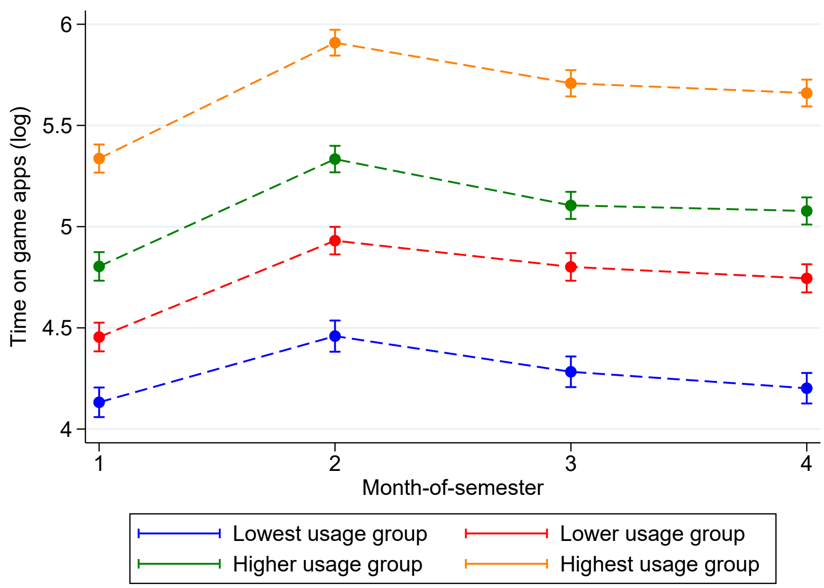
Notes: These graphs present the event study coefficients for the interaction between Yuanshen × pre-college game app usage (Panel A) and coefficients for the interaction between minors' game restriction policy × the number of underage pre-college friends (Panel B), showing the impact of the two shocks on game app time. The regression follows Equation (8), except that the dependent variable is game app usage. The coefficient for one month prior to each shock is normalized to zero. The dots are point estimates, and the solid grey lines represent the 95% confidence intervals.

Figure B.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.

Table B.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) *Pre* news	(6) *Pre* shopping	(7) Age	(8) Rural Residency	(9) Social science track	(10) CEE scores	(11) Housin price
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)							
Pre news					-0.014						
					(0.026)						
Pre shopping						-0.030					
						(0.021)					
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	6,340	6,340
R-squared	0.05	0.05	0.04	0.06	0.06	0.03	0.22	0.31	0.59	0.80	0.14
Class-gender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dorm-size FE	Yes	Yes	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)-(11) 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 B.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	0	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. Refer to Appendix C 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 B.3: Effect of mobile app usage on academic performance (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GPA (required courses)						
Variables: log(hours)							
Own total app time	-0.546***						
	(0.036)						
Roommates' total app time	-0.112***						
	(0.024)						
Own social media		-0.577***					
		(0.040)					
Roommates' social media		-0.131***					
		(0.026)					
Own video			-0.329***				
			(0.018)				
Roommates' video			-0.117***				
			(0.027)				
Own game				-0.616***			
				(0.030)			
Roommates' game				-0.166***			
				(0.028)			
Own news					-0.540***		
					(0.034)		
Roommates' news					-0.143***		
					(0.027)		
Own shopping						-0.296***	
						(0.034)	
Roommates' shopping						-0.097***	
						(0.032)	
Own game + video							-0.533***
							(0.028)
Roommates' game + video							-0.139***
							(0.024)
Observations	15,508	15,508	15,508	15,508	15,508	15,508	15,508
R-squared	0.80	0.80	0.80	0.81	0.80	0.80	0.81
Student FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class-semester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEE scores×semester linear trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the effect of mobile app usage (in logarithm) on student academic performance. Each observation denotes a student-semester cell. All regressions control for student and class-by-semester fixed effects and the interaction between own CEE scores and 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 under the coefficient estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.4: Effect of mobile app usage on wages (OLS model)

Variable	(1)	(2) Wage (in log)	(3)	(4)	(5) Top 25% Wage (=1)	(6)	(7)	(8) Bottom 25% Wage (=1)	(9)
Variables: log(hours)									
Own total app time	-0.015***			-0.010**			0.026***		
	(0.005)			(0.005)			(0.005)		
Roommates' total app time	-0.008*			-0.007			0.006		
	(0.004)			(0.004)			(0.006)		
Own game		-0.015***			-0.007*			0.029***	
		(0.003)			(0.004)			(0.004)	
Roommates' game		-0.008			-0.006			0.009	
		(0.005)			(0.005)			(0.007)	
Own game + video			-0.014***			-0.009**			0.026***
			(0.003)			(0.004)			(0.004)
Roommates' game + video			-0.008*			-0.005			0.007
			(0.004)			(0.005)			(0.006)
Ability proxy	0.006**	0.006**	0.006**	0.005*	0.005*	0.005*	-0.007**	-0.007**	-0.007**
	(0.002)	(0.002)	(0.002)	(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	2,812	2,812	2,812
R-squared	0.23	0.23	0.23	0.21	0.21	0.21	0.20	0.21	0.21
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hometown FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 shows the effect of in-college app usage (in logarithm) on wages using OLS regressions. Each observation denotes a student cell. The sample consists of students in cohorts 2018 and 2019. The dependent variables in Columns (1)-(9) are wages upon graduation (in log), an indicator for the top quartile wage distribution, and an indicator for the bottom quartile wage distribution. All regressions control for own and average roommate's pre-college app usage and characteristics (including age, rural residency, social science track in high school, CEE scores, and housing prices) and hometown, class-by-gender, and dorm-size fixed effects. Ability proxy refers to $\hat{\eta}_i$ estimated from Equation (5). 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 B.5: Dynamic reduced-form peer effects in mobile app usage

Variables: log(hours)	(1) Total app time	(2) Social media	(3) Video	(4) Game	(5) News	(6) Shopping
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)		
Own *pre* news (FY)					0.222*** (0.015)	
Roommates' *pre* news (FY)					0.025* (0.013)	
Own *pre* news (SY)					0.147*** (0.024)	
Roommates' *pre* news (SY)					0.039** (0.019)	
Own *pre* news (TY)					0.150*** (0.017)	
Roommates' *pre* news (TY)					0.028 (0.023)	
Own *pre* shopping (FY)						0.193*** (0.013)
Roommates' *pre* shopping (FY)						0.001 (0.010)
Own *pre* shopping (SY)						0.147*** (0.014)
Roommates' *pre* shopping (SY)						0.009 (0.010)
Own *pre* shopping (TY)						0.111*** (0.018)
Roommates' *pre* shopping (TY)						-0.003 (0.025)

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 B.6: Alternative IV estimates of behavioral spillover effects in mobile app usage

Variables: log(hours)	(1) Total app time	(2) Game	(3) Game + Video	(4) Total app time	(5) Game	(6) Game + Video
Average roommate:						
Total app time	0.025***			0.025***		
	(0.008)			(0.007)		
Game		0.039***			0.039***	
		(0.007)			(0.007)	
Game + Video			0.033***			0.033***
			(0.008)			(0.008)
Kleibergen-Paap rk Wald F stat.	2.0×10^4	4.2×10^4	3.7×10^4	3.1×10^4	6.3×10^4	5.6×10^4
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

Notes: This table replicates Panel A in Table 3, except using the predicted value derived from Panel B in Table 3 as a single IV. 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 B.7: 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 B.8: 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 B.9: Does *contagion* effect vary by month within a semester?

Variables: log(hours)	(1) Total app time	(2) Game	(3) Game + Video	(4) Total app time	(5) Game	(6) Game + Video
Average roommate:						
Total app time	0.039			0.052*		
	(0.028)			(0.030)		
Total app time × Final month	-0.007			-0.008		
	(0.027)			(0.030)		
Game		0.078**			0.086**	
		(0.031)			(0.035)	
Game × Final month		-0.037			-0.043	
		(0.032)			(0.034)	
Game + Video			0.054*			0.059
			(0.031)			(0.036)
Game + Video × Final month			-0.017			-0.018
			(0.035)			(0.039)
Kleibergen-Paap rk Wald F stat.	11.6	13.5	12.7	10.4	13.0	11.8
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

Notes: This table replicates Panel A in Table 3, except that it adds the interaction between average roommates' app usage and the final month of a semester, as well as the interaction between individuals' app usage and the final month of a semester. 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 B.10: Alternative IV estimates of the effect of app usage on GPAs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IV model				GPA (required courses)					
		Yuanshen IV			Game restriction policy IV			Random-forest-predicted IV	
Variables: log(hours)									
Own total app time	-0.595**			-0.856***			-0.859***		
	(0.247)			(0.305)			(0.175)		
Roommates' total app time	-0.523*			-0.307*			-0.100**		
	(0.310)			(0.168)			(0.039)		
Own game		-0.836***			-0.884***			-1.289***	
		(0.276)			(0.305)			(0.185)	
Roommates' game		-0.307*			-0.324*			-0.150***	
		(0.170)			(0.195)			(0.055)	
Own game + video			-0.654***			-0.912***			-0.971***
			(0.227)			(0.267)			(0.159)
Roommates' game + video			-0.435*			-0.313***			-0.143***
			(0.226)			(0.181)			(0.051)
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	15,508	15,508	15,508
R-squared	0.80	0.81	0.80	0.80	0.81	0.80	0.80	0.81	0.81
Student 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

Notes: This table replicates Table 5, except that it considers alternative IVs. We use Yuanshen shock shift-share IVs in Columns (1)-(3), minors' game restriction policy shift-share IVs in Columns (4)-(6), and random-forest predicted IVs in Columns (7)-(9). 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 B.11: 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
News	12.0	7.3	11.8	8.0	10.4	8.4
Shopping	16.3	5.8	9.6	8.7	8.7	10.9
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
News	9.7	10.0	9.8	10.0	9.3	10.4
Shopping	12.8	7.2	9.2	10.2	9.8	8.9
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). The classification of mobile apps is the same as those provided by the Android and Apple app stores. Family wealth is measured by the average listed housing prices of 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.

C Survey Questions

The online survey, conducted in Chinese, was distributed via a WeChat application in June 2022 (wave 1, focusing on the 2018 cohort) and March 2023 (wave 2, targeting the 2019-2020 cohorts). Due to different university staff reviewing 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.[33]

Questionnaires for the Field Surveys *We need your feedback to help improve your campus life and career development! We would appreciate it if you would take a few minutes to tell us how you feel and give suggestions for improvements. Your ideas mean a lot to us, so please join us. Please note that the content filled in will be kept strictly confidential. There is no right or wrong answer for each question; please fill it out according to your actual situation. Let's get started!*

[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
- 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

[33]It is worth mentioning that the order of the survey questions aligns with the flow of related topics in the main text, rather than their actual sequence in the survey.

- 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]