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Abstract

This paper examines gender disparities in parenting in the digital domain, using a novel dataset that records the gender composition of users across more than 6,000 app-level observations in China. Two patterns stand out. First, parenting apps are strongly feminized: women account for nearly two-thirds of users, compared to fewer than half for the typical non-parenting app. Second, the female share is *highest* in cities where women enjoy greater income and educational attainment, and *lowest* in areas marked by more entrenched gender inequality. The women most engaged in digital caregiving are therefore those best positioned to transcend traditional roles. Mechanism analysis suggests that this is not driven by broader digital fluency among affluent women, but rather reflects their intentional choice for intensive parenting practices.

Keywords: Gender Inequality, Digital Technology, Parenting, Unpaid labor, China
JEL codes : J13, J16, O33

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1 Introduction

A defining feature of modern parenthood is the growing reliance on digital tools. From tracking feeding schedules to sourcing educational content, mobile apps have become central to how fathers and mothers access information and coordinate caregiving. This digitization offers a new empirical window into the gendered division of parental labor. A broad literature documents a persistent "child penalty" in earnings, employment, and hours worked (see Cortés and Pan, 2023); recent Chinese evidence, for instance, finds that mothers still earn roughly one-fifth less than comparable fathers several years after childbirth (Zhang, Wang and Hou, 2024). Much less is known, however, about the behavioral mechanisms underlying these costs. Proposed explanations include biological constraints and comparative advantage in early childcare (Bertrand, Kamenica and Pan, 2015; Kleven, Landais and Søgaard, 2021; Andresen and Nix, 2022). Others emphasize gendered preferences, noting that women are more likely to prioritize family-oriented life plans and self-select into family-friendly occupations (Bursztyn, Fujiwara and Pallais, 2017; Wiswall and Zafar, 2018; Mas and Pallais, 2017; Adda, Dustmann and Stevens, 2017; Wasserman, 2023). Yet these explanations primarily infer parenting behavior from labor market outcomes, offering little direct evidence on how much time and cognitive effort mothers actually invest in childrearing—or how that investment compares to that of fathers.

A major obstacle to answering these questions is measurement. While time-diary surveys, such as the well-maintained American Time Use Survey, are commonly used in high-income settings, they remain scarce in many other countries and are often subject to recall bias. Surveys of this nature may also be influenced by social desirability bias, wherein parents might inaccurately report their caregiving roles to conform to societal norms (Bursztyn et al., 2025). An alternative is to use app usage trace data to capture the intensity and heterogeneity of parental engagement. While not a direct measure of time, digital engagement offers a behaviorally grounded proxy for parental involvement. Activities captured through passive data from parenting app usage reflect intentional and meaningful interaction with childrearing. These digital traces provide a unique empirical lens on the distribution of caregiving effort. Borrowing Hochschild and Machung (1989) term, we call this online caregiving the *digital second shift*, in which unpaid labor that now leaves measurable app traces.

Relatedly, a growing literature has documented a pronounced socioeconomic gradient in maternal investment: mothers with higher levels of education and income tend to devote more time, money, and cognitive effort to their children's development (Ramey and Ramey, 2010; Lareau, 2018; Doepke, Sorrenti and Zilibotti, 2019; Kalil et al., 2025). This pattern is frequently interpreted through the lens of "intensive parenting" or "concerted cultivation," whereby childrearing is seen as a deliberate strategy for transmitting class advantage. A competing hypothesis suggests that women's disproportionate time in childrearing may instead reflect labor market constraints—particularly in settings where women possess a lower comparative advantage in earnings and are thus more likely to be relegated to unpaid caregiving roles (Cortés and Pan, 2023; Kleven, Landais and Søgaard, 2019). The observational and survey-based evidence underlying both views remains limited in scope and scale. Leveraging large-scale digital trace data, we aim to test these competing accounts directly, assessing whether disparities in parenting app usage are better explained by women's socioeconomic empowerment or by binding structural constraints.

To be concrete, we compile a dataset linking mobile application usage with city-level socioeconomic indicators across China. Our primary data come from Qianfan,[1] a digital analytics platform that provides information on active users disaggregated by gender for more than 6,000 app-level observations between 2022 and 2023. It also offers information on the distribution of total active users across Chinese cities for each app. We identify parenting-related apps based on their category descriptions and measure gender gaps in usage at the app level. These measures are then merged with city-level indicators of women's education, income, and gender inequality, drawn from the China Population Census. This data allows us to observe how caregiving is distributed across genders and how that distribution varies with local structural conditions.

Our first empirical finding is hardly surprising: parenting apps are disproportionately used by women. On average, the female share of active users is 17 percentage points higher for parenting apps than for non-parenting categories. In several parenting app categories focused on the early stages of child development, female user shares exceed 80%. To identify the sources of variation in women's digital caregiving, we adopt two complementary strategies. First, we combine app usage data with city-level socioeconomic indicators to examine whether gender skew in parenting app usage is amplified in contexts where women are more economically and educationally advantaged. We focus on three dimensions of local female status—educational attainment, income, and urban development—to test whether the observed patterns are consistent with theories of the class-based parenting investment (Ramey and Ramey, 2010; Lareau, 2002) . Second, we assess whether traditional gender norms exacerbate the division of digital caregiving labor. Specifically, we test whether the female share of parenting app users is higher in cities where caregiving is more traditionally assigned to women. To capture these normative environments, we construct a set of gender inequality measures at the city level, including gaps in income, labor force participation, and educational attainment, as well as the share of male-headed households. These two empirical lenses—empowerment

[1] Qianfan Mobile App Analytics. Accessed July 21, 2025. https://www.qianfan.tech/.

versus constraint—allow us to disentangle whether digital caregiving reflects deliberate parental choice or the persistence of traditional role expectations.

We find that gender skew in parenting app usage is significantly larger in cities where women are more educated, earn higher incomes, and live in more developed urban areas. These patterns are consistent with the "intensive parenting" view, where high-SES (high socioeconomic status) mothers actively invest in childrearing measured by digital trace data. By contrast, in cities marked by greater gender inequality—larger income or education gaps, or a higher share of male-headed households—the female share of parenting app users is lower. Together, these findings suggest that digital caregiving is shaped less by structural constraints and more by women with greater agency and resources, reflecting intentional investments rather than obligations driven by traditional gender norms.

Next, we examine the overall prevalence of parenting app usage across cities to complement early analysis of gender composition. Using three metrics—active users per capita, per child, and share of total city-level app users, we find that parenting app uptake is markedly higher in cities with more educated and higher-income women. These results reinforce our earlier findings that parenting app adoption is not merely a continuation of caregiving driven by traditional gender norms, but is instead strongly associated with maternal capacity and socioeconomic advantage.

To assess whether the observed gradient in parenting app usage merely reflects broader patterns of digital engagement, we conduct a placebo analysis using non-caregiving app categories that are also female-skewed—specifically, beauty and shopping apps. These domains attract high female usage overall, yet we find no meaningful heterogeneity across cities with varying levels of female socioeconomic status. That is, high-SES environments do not systematically predict greater female representation in non-caregiving digital domains. This contrast suggests that the socioeconomic gradient we observe is not driven by generalized digital fluency among affluent women, but rather reflects domain-specific engagement with parenting. High-SES women's disproportionate use of parenting apps is more likely to be driven by caregiving motivations than by digital access.

We next examine whether engagement with parenting apps comes at the expense of women's digital participation in other domains, particularly those linked to productivity and leisure. This analysis probes a crowding-out mechanism: if caregiving demands sustained attention, it may displace alternative uses of women's time. This question is especially relevant to the maternal penalty literature. Using data on Office, News, and Game app usage, we find that women are consistently underrepresented in these categories. However, the gender gap is not significantly more pronounced in cities where women have higher SES. While the evidence is correlational, this pattern is consistent with the idea that time-intensive caregiving limits broader forms of digital participation, offering indirect support for time-allocation channels in the labor market gender inequality.

Finally, we examine whether women's digital engagement with parenting apps aligns with offline childrearing behavior. Using survey data from the China Family Panel Studies (CFPS), we analyze gender gaps in parenting behavior and educational expectations—specifically, time spent supervising children's homework and the academic aspirations parents hold for their children—and test whether these gaps widen with maternal education and income. We find that women spend more time supervising homework and hold higher academic expectations for their children than men, with these patterns more pronounced among high-SES women. This suggests that the parenting behavior observed in digital app usage reflects the intensive parenting practices of high-SES women.

This finding is particularly striking given the profile of these women. Those most active in digital parenting are also those best positioned to close gender gaps in the labor market—women with high education and income who might otherwise be expected to prioritize career advancement. That their digital activity skews so heavily toward caregiving, even in private and voluntary domains, suggests a self-directed reallocation of attention that may reinforce traditional gender roles. These results complicate standard accounts that attribute women's labor market gaps primarily to external constraints, highlighting how gender norms, parental priorities, and digital behavior intersect—even among the most empowered segments of the population.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on gender inequality, the maternal penalty, and the adoption of digital technologies in the labor market. Section 3 describes the data sources and construction of key variables. Section 4 presents the baseline estimates of gender disparities in parenting app usage. Section 5 examines how these disparities vary with local socioeconomic conditions and gender norms. Section 6 documents patterns in the prevalence of digital parenting across cities that differ in women's socioeconomic status. Section 7 explores potential mechanisms. Section 8 reports a series of robustness checks and Section 9 concludes. Additional results and supplementary material are included in the Appendix.

2 Literature Review

First, we contribute to the large literature on the gendered division of caregiving labor and its labor market consequences. A substantial body of administrative and survey evidence shows that childbirth triggers large and persistent earnings penalties for women, with little comparable cost to men (Graves, 2013; Angelov, Johansson and Lindahl, 2016; Adda, Dustmann and Stevens, 2017; Bertrand, 2018; Kleven, Landais and Søgaard, 2021; Goldin, 2021; Cortés and Pan, 2023; Kleven, Landais and Leite-Mariante, 2024; Lundborg, Plug and Rasmussen, 2017). These penalties are partly driven by the unequal division of household labor: women disproportionately assume unpaid caregiving and domestic responsibilities, leading to career interruptions and slower wage progression (Graves, 2013; Adams et al., 2025; Buzard, Gee and Stoddard, 2025). Recent research has debated the sources of this inequality—whether it reflects biological constraints and pecuniary comparative advantage (Kleven, Landais and Søgaard, 2021; Andresen and Nix, 2022), or stems from behavioral factors, such as internalized gender norms where women may voluntarily adjust labor supply to conform to traditional roles (Bertrand, Goldin and Katz, 2010; Bursztyn, Fujiwara and Pallais, 2017; Wiswall and Zafar, 2018; Lordan and Pischke, 2022), or there is social expectations about whether mothers should work (Bursztyn, Egorov and Fiorin, 2020; Bursztyn et al., 2023; Cortés et al., 2024). While both structural constraints and internal preferences are plausible, direct evidence on how much time and cognitive effort mothers actually devote to parenting—especially relative to fathers—remains limited. We use mobile app data to capture gendered patterns in parenting-related activities during discretionary, voluntary engagement, offering new evidence on the disparity of caregiving effort.

Second, we contribute to the literature on “intensive parenting" and socioeconomic gradients in parental investment. A large literature has documented that high-income, highly educated parents have adopted increasingly intensive approaches to childrearing—devoting more time, money, and cognitive effort to their children's development (Ramey and Ramey, 2010; Guryan, Hurst and Kearney, 2008; Doepke and Zilibotti, 2017; List, Pernaudet and Suskind, 2021). These investments begin early and compound over time, shaping developmental trajectories and skill acquisition. The resulting SES-based gaps in parenting are substantial: studies report large disparities in reading time, educational engagement, and responsive interactions. Theoretical and empirical work has framed these patterns as a form of “concerted cultivation," whereby parenting becomes a vehicle for transmitting class advantage (Lareau, 2018). Most research implicitly treats mothers' input as the primary agents of human capital cultivation, assuming rather than testing mothers' dominant role in childrearing (Attanasio et al., 2020; Heckman and Mosso, 2014; Anderson, Butcher and Levine, 2003). Yet empirical evidence remains constrained by data limitations, we extend this literature by linking large-scale parenting app usage data with city-level indicators of women's education and income, enabling us to examine how socioeconomic status shapes caregiving behavior in practice.

Third, we contribute to the growing methodological literature on measuring unpaid care work. While time-use diaries—where individuals log activities in short intervals—remain the gold standard for capturing time allocation (Guryan, Hurst and Kearney, 2008), they are expensive, infrequent, and prone to recall and social desirability biases. In China, for example, there are only a handful of nationally representative time-use survey (Dong and An, 2015; NBS, National Bureau of Statistics of China, 2024). Recent innovations have begun leveraging digital tools to passively capture behavioral traces, including GPS tracking, app usage, and sensor-based movement logging (Marra et al., 2019; Maharjan et al., 2021; Harari et al., 2016; Okmi et al., 2023; Zhang et al., 2023; Apte et al., 2019). These approaches offer several advantages: lower respondent burden, reduced measurement error, and relatively lower cost. Our paper extends this line of work by using mobile app data to observe parenting-related engagement at scale, across all cities in China. Unlike traditional surveys, app usage is voluntary and private; they capturing intentional actions such as searching for educational content or tracking child development. In doing so, we demonstrate how digital trace data can serve as a scalable, low-cost proxy for parental involvement.

Fourth, we contribute to a growing literature on how digital technologies mediate gender roles. Much of the existing research focuses on how digital platforms—such as fintech, ride-hailing, and crowd work—reshape women's economic opportunities (Cullen, Humphries and Pakzad-Hurson, 2018; Chen et al., 2019; Cook et al., 2021; Adams et al., 2025; Angrist, Caldwell and Hall, 2021). These technologies are often celebrated for reducing barriers to entry and offering flexible work arrangements. Yet even in settings without overt discrimination, such as Uber or MTurk, women consistently earn less than men. This disparity is commonly attributed to contextual constraints, including childcare responsibilities that limit work hours, reduce scheduling flexibility, or interrupt careers—particularly when children are young or during school breaks (Adams et al., 2025; Andrew et al., 2022; Alon et al., 2022). Our study offers a different perspective. Rather than examining how digital technologies affect labor market outcomes, we shift the focus to women's private digital lives and explore women's voluntary engagement with parenting apps. We find that women's disproportionate use of such tools does not stems from structural constraints, but rather from their own empowerment.

3 Data and Variables

3.1 Overview of Data Sources

Our analysis draws on a dataset constructed by merging mobile application usage data with city-level demographic indicators. The data come from three main sources: Qianfan, Qimai,[2] and the 2005 China Population Census conducted by the National Bureau of Statistics.

The first data source is Qianfan, a leading mobile analytics platform that tracks app usage across China. Qianfan compiles usage data from mobile network operators and a network of partner applications. From this platform, we obtain app-level statistics on monthly active users, disaggregated by gender. A user is classified as active if they open and engage with an app for at least five consecutive seconds within a given calendar month. The data were collected in two waves—January 2022 and July 2023—enabling us to examine usage patterns over time and mitigate concerns related to transitory shocks in any single period. For each app in each wave, we observe both the total number of active users and the share who are female, which serves as our primary outcome variable. It also provides basic app characteristics, such as the app category and the developer company. In addition, Qianfan reports the number of monthly active users at the city level, allowing for heterogeneity analysis by local characteristics. However, the platform does not provide joint disaggregation by city and gender.

The second data source is Qimai, a platform that provides detailed metadata on mobile applications. The dataset includes various app characteristics, such as app size (in megabytes), price, number of in-app purchases, the app's age rating, user ratings, supported languages, release year, and compatibility with both Android and iOS platforms.[3] We use these variables as controls in our empirical analysis to account for differences in app quality, pricing, accessibility, and other features that may influence the gender composition of users.

The third data source is the 2005 Population Census of China, conducted by the National Bureau of Statistics. We use individual-level microdata from this census to construct city-level measures of women's socioeconomic status and gender inequality. Specifically, we calculate the average educational attainment and income of working-age women (ages 25–49) in each city, and divide cities into six ranked intervals based on each of these characteristics. We adopt this six-interval classification to remain consistent with Qianfan, which categorizes cities into six tiers according to their level of economic development. We also construct broader indicators of gender inequality, capturing city-level gaps between men and women in earnings, labor force participation, educational attainment, and household headship. We rely on the 2005 census for two main reasons. First, it predates the widespread diffusion of mobile applications, ensuring that our city-level measures are predetermined with respect to app usage. Second, it remains the only national census to report individual-level wage data, enabling us to compute income-based

[2] Qimai Mobile App Intelligence Platform. Accessed July 21, 2025. https://www.qimai.cn/.

[3] The app's age rating refers to the recommended minimum age for using the app.

measures of gender disparity.

To construct our analytical dataset, we merge app usage data from Qianfan with app-level metadata from Qimai and link this combined information to city-level indicators derived from the 2005 Population Census. The resulting dataset allows us to observe both the gender composition of app users and the geographic distribution of usage across cities, alongside socioeconomic characteristics of those cities. The final panel includes 3,571 app-level observations from 2022 and 2,496 from 2023, with the 2023 sample representing a strict subset of the 2022 cohort. In total, the analysis covers 6,067 app-level observations. While the dataset captures all major mobile applications in China, smaller apps are excluded due to missing values for key control variables.[4] Summary statistics for the app-level analysis are reported in Table A.1 in the appendix.

3.2 Classification of Parenting Apps

Our study defines "parenting apps" as mobile applications explicitly designed to aid the parenting process. Using Qianfan's classification tags, we code an app as parenting-related if its primary purpose targets caregiving tasks or developmental support for children. These apps fall into the following six categories:

- **Pregnancy and Childbirth Assistance:** These apps are designed to guide expectant mothers throughout pregnancy. Key features include pregnancy calendars, fetal development tracking, nutritional advice, and reminders for prenatal check-ups. Many incorporate educational content on childbirth preparation and high-risk symptom alerts. Their purpose is to reduce anxiety and improve prenatal care through accessible digital support.

- **Maternal and Infant Health:** These apps primarily support mothers and infants during the postpartum period. They often provide information on infant development, breastfeeding guidance, vaccination schedules, and maternal physical recovery. Some include features such as health record management, symptom checkers, and online consultations with pediatricians or obstetricians.

- **Baby E-Commerce:** These platforms specialize in selling goods tailored to infants and young children, such as formula, diapers, clothing, toys, and strollers. They often provide curated product recommendations based on the child's age and development stage.

[4]Qianfan provides gender-disaggregated usage data for 10,493 apps in 2022 and 7,631 in 2023. Our analysis focuses on the 3,571 apps from 2022 and 2,496 apps from 2023 for which complete information on app-level characteristics is available from Qimai, covering over 85% of total users in each year. These are the most widely used apps. Our results are robust to including all smaller apps.

- **Parenting Communities:** Parenting community apps serve as digital forums where parents can exchange experiences, seek advice, and form peer support networks. Users can post questions, share milestones, or discuss challenges related to child-rearing. Expert Q&A, user-generated content, and real-time chat groups are commonly featured. These communities reduce information asymmetry and emotional isolation among caregivers.

- **Children's Education:** These apps target early childhood education, typically for users aged 2 to 6. They include interactive games, animated storytelling, and learning modules on basic literacy, numeracy, and social skills. Designed with age-appropriate interfaces, they aim to foster cognitive development.

- **Primary and Secondary Education Tools:** These apps provide academic support to students in elementary and secondary school. Common functions include homework assistance, video lectures, test preparation, and personalized learning paths. Many platforms offer subject-specific modules, especially in mathematics, Chinese, and English. Parent-teacher communication tools and performance dashboards are often embedded.

We exclude general-purpose tools unless they explicitly market themselves to caregivers or structure their content around parenting stages. This conservative approach ensures that we captures apps that genuinely function as parenting technologies, rather than generic utilities. Based on this classification strategy, we identify 290 parenting-related apps out of the 6,067 app-level observations in our dataset.

This classification captures the core digital tools parents use to manage childcare responsibilities. Recent industry estimates indicate that the global market for parenting apps reached $1.45 billion in 2023, with projected annual growth rates exceeding 11 percent.[5] Though our dataset is aggregated at the app level and does not permit fine-grained behavioral analysis, it nonetheless offers a valuable lens into parenting behavior in the digital age. Features such as developmental milestone trackers and structured educational routines make these apps a meaningful proxy for modern caregiving investment. By systematically identifying parenting-related applications, we are able to uncover a novel dimension of parenting behavior: the extent to which mothers and fathers engage with digital tools to support their children's development.

[5] Maximize Market Research (2024). Parenting app market: Global industry analysis and forecast (2024–2030). Retrieved July 21, 2025, from https://www.maximizemarketresearch.com/market-report/parenting-app-market/213688/

4 Gender Disparity

We begin by documenting a hardly surprising fact: parenting apps in China are disproportionately used by women. Figure 1 plots the average share of female and male users across two broad categories: parenting apps and all other apps. On average, around 65% of users of parenting apps are women, compared to 36% who are men. This pattern reverses for non-parenting apps, where male users are the majority (56% compared to 45%). This descriptive evidence suggests that digital engagement related to caregiving is strongly gendered.

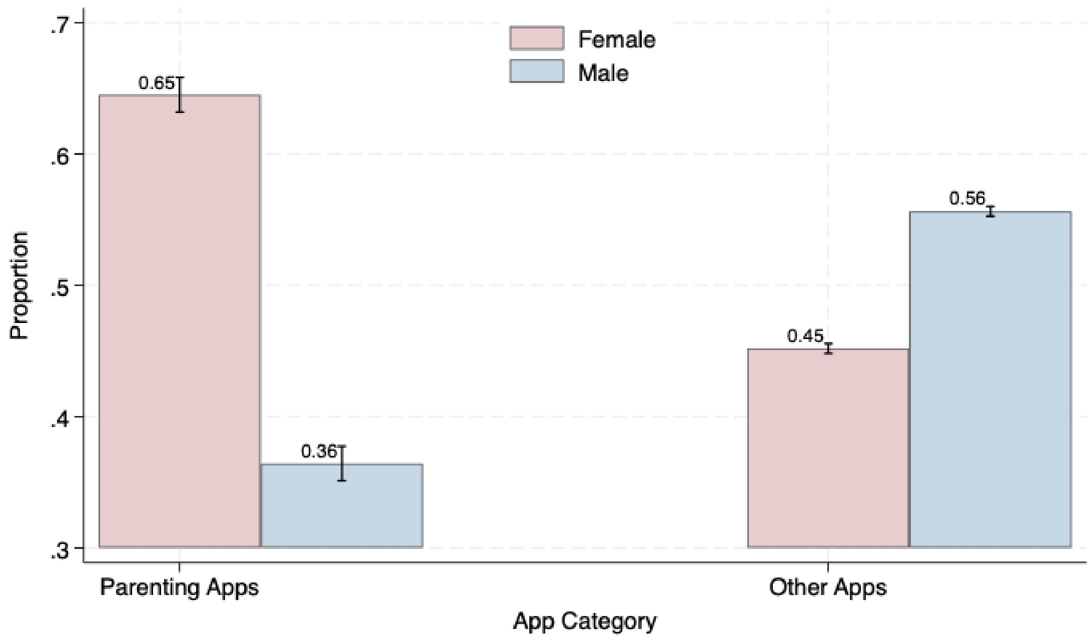


Figure 1: The proportion of female and male users by app category

To provide an estimate that accounts for other app characteristics, we use the following specification at the app level:

$$Y_i = \beta_0 + \beta_1 ParentingApp_i + X_i'\delta + \varepsilon_i \tag{1}$$

Here, Y_i is the proportion of female users of app i, and $ParentingApp_i$ is an indicator equal to one if the app is classified as parenting-related, as defined in Section 3.2. The coefficient β_1 captures the average difference in female user share between parenting and non-parenting apps. To account for potential confounding factors, we include a set of control variables X_i, ensuring that the relationship between app type and gender disparity is not driven by other app characteristics. The control vector X_i includes a set of app-level covariates: whether the data is from 2023, the app's price, the number of in-app purchases, app size (in megabytes), app age rating, user rating, release year, num-

Table 1: Gender Disparity in Parenting App Usage

Dependent Variable:	Proportion of Female Users	
	(1)	(2)
Parenting App	0.1626***	0.1697***
	(0.0386)	(0.0403)
Controls	No	Yes
Observations	6067	6067
Adjusted R^2	0.0253	0.1848
Mean Dependent Var.:	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size,the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

ber of supported languages, and compatibility with both Android and iOS platforms.[6] Regressions are weighted by the number of active users to reflect the behavior of the overall user population.[7] Standard errors are clustered at the app level.[8]

Table 1 reports the results. Without controls (column (1)), parenting apps exhibit a 16.3 percentage point higher female share relative to other app categories. When controlling for app characteristics (column (2)), which represents our preferred specification, the gender gap slightly increases to 16.97 percentage points and remains highly significant. These results indicate that, conditional on app features, parenting apps systematically attract more female users than other digital platforms. Given that app usage is voluntary and conducted in private, such a pronounced gender disparity is unlikely to be driven by institutional constraints such as employer requirements or state policy. Moreover, because the data are based on observed behavior rather than self-reports, recall bias or social desirability bias are absent—offering a relatively objective measure of gendered engagement with digital parenting technologies.

As discussed in Section 3, we classify six types of applications as parenting apps. We plot the average proportion of female users for each type and estimate regression models to test whether the proportion of female users differs between each parenting app type and other apps. We find that the share of female users is particularly high—exceeding 80%—for several categories of parenting apps primarily used during the early stages of

[6]To ensure that our results are not driven by app pricing, we conduct an additional robustness check by restricting the sample to free apps. The results, reported in Table A.12, are consistent with our baseline findings.

[7]Our results remain robust when the regressions are estimated without weights.

[8]Our results remain robust when standard errors are clustered at the app-developer (company) level.

child development. Additional details are provided in Appendix Section A.2.

5 Heterogeneity

We now turn to a more granular question: which women are driving the observed gender gap in parenting app usage? To answer this, we examine how the gender composition of users varies with local socioeconomic context, focusing on two complementary dimensions. In Section 5.1, we ask whether the female share of usage is more pronounced in economically developed cities—those with higher levels of education and income among women. This allows us to test whether greater resources and opportunities are associated with higher digital engagement in caregiving. In Section 5.2, we explore the flip side: whether the gender skew is intensified in cities characterized by more traditional gender roles, proxied by structural disparities in income, labor force participation, educational attainment, and household headship between men and women. While women's socioeconomic advancement may enable greater engagement with parenting technologies, traditional gender norms may reinforce caregiving as a female role. Examining both dimensions jointly helps illuminate how local context shapes the digital division of parental labor.

5.1 Heterogeneous Effects: City Development and Women's Socioeconomic Status

To examine how women's engagement with parenting apps varies across cities, we estimate how the gender composition of app users—measured as the proportion of female active users—differs between parenting and non-parenting apps, conditional on local socioeconomic characteristics. Our estimating equation is:

$$Y_i = \beta_0 + \beta_1 ParentingApp_i \times Ratio_{i,int,s} + \beta_2 ParentingApp_i + \beta_3 Ratio_{i,int,s} + X_i' \delta + \varepsilon_i \quad (2)$$

where Y_i denotes the female share of active users for app i, and $ParentingApp_i$ is an indicator for whether the app is a parenting app. We divide cities into six ranked intervals for each socioeconomic characteristic, as described below. The variable $Ratio_{i,int,s}$ captures the ratio of app i's users residing in cities within each interval int of the corresponding socioeconomic trait s. The interaction term, $ParentingApp_i \times Ratio_{i,int,s}$, captures whether the gender composition of parenting app usage, relative to non-parenting app usage, systematically varies with the share of users residing in cities that differ in a given socioeconomic trait. We adopt this specification because our data on the number of active users allow for disaggregation by city and by gender separately, but not jointly by both dimensions. All specifications include the full set of app-level controls from Equation 1, are weighted by the number of active users, and cluster standard errors at the app level.

We focus on three socioeconomic traits of cities, each reflecting a distinct dimension of the local socioeconomic context in which app users are embedded:

- **City development:** Following the taxonomy used by Qianfan (and consistent with National Bureau of Statistics benchmarks), all prefecture-level cities are ranked into six mutually exclusive "tiers": tier-one, new tier-one, tier-two, tier-three, tier-four, and tier-five.[9] Tier-one cities are the most economically developed. For every app i we compute $Ratio_{i,int,\text{tier}}$, the ratio of its active users residing in cities that fall into tier $int \in \{1,\ldots,6\}$. This construct allows us to test whether the female skew in parenting-app usage is systematically larger (or smaller) in more developed urban markets.

- **Female education:** Using microdata from the 2005 Population Census, we calculate the average educational attainment among working-age women for every city. Cities are then ranked in descending order based on this measure and partitioned into six equal-sized groups.[10] We form $Ratio_{i,int,\text{edu}}$ as the ratio of app i's users living in cities that belong to education sextile int. This variable captures differential exposure to female human-capital environments across an app's user base.

- **Female income:** Analogously, we use city-level averages of annual wage earnings for employed working-age women to rank cities in descending order and divide them into six income sextiles. For each app we construct $Ratio_{i,int,\text{inc}}$, the ratio of users located in cities within income sextile int. This indicator proxies the affluence of the local female workforce and enables us to examine whether higher levels of women's economic empowerment correlate with greater engagement in parenting technologies.

Table 2 reports the results. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app i's users residing in cities within

[9] The six-tier scheme was first popularised by *CBN Weekly* in 2013 and has since been widely adopted by government agencies, media outlets and private data vendors. Tier-one comprises Beijing, Shanghai, Guangzhou and Shenzhen; the sixteen "new" tier-one cities include Chengdu, Hangzhou, Chongqing, Wuhan, Suzhou, Xi'an, Nanjing, Changsha, Zhengzhou, Tianjin, Hefei, Qingdao, Dongguan, Ningbo and Foshan.

[10] We follow a six–group partition for education and income to mirror the six-tier city classification. This yields bins of roughly equal size, preserves sufficient within–group variation for precise estimation, and avoids imposing a strong linear functional-form assumption.

Table 2: Heterogeneous Effects on Parenting App Usage by Socioeconomic Context

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Parenting App × Ratio	1.1464**	1.0745**	0.7556	-1.1239***	-1.1755***	-1.3340**
	(0.4490)	(0.4299)	(0.4697)	(0.4336)	(0.3762)	(0.5756)
Parenting App	0.0794	-0.0330	0.0145	0.4468***	0.4564***	0.3634***
	(0.0506)	(0.0952)	(0.1149)	(0.1137)	(0.0941)	(0.0755)
Adjusted. R^2	0.1903	0.2064	0.1955	0.1910	0.1950	0.2006
Panel B: Intervals Based on Female Education						
Parenting App × Ratio	0.9973***	0.0210	-1.7592***	-0.6031	-1.4560	-1.8935
	(0.3303)	(0.8952)	(0.5587)	(0.6497)	(0.6181)	(1.1511)
Parenting App	-0.0945	0.1582	0.4970***	0.2604***	0.3415***	0.2921***
	(0.0995)	(0.1789)	(0.0972)	(0.0995)	(0.0843)	(0.0738)
Adjusted. R^2	0.2100	0.1923	0.1870	0.1988	0.2255	0.2203
Panel C: Intervals Based on Female Income						
Parenting App × Ratio	0.6476***	0.3127	-1.1525	-1.3541**	-2.0411***	-2.2374***
	(0.2502)	(0.4012)	(0.5587)	(0.6612)	(0.6279)	(0.7535)
Parenting App	-0.0430	0.1086	0.3362***	0.3164***	0.3935***	0.3628***
	(0.0926)	(0.1000)	(0.0983)	(0.0677)	(0.0698)	(0.0674)
Adjusted. R^2	0.1995	0.1926	0.1930	0.1994	0.2123	0.2130
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

each interval of the corresponding socioeconomic trait. Column (1) corresponds to the highest interval, while column (6) corresponds to the lowest. The dependent variable is the proportion of active users who are women; therefore, the coefficients reflect differential *maternal versus paternal adoption* of a given app, rather than overall user adoption.

Panel A: City Development. Column (1) of Panel A shows that, conditional on a rich set of app-level controls, a one percentage point increase in the share of users from tier-one cities is associated with a 1.146 percentage point increase in the share of female users for parenting apps, relative to the same change in non-parenting apps. In column (2), the estimate for the new tier-one cities is nearly identical (1.075; s.e. 0.430). Given that the average female share across all apps is 44.6 percent (bottom panel of the table), these coefficients translate into an economically meaningful shift in a highly saturated mobile market. In column (3), the interaction for tier-two cities is positive but imprecisely estimated at conventional levels, whereas the coefficients for tiers 3-5, reported in columns (4) to (6), are *negative* and statistically significant. Hence, the gender imbalance in parenting-app use widens monotonically with city economic development.

This pattern is consistent with the interpretation that modern urban environments reinforce "concerted cultivation" norms, which place mothers at the center of intensive child-development efforts. In such contexts, digital platforms serve to complement—rather than substitute for—maternal caregiving time.

Panel B: Female Education. Panel B shows an analogous gradient when cities are ranked by women's average education. In the top sextile of female education (column (1)), the interaction coefficient is 0.997 (s.e. 0.330; $p < 0.01$). That is, parenting apps exhibit a 0.997 percentage point greater increase in the share of female users than non-parenting apps when the share of users from cities in the top sextile of female education increases by one percentage point. The estimate for the second sextile in column (2) is small and statistically insignificant, but once the sample moves into the third sextile and below the coefficients become large, negative, and significant—for example, –1.759 (s.e. 0.559) in column (3). Higher local female human capital therefore magnifies, rather than attenuates, maternal engagement with digital parenting tools. A plausible explanation is that more educated mothers invest greater effort in childrearing, encompassing both online and offline activities.

Panel C: Female Income. Panel C completes the picture by partitioning cities into sextiles of women's mean wage income. The coefficient for the richest sextile is 0.648 (s.e. 0.250; $p < 0.01$) in column (1); the interaction falls close to zero in the second sextile in column (2) and turns increasingly negative thereafter. In combination with the education results, this income gradient suggests that local female earning power—arguably a proxy for both opportunity cost and bargaining strength—does not displace mothers from the digital parenting sphere. Instead, higher income raises the perceived returns to investing in digitally mediated childcare, reinforcing intensive-mothering norms.

Taken together, the evidence indicates that socioeconomic progress does not dilute women's disproportionate engagement with caregiving technologies. Rather, it *intensifies* that engagement, repackaging maternal responsibilities into digitised, cognitively demanding forms that continue to be borne primarily by women.

5.2 Heterogeneous Effects: Gender Inequality

The evidence so far indicates that parenting apps skew more heavily toward female users in cities that score highly on conventional markers of socioeconomic progress. We now ask the mirror-image question: is the gender imbalance *also* larger where women face greater structural disadvantage? Put differently, do traditional norms that assign mothers primary responsibility for childcare translate into a higher *relative* rate of maternal adoption of digital parenting tools?

To address this question we re-estimate Equation (2), but replace the three socioeconomic moderators with four city-level indicators of gender inequality as below, all derived from the 2005 Population Census.[11]

- **Income gap:** the difference between the average earnings of employed men and women, normalized by male income.
- **Labor force participation gap:** the difference in labor force participation rates between men and women, normalized by male participation rate.
- **Education gap:** the difference in years of schooling between men and women, normalized by male education.
- **Male-headed household share:** the proportion of households in a city headed by men, based on household registration records.

Each of these variables captures a distinct dimension of gender stratification—namely, income, employment, education, and domestic authority. For each variable, we rank cities and divide them into six equally sized intervals. For each app, we then calculate the ratio of users residing in cities within each interval. We replace the original ratios based on the three city-level socioeconomic variables in Equation 2 with the newly constructed ratios based on the four gender inequality indicators. The interaction between *Parenting App* and the ratio of an app's users residing in cities within a given inequality interval

[11] The first three measures are calculated for individuals aged 25–49; the fourth covers the full age distribution.

tests whether the female user share increases more for parenting apps than for non-parenting apps as a larger proportion of users are drawn from cities with varying levels of gender inequality. The regression results are presented in Table 3, where each column corresponds to a different interval ranked in descending order. Each panel reports the results based on one of the four gender inequality measures.

Panel A: Income Gap. Column (1) shows that a one percentage point increase in the share of an app's users from the one-sixth of cities with the *widest* male–female wage differential is associated with a 1.607 percentage point (s.e. = 0.577; $p < 0.01$) decrease in the female user share for parenting apps, relative to the corresponding change for non-parenting apps. A similarly negative and significant effect appears in column (2). The point estimate becomes indistinguishable from zero in column (3) and turns positive in columns (4)–(6), reaching 1.378 in the sextile of cities with small income gap in column (5), ($p < 0.01$). Hence, severe earnings inequality is associated with a markedly lower *relative* rate of maternal adoption. A plausible mechanism is that wage discrimination constrains women's financial and time resources, limiting uptake of technologies that facilitate unpaid care work.

Panel B: Labor Force Participation Gap. The interaction in column (1) is negative and significant at the 10 percent level, indicating fewer female users in cities where women's labor market participation is weakest. Beyond this extreme, the coefficients are imprecisely estimated and hover around zero, suggesting that participation gaps must be very large before they materially reduce women's share of parenting-app users.

Panel C: Educational Attainment Gap. Parenting apps are substantially less female-skewed in cities where women lag furthest behind men in schooling. The interaction coefficients are –2.131 (s.e. 0.635) and –1.585 (s.e. 0.552) in the first two sextiles, both significant at the one-percent level. As educational disparity narrows the point estimates flip sign, becoming positive—and marginally significant—in column (5). Limited schooling likely suppresses digital literacy and self-efficacy, dampening women's adoption of information-intensive caregiving technologies.

Panel D: Male-headed Household Ratio. Cities in which household authority is most concentrated in men also display a smaller female share among parenting-app users: the interaction coefficients are negative and significant in the first three sextiles (e.g. –1.449, s.e. 0.854, column (1)). The estimates become positive in the least patriarchal locales, reaching 1.433 in column (6) ($p < 0.01$). These results are consistent with the view that patriarchal household structures curb women's autonomous use of digital resources.

Together, these results complicate the notion that traditional gender inequality naturally translates into stronger maternal involvement in caregiving. One might expect that in

Table 3: Heterogeneous Effects on Parenting App Usage by Gender Inequality

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on Income Gap						
Parenting App × Ratio	-1.6065***	-1.7467***	-0.8680	0.5231	1.3776***	0.0239
	(0.5772)	(0.6352)	(0.5892)	(0.6419)	(0.5232)	(0.5874)
Parenting App	0.3705***	0.4490***	0.3353***	0.0540	-0.1074	0.1593**
	(0.0844)	(0.1044)	(0.1189)	(0.1491)	(0.1110)	(0.0656)
Adjusted. R^2	0.1894	0.1893	0.1855	0.1880	0.1893	0.1906
Panel B: Intervals Based on Labor Gap						
Parenting App × Ratio	-1.3619*	0.6284	0.7504	-0.4598	-0.4410	-0.7043
	(0.7015)	(0.4179)	(0.4771)	(0.3687)	(0.5131)	(0.6139)
Parenting App	0.3017***	0.0236	0.0248	0.2542***	0.2411***	0.2355***
	(0.0756)	(0.1157)	(0.1156)	(0.0838)	(0.0805)	(0.0708)
Adjusted. R^2	0.1860	0.1927	0.1880	0.1847	0.1902	0.2086
Panel C: Intervals Based on Education Gap						
Parenting App × Ratio	-2.1309***	-1.5848***	0.6035	-0.4880	0.7459*	0.5924
	(0.6346)	(0.5521)	(0.6112)	(0.5838)	(0.4278)	(0.4741)
Parenting App	0.3745***	0.3598***	0.0508	0.2681**	0.0312	0.0440
	(0.0551)	(0.0757)	(0.1257)	(0.1073)	(0.1019)	(0.1026)
Adjusted. R^2	0.2208	0.2150	0.1891	0.1857	0.1866	0.2118
Panel D: Intervals Based on Male-headed Gap						
Parenting App × Ratio	-1.4486*	-0.9892*	-1.1310*	0.1076	0.5263	1.4330***
	(0.8540)	(0.5969)	(0.6074)	(0.3425)	(0.5093)	(0.4589)
Parenting App	0.2910***	0.3128***	0.4149***	0.1438*	0.0728	-0.0191
	(0.0814)	(0.0922)	(0.1348)	(0.0835)	(0.0802)	(0.0634)
Adjusted. R^2	0.1866	0.1869	0.1867	0.1859	0.1847	0.1900
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. "Parenting App × Ratio" is the interaction between a parenting-app indicator and the share of the app's users located in cities that fall within the indicated sextile of the gender-inequality measure shown in the panel heading. Sextiles are ordered from the most unequal cities in column (1) to the least unequal in column (6). Panels A, B, C, and D construct the six city sextiles on the basis of (i) the male–female wage *income gap*, (ii) the male–female *labour force participation gap*, (iii) the male–female *education gap*, and (iv) the *share of male-headed households*, respectively. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

cities where women face greater structural disadvantage, where traditional roles are more entrenched, women would be more likely to assume caregiving responsibilities, including through parenting apps. Yet we find the opposite: female engagement with parenting technologies is lower in precisely those settings. Instead, the women most active on these platforms are from more economically empowered contexts. This suggests that digital caregiving is not a default extension of traditional roles but rather a behavior that emerges when women have both the resources and agency to engage more intensively with childrearing.

6 Prevalence

We now shift from a *relative* perspective—how the *share* of female users varies across apps and cities—to an *absolute* one: how widely parenting apps are adopted in each city. Studying prevalence complements the heterogeneity results in two ways. First, a city can display a large female share yet have very few users overall (or vice-versa); analyzing prevalence reveals whether women's socioeconomic position shapes the *size* of the digital-parenting market, not just its gender mix. Second, combining the two margins allows us to see whether the same city characteristics that tilt adoption toward mothers also expand (or contract) total uptake. We focus on four women-centered city-level characteristics drawn from the 2005 Population Census: (i) average female income, (ii) the gender income gap, (iii) average female education, and (iv) the gender education gap. Variables (i) and (iii) capture women's *absolute* endowments, while (ii) and (iv) reflect women's *relative* status within local labor and human capital markets.

We estimate the following regression model:

$$Prevalence_{i,c} = \beta_0 + \beta_1 WomenEndow_c + \beta_2 AppControls_i + \beta_3 CityControls_c + \varepsilon_{i,c} \qquad (3)$$

where $Prevalence_{i,c}$ measures how extensively parenting app i is used in city c. We examine three prevalence indicators: *(i) active users per capita*, *(ii) active users per child*—the number of active users normalized by 2019 births,[12] and *(iii) the app's share of total active users* in the city.[13] Taken together, these metrics capture overall penetration, intensity relative to parenting demand, and the salience of parenting apps in the local digital ecosystem.

[12] 2019 is the last year with publicly available city-level birth counts; using earlier years or population aged 0–5 yields similar results.

[13] The denominator is the total number of active users across *all* apps in city c for the January 2022 wave.

App-level controls include the app's price, the number of in-app purchases, app size (in megabytes), the app's age rating, user ratings, release year, number of supported languages, and compatibility with both Android and iOS platforms. City-level controls include a range of demographic, economic, and cultural variables that may be correlated with women's endowments: demographic variables consist of the log of registered population, the log of the 2019 birth population, the proportion of minority population, and the gender ratio; economic variables include GDP per capita, a provincial capital indicator, Internet penetration rate, and the number of hospitals per capita, and the ratio of export value to GDP; cultural variables include genealogy density, the number of Confucian temples, rice suitability, and wheat suitability.[14] Data on active users of parenting apps are drawn from the January 2022 wave. Outcome variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. Standard errors are clustered at the city level throughout.

Table 4: Parenting App Prevalence and Women's Endowments

	Active Users per Capita		**Active Users per Child**		**Share of Active Users**	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average Female Income						
Average Female Income	0.2147***	0.0953***	0.1384***	0.0603***	1.7294***	0.6726**
	(0.0251)	(0.0262)	(0.0186)	(0.0176)	(0.2104)	(0.2669)
Panel B: Gender Income Gap						
Gender Income Gap	-0.0426*	-0.0368**	-0.0028	-0.0301**	-0.6480*	-0.6453**
	(0.0223)	(0.0155)	(0.0168)	(0.0117)	(0.3417)	(0.2649)
Panel C: Average Female Education						
Average Female Education	0.0553***	0.0344***	0.0531***	0.0220***	0.4409***	0.5785***
	(0.0079)	(0.0066)	(0.0043)	(0.0049)	(0.1013)	(0.1079)
Panel D: Gender Education Gap						
Gender Education Gap	-0.1446***	-0.1954***	-0.2661***	-0.1464***	-1.3119*	-3.5879***
	(0.0489)	(0.0384)	(0.0296)	(0.0277)	(0.7063)	(0.6715)
City Controls	No	Yes	No	Yes	No	Yes
App Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49224	49224	49224	49224	49224	49224
Adjusted R^2	0.1107	0.1312	0.1176	0.1280	0.1210	0.1225
Mean Dependent Var.:	0.0899	0.0899	0.0803	0.0803	3.1716	3.1716

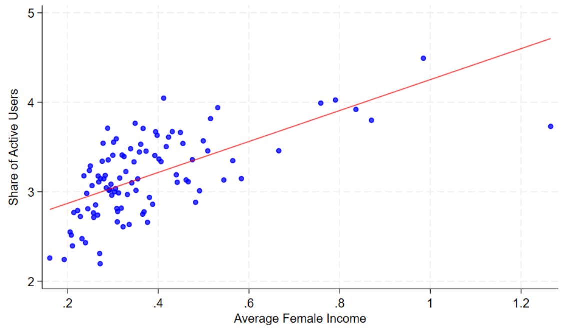
Notes: Each row presents estimates from a separate regression of parenting app prevalence on the indicated variable. Columns correspond to different outcome measures: active users per capita, per child, and the app's share of total city-level users. All specifications include app-level controls; even-numbered columns also include city-level controls. Standard errors are clustered at the city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 presents the results. Panel A shows strong positive correlations between average female income and digital caregiving engagement, both with and without city-level controls, and the results are robust across different outcome measures. Figure 2a visually displays the relationship between average female income and the parenting app's share of total city-level users, confirming a strong positive correlation. Panel C presents

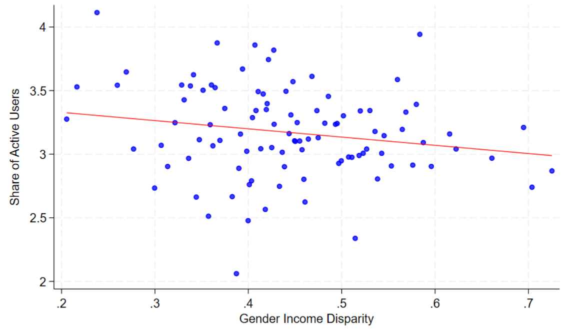
[14] Summary statistics for these variables are presented in Table A.2.

similarly strong positive correlations between average female education and parenting app prevalence, with Figure 2c providing visual confirmation.

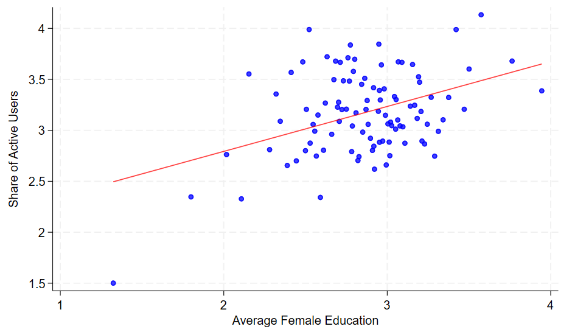
Panels B and D show that gender inequality is also predictive: cities with larger gender gaps (disadvantaging women) in income and education systematically exhibit lower levels of parenting app usage. Figures 2b and 2d confirm these negative correlations. Taken together, the results suggest that parenting app usage responds strongly to women's underlying resources and constraints. Specifically, women's endowments enhance digital caregiving engagement. Digital parenting does not simply follow affluence; it follows empowerment. This distinction motivates the mechanism analysis that follows.



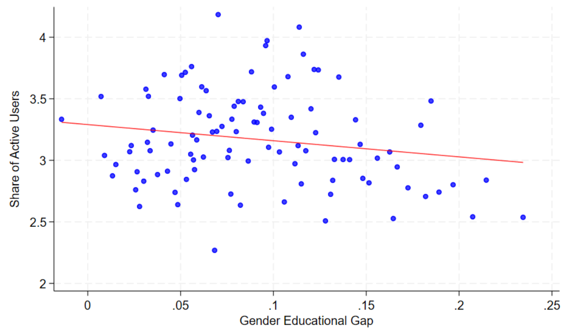
(a) Average Female Income



(b) Gender Income Gap



(c) Average Female Education



(d) Gender Education Gap

Figure 2: Parenting App Prevalence and Women's Endowments

Note: These four figures illustrate the relationship between the share of parenting app users relative to total active users and four city-level characteristics related to women's endowments: average female income, the gender income gap, average female education, and the gender education gap.

7 Mechanism

The preceding analyses have established two key facts: parenting apps are disproportionately used by women, and this gender gap is especially pronounced in more affluent, educated, and urban contexts. In this section, we explore the mechanisms underlying these patterns. We consider three possibilities. First, we examine whether the observed gradients merely reflect broader digital fluency—i.e., whether women in high-SES areas are more likely to adopt digital tools of all types. Second, we investigate whether engagement with parenting apps displaces other forms of digital participation, particularly in domains associated with professional productivity. Finally, we test whether digital caregiving reflects deeper normative commitments to intensive parenting, especially among highly educated women.

7.1 Digital Caregiving Versus General Technology Adoption

To address the concern that elevated parenting app usage in higher-SES areas may reflect broader patterns of technology adoption rather than caregiving-specific behavior, we examine whether similar patterns appear in other popular app categories used predominantly by women. Specifically, we analyze beauty apps and shopping apps—two domains that are both female-skewed in aggregate usage and non-caregiving in function. Table A.4 shows that, compared to other app categories, beauty apps have a 26% higher proportion of female users, while shopping apps have a 22% higher proportion. If the positive associations between parenting app usage and city-level education, income, or development simply reflect general digital engagement among affluent women, we should observe similar interactions for these app types.

Table A.5 and Table A.6 present regression results based on interaction models structurally identical to Equation 2, with the parenting app indicator replaced by indicators for beauty apps and shopping apps, respectively. Across all specifications, the interaction terms between app type and socioeconomic status indicators—including education, income, and urban development—are consistently small in magnitude and statistically insignificant. Additionally, in the first column of both tables, the main effects of high-SES indicators are generally negative and not statistically significant, suggesting that the overall female share in these app categories is not systematically higher in more educated or affluent regions.

These findings stand in contrast to the patterns observed for parenting apps and provide a falsification test of the general technology adoption hypothesis. The absence of positive interactions in placebo categories implies that the SES gradient in parenting app use is not simply a reflection of broader digital uptake among affluent women. Rather, the pattern is caregiving-specific: it suggests that digital engagement in high-SES contexts is selectively mobilized toward domains associated with intensive parenting. In this light, parenting app usage should be understood not as a proxy for general digital literacy or access, but rather as a context-contingent expression of maternal investment, shaped by affluent women's voluntary engagement in caregiving.

7.2 Digital Crowding Out: Women's Other Online Activity

Having ruled out general technology adoption as the primary driver, we next examine whether the uptake of parenting apps among women coincides with a reallocation of digital time away from other functional categories. If digital time is scarce, the uptake of parenting apps may reallocate women's attention away from other app domains. This crowding-out mechanism may have particular implications for professional women—those closest to shattering the "glass ceiling"—for whom time spent on caregiving apps may come at the expense of productivity-oriented or personally enriching digital activities.

To test this, we focus on three categories of non-caregiving apps: Office, News, and Games. These categories represent professional engagement, information acquisition, and recreational use, respectively. Table A.7 shows that the three app categories under consideration tend to have significantly fewer female users. Specifically, compared to other app categories, the proportion of female users is approximately 5% lower in office apps, 19% lower in news apps, and 8% lower in game apps. These findings suggest that women's digital caregiving responsibilities may come at the expense of their participation in other online domains.

To examine whether the crowding-out effect is particularly pronounced for women in cities where women have higher SES, we estimate interaction models structurally identical to Equation 2, replacing the parenting app indicator with indicators for office apps, news apps, and game apps, respectively. Table A.8, Table A.9, and Table A.10 report the results. Across the three tables, the vast majority of the interaction term coefficients are statistically insignificant. An exception appears in the first column of Panel A in Table A.10, where we find a significantly negative coefficient, suggesting that women in tier-one cities are particularly less likely to use game apps. However, similar patterns do not emerge in the other tables. Overall, there is insufficient evidence to suggest that the crowding-out effect of parenting app usage is particularly more pronounced for high-SES women.

7.3 Intensive Parenting Norms

Third, we ask whether women's digital engagement reflects broader patterns of maternal investment. Prior sections show that more educated and economically empowered women are disproportionately active on parenting apps. Does it indicate more intensive parenting practices among these women? To explore this, we turn to external survey data from the 2022 wave of the China Family Panel Studies (CFPS), which includes measures of parental education, income, and instructional support, and was conducted around the same time as our app data. We assess whether maternal investment in children's education exceeds that of fathers, and whether this gap increases with mothers' educational attainment and income—specifically, in time spent supervising homework and in the academic expectations they set. These behaviors proxy for time and cognitive engagement—core elements of intensive parenting. If digital parenting is a technological expression of intensive parenting norms, we would expect to observe these behavioral commitments outside the digital sphere as well. Specifically, we estimate the following equation:

$$Y_i = \beta_0 + \beta_1 Mother_i \times SES_i + \beta_2 Mother_i + \beta_3 SES_i + X_i' \delta + \lambda_c + \mu_h + \varepsilon_i \tag{4}$$

where the dependent variable Y_i captures two dimensions of parental investment for child i. $Mother_i$ is an indicator variable that takes the value one if the respondent is the child's mother, and zero if the father. Socioeconomic status SES_i is measured using parental education and income. The interaction term between $Mother_i$ and SES_i captures how the gender gap in educational investment varies with parental SES. Control variables include the number of children and the number of boys in the household. We also control for county fixed effects λ_c and hukou status fixed effects μ_h to address unobserved heterogeneity at the county and hukou level. Standard errors are clustered at the county level.

Table A.11 presents the estimation results. In columns (1) and (4), we estimate a simplified specification that compares mothers' and fathers' educational investments in children without interacting parental SES. As shown, mothers spend more time supervising homework and report higher academic expectations for their children. Columns (2) and (5) report results from Equation 4, where parental SES is proxied by educational attainment. Across both outcome variables, we find that maternal education significantly amplifies the gap in parenting investment. Specifically, the interaction between the mother indicator and parental education is positive and statistically significant: for time spent supervising homework, the coefficient is 0.317 ($p < 0.1$), and for expected academic performance, it is 0.653 ($p < 0.1$). These results suggest that more educated mothers spend approximately one-third of an hour more per week on homework supervision and set higher academic expectations for their children. Columns (3) and (6) show similar patterns when parental income is used to measure SES. Taken together, the results suggest that more educated and economically empowered women invest disproportionately more time and effort in their children's education.

8 Robustness

We find that parenting apps exhibit an approximately 17 percentage point higher female user share relative to other app categories. This gender gap is particularly pronounced in more developed cities, where women tend to have higher levels of education and income. These main results are presented in Table 1 and Table 2, respectively. To assess the robustness of these findings, we conduct two sets of robustness checks.

First, we test the sensitivity of our results to alternative samples. Our main analysis includes 3,571 apps from 2022 and 2,496 apps from 2023, after excluding 6,922 small apps in 2022 and 5,135 small apps in 2023 due to missing values in control variables. However, given the highly skewed distribution of active users, these excluded apps account for only approximately 13% of total users in 2022 and 12% in 2023. To examine whether excluding these small apps biases our results, we re-estimate Equation 1 and Equation 2 without including control variables, thus retaining the full sample. The corresponding results are reported in Table A.13 and Table A.20. Additionally, we assess whether our results are sensitive to sample year by estimating the same regressions separately for the 2022 and 2023 samples. Results based on the 2022 sample are presented in Table A.14 and Table A.21, while results based on the 2023 sample appear in Table A.15 and Table A.22. Across all six tables, the results are highly consistent with those in Table 1 and Table 2, suggesting that our findings are not driven by sample selection.

Second, we perform robustness checks using alternative model specifications. (1) We re-estimate Equation 1 and Equation 2 without weighting by the number of active users. The results are shown in Table A.16 and Table A.23. (2) We winsorize the outcome variable at the 1st and 99th percentiles to mitigate the influence of outliers; the results are reported in Table A.17 and Table A.24. (3) We cluster standard errors at the developer company level rather than at the app level; the results are displayed in Table A.18 and Table A.25. (4) Since the outcome variable is a proportion bounded between 0 and 1, we use a fractional logit model. The results are presented in Table A.19 and Table A.26. Across all specifications, the estimated coefficients remain highly consistent with our baseline results, confirming the robustness of our findings.

9 Final Remarks

This study investigates gender disparities in parenting by leveraging data on mobile application usage. Three facts emerge. First, parenting apps are unequivocally feminised: roughly two-thirds of their active users are women, compared with fewer than one-half for the average non-parenting app. Second, the female skew *widens* in cities where women possess greater economic and human capital resources, but *narrows* in cities where gender gaps in income, education, labor force participation, and household authority are most pronounced. Third, those same city traits shape the *scale* of adoption: places that endow women with higher income and schooling host more parenting-app users per capita and per child, whereas structural disadvantage dampens diffusion. Together, the composition and prevalence results reveal a digital incarnation of the "second shift"—one that is most pronounced among socio-economically empowered mothers.

These patterns challenge two common narratives. The first is technological optimism: access to digital tools does not, by itself, redistribute caregiving. Instead, it allows mothers—especially highly educated, high-income mothers—to intensify an already demanding role. The second concerns digital equality. Because the SES gradient we document is *specific* to parenting apps and not to apps in general, it cannot be attributed to generic digital literacy. Rather, it is consistent with theories of "concerted cultivation" that predict higher parental investment, including online investment, among advantaged families. If such effort translates into differential developmental inputs for children, the rise of digital parenting tools may widen intergenerational skill gaps even as overall connectivity improves.

The findings also recast the maternal penalty. The very women who, by virtue of higher earnings and education, stand on the cusp of breaking through the glass ceiling are also those who invest the most time and cognitive effort in digital childcare. Because parenting apps demand attention outside standard working hours, their pull is likely to compress the discretionary time that highly skilled mothers could otherwise allocate to career advancement; policies designed to narrow workplace gender gaps must therefore reckon with this invisible, screen-based time tax.

Several caveats point to a future research agenda. Our usage logs record log-ins but not minutes on task, the type of content viewed, or the emotional and cognitive load imposed. Nor do we observe whether digital parenting substitutes for or complements offline care, or how it affects labor-supply choices and child outcomes. Addressing these questions will require richer linkages—between server logs, representative time-diary surveys, and administrative labor records—and, ideally, experimental variation in app design or parental nudges. Replicating the analysis in other cultural contexts will clarify whether the Chinese experience is idiosyncratic or emblematic of middle- and high-income economies undergoing rapid digital transformation.

More broadly, the paper illustrates the promise of newly available behavioural data. App-usage traces, online purchase histories, and sensor readings offer granular windows into household production that were unobservable to earlier cohorts of researchers. Exploiting such data responsibly can uncover how preferences, constraints, and norms interact in real time—whether in childcare, elder care, or health management—and can identify unintended distributional consequences long before they appear in traditional surveys. As the economic life of households increasingly migrates to digital platforms, so too should our empirical toolkit for studying them.

References

Adams, Abi, Kotaro Hara, Kristy Milland, and Chris Callison-Burch. 2025. "The gender wage gap in an online labor market: The cost of interruptions." *Review of Economics and Statistics*, 107(1): 55–64.

Adda, Jérôme, Christian Dustmann, and Katrien Stevens. 2017. "The career costs of children." *Journal of Political Economy*, 125(2): 293–337.

Alon, Titan, Sena Coskun, Matthias Doepke, David Koll, and Michèle Tertilt. 2022. "From mancession to shecession: Women's employment in regular and pandemic recessions." *NBER Macroeconomics Annual*, 36(1): 83–151.

Anderson, Patricia M, Kristin F Butcher, and Phillip B Levine. 2003. "Maternal employment and overweight children." *Journal of Health Economics*, 22(3): 477–504.

Andresen, Martin Eckhoff, and Emily Nix. 2022. "What causes the child penalty? Evidence from adopting and same-sex couples." *Journal of Labor Economics*, 40(4): 971–1004.

Andrew, Alison, Sarah Cattan, Monica Costa Dias, Christine Farquharson, Lucy Kraftman, Sonya Krutikova, Angus Phimister, and Almudena Sevilla. 2022. "The gendered division of paid and domestic work under lockdown." *Fiscal Studies*, 43(4): 325–340.

Angelov, Nikolay, Per Johansson, and Erica Lindahl. 2016. "Parenthood and the gender gap in pay." *Journal of Labor Economics*, 34(3): 545–579.

Angrist, Joshua D, Sydnee Caldwell, and Jonathan V Hall. 2021. "Uber versus taxi: A driver's eye view." *American Economic Journal: Applied Economics*, 13(3): 272–308.

Apte, Aditi, Vijendra Ingole, Pallavi Lele, Andrew Marsh, Tathagata Bhattacharjee, Siddhivinayak Hirve, Harry Campbell, Harish Nair, Sarah Chan, and Sanjay Juvekar. 2019. "Ethical considerations in the use of GPS-based movement tracking in health research–lessons from a care-seeking study in rural west India." *Journal of Global Health*, 9(1): 010323.

Attanasio, Orazio, Sarah Cattan, Emla Fitzsimons, Costas Meghir, and Marta Rubio-Codina. 2020. "Estimating the production function for human capital: results from a randomized controlled trial in Colombia." *American Economic Review*, 110(1): 48–85.

Bertrand, Marianne. 2018. "Coase lecture–the glass ceiling." *Economica*, 85(338): 205–231.

Bertrand, Marianne, Claudia Goldin, and Lawrence F Katz. 2010. "Dynamics of the gender gap for young professionals in the financial and corporate sectors." *American Economic Journal: Applied Economics*, 2(3): 228–255.

Bertrand, Marianne, Emir Kamenica, and Jessica Pan. 2015. "Gender identity and relative income within households." *The Quarterly Journal of Economics*, 130(2): 571–614.

Bursztyn, Leonardo, Alexander W Cappelen, Bertil Tungodden, Alessandra Voena, and David H Yanagizawa-Drott. 2023. "How are gender norms perceived?" National Bureau of Economic Research.

Bursztyn, Leonardo, Georgy Egorov, and Stefano Fiorin. 2020. "From extreme to mainstream: The erosion of social norms." *American Economic Review*, 110(11): 3522–3548.

Bursztyn, Leonardo, Ingar K Haaland, Nicolas Röver, and Christopher Roth. 2025. "The Social Desirability Atlas." National Bureau of Economic Research.

Bursztyn, Leonardo, Thomas Fujiwara, and Amanda Pallais. 2017. "'Acting wife': Marriage market incentives and labor market investments." *American Economic Review*, 107(11): 3288–3319.

Buzard, Kristy, Laura K Gee, and Olga Stoddard. 2025. "Who you gonna call? gender inequality in external demands for parental involvement." *The Quarterly Journal of Economics*, qjaf027.

Chen, M Keith, Peter E Rossi, Judith A Chevalier, and Emily Oehlsen. 2019. "The value of flexible work: Evidence from Uber drivers." *Journal of Political Economy*, 127(6): 2735–2794.

Cook, Cody, Rebecca Diamond, Jonathan V Hall, John A List, and Paul Oyer. 2021. "The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers." *The Review of Economic Studies*, 88(5): 2210–2238.

Cortés, Patricia, and Jessica Pan. 2023. "Children and the remaining gender gaps in the labor market." *Journal of Economic Literature*, 61(4): 1359–1409.

Cortés, Patricia, Gizem Koşar, Jessica Pan, and Basit Zafar. 2024. "Should mothers work? how perceptions of the social norm affect individual attitudes toward work in the us." *Review of Economics and Statistics*, 1–28.

Cullen, Zoe B, John Eric Humphries, and Bobak Pakzad-Hurson. 2018. "Gender and sorting in the on-demand economy."

Doepke, Matthias, and Fabrizio Zilibotti. 2017. "Parenting with style: Altruism and paternalism in intergenerational preference transmission." *Econometrica*, 85(5): 1331–1371.

Doepke, Matthias, Giuseppe Sorrenti, and Fabrizio Zilibotti. 2019. "The economics of parenting." *Annual Review of Economics*, 11(1): 55–84.

Dong, Xiao-yuan, and Xinli An. 2015. "Gender patterns and value of unpaid care work: Findings from C hina's first large-scale time use survey." *Review of Income and Wealth*, 61(3): 540–560.

Goldin, Claudia. 2021. "Career and family: Women's century-long journey toward equity."

Graves, Jennifer. 2013. "The effects of school calendar type on maternal employment across racial groups: A story of child care availability." *American Economic Review*, 103(3): 279–283.

Guryan, Jonathan, Erik Hurst, and Melissa Kearney. 2008. "Parental education and parental time with children." *Journal of Economic Perspectives*, 22(3): 23–46.

Harari, Gabriella M, Nicholas D Lane, Rui Wang, Benjamin S Crosier, Andrew T Campbell, and Samuel D Gosling. 2016. "Using smartphones to collect behavioral data in psychological science: Opportunities, practical considerations, and challenges." *Perspectives on Psychological Science*, 11(6): 838–854.

Heckman, James J, and Stefano Mosso. 2014. "The economics of human development and social mobility." *Annual Review of Economics*, 6(1): 689–733.

Hochschild, Arlie, and Anne Machung. 1989. *The second shift: Working families and the revolution at home.* Penguin.

Kalil, Ariel, Susan E Mayer, William Delgado, and Lisa A Gennetian. 2025. "Education gradients in parental time investment and subjective well-being." *Review of Economics of the Household*, 23(2): 661–706.

Kleven, Henrik, Camille Landais, and Gabriel Leite-Mariante. 2024. "The child penalty atlas." *Review of Economic Studies*, rdae104.

Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard. 2019. "Children and gender inequality: Evidence from Denmark." *American Economic Journal: Applied Economics*, 11(4): 181–209.

Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard. 2021. "Does biology drive child penalties? Evidence from biological and adoptive families." *American Economic Review: Insights*, 3(2): 183–198.

Lareau, Annette. 2002. "Invisible inequality: Social class and childrearing in black families and white families." *American Sociological Review*, 67(5): 747–776.

Lareau, Annette. 2018. "Unequal childhoods: Class, race, and family life." In *Inequality in the 21st Century*. 444–451. Routledge.

List, John A, Julie Pernaudet, and Dana L Suskind. 2021. "Shifting parental beliefs about child development to foster parental investments and improve school readiness outcomes." *Nature Communications*, 12(1): 5765.

Lordan, Grace, and Jörn-Steffen Pischke. 2022. "Does Rosie like riveting? Male and female occupational choices." *Economica*, 89(353): 110–130.

Lundborg, Petter, Erik Plug, and Astrid Würtz Rasmussen. 2017. "Can women have children and a career? IV evidence from IVF treatments." *American Economic Review*, 107(6): 1611–1637.

Maharjan, Sujen Man, Anubhuti Poudyal, Alastair van Heerden, Prabin Byanjankar, Ada Thapa, Celia Islam, Brandon A Kohrt, and Ashley Hagaman. 2021. "Passive sensing on mobile devices to improve mental health services with adolescent and young mothers in low-resource settings: the role of families in feasibility and acceptability." *BMC Medical Informatics and Decision Making*, 21(1): 117.

Marra, Alessio D, Henrik Becker, Kay W Axhausen, and Francesco Corman. 2019. "Developing a passive GPS tracking system to study long-term travel behavior." *Transportation Research Part C: Emerging Technologies*, 104: 348–368.

Mas, Alexandre, and Amanda Pallais. 2017. "Valuing alternative work arrangements." *American Economic Review*, 107(12): 3722–3759.

NBS, National Bureau of Statistics of China. 2024. "Communiqué on China's Third National Time Use Survey (No. 2)."

Okmi, Mohammed, Lip Yee Por, Tan Fong Ang, and Chin Soon Ku. 2023. "Mobile phone data: A survey of techniques, features, and applications." *Sensors*, 23(2): 908.

Ramey, Garey, and Valerie A. Ramey. 2010. "The Rug Rat Race." *Brookings Papers on Economic Activity*, 41(1 (Spring)): 129–199.

Wasserman, Melanie. 2023. "Hours constraints, occupational choice, and gender: Evidence from medical residents." *The Review of Economic Studies*, 90(3): 1535–1568.

Wiswall, Matthew, and Basit Zafar. 2018. "Preference for the workplace, investment in human capital, and gender." *The Quarterly Journal of Economics*, 133(1): 457–507.

Zhang, Heng, Ahmed Ibrahim, Bijan Parsia, Ellen Poliakoff, and Simon Harper. 2023. "Passive social sensing with smartphones: a systematic review." *Computing*, 105(1): 29–51.

Zhang, Mingxue, Yue Wang, and Lingling Hou. 2024. "Gender norms and the child penalty in China." *Journal of Economic Behavior & Organization*, 221: 277–291.

Appendices for Online Publication Only

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A Appendices

A.1 Summary Statistics

Table A.1: Summary Statistics

Variable	Observations	Mean	SD	Min	Max
Proportion of Female Users	6067	0.446	0.162	0.000	1.000
Parenting App	6067	0.048	0.213	0.000	1.000
Number of Active Users	6067	662.787	4767.258	0.013	101186.400
Developed City Ratio	6067	0.147	0.162	0.000	1.000
High Female Education Ratio	6067	0.356	0.199	0.000	1.000
High Female Income Ratio	6067	0.458	0.222	0.000	1.000
High Income Disparity	6067	0.111	0.111	0.000	0.974
High Labor Gap	6067	0.097	0.103	0.000	0.961
High Educational Gap	6067	0.066	0.082	0.000	0.952
High Male-headed Ratio	6067	0.090	0.108	0.000	0.974
Office App	6067	0.040	0.197	0.000	1.000
News App	6067	0.050	0.218	0.000	1.000
Game App	6067	0.063	0.243	0.000	1.000
Beauty App	6067	0.044	0.002	0.000	1.000
Shopping App	6067	0.089	0.008	0.000	1.000
Year 2023	6067	0.411	0.492	0.000	1.000
Price	6067	0.155	3.840	0.000	198.000
In-app Purchase	6067	3.214	4.334	0.000	10.000
App Size	6067	237.072	417.117	0.560	3904.120
App Age Rating	6067	9.120	5.929	4.000	17.000
User Ratings	6067	3.769	1.104	0.000	5.000
Release Year	6067	2015.498	3.187	2008.000	2024.000
Number of Languages	6067	3.529	6.972	1.000	90.000
Compatibility with both platforms	6067	0.234	0.423	0.000	1.000

Notes: The unit for the number of active users is ten thousand (10,000), and the unit for price is Chinese Yuan (CNY). The Developed City Ratio, High Female Education Ratio, High Female Income Ratio, High Income Disparity, High Labor Gap, High Educational Gap, and High Male-headed Ratio represent the proportions of users in the top one-sixth of cities.

Table A.2: Summary Statistics

Variable	Observations	Mean	SD	Min	Max
Active Users per capita	49224	0.090	0.301	0.000	2.209
Active User per Children	49224	0.080	0.262	0.000	1.897
Share of Active Users	49224	3.172	10.204	0.000	74.594
Average Female Income	49224	0.374	0.166	0.131	1.467
Average Female Education	49224	2.857	0.383	1.086	3.950
Gender Income Gap	49224	0.443	0.103	0.205	0.728
Gender Education Gap	49224	0.091	0.052	-0.032	0.236
ln(Population)	49224	15.020	0.744	12.247	17.317
ln(2019 Births)	49224	10.467	0.860	7.843	12.718
Minority Ratio	49224	9.426	19.301	0.010	97.190
Sex Ratio	49224	105.205	4.091	89.650	132.580
Provincial Capital Dummy	49224	0.106	0.308	0.000	1.000
GDP per capita	49224	3.207	2.102	0.553	13.811
Export Value to GDP	49224	0.094	0.156	0.000	1.531
Internet Penetration Rate	49224	0.604	0.092	0.000	0.886
Hospitals per capita	49224	0.290	0.138	0.077	1.051
Genealogy Density	49224	0.379	0.974	0.000	7.876
Confucian Temples	49224	1.232	1.436	0.000	7.000
Rice Suitability	49224	0.064	1.018	-0.819	1.653
Wheat Suitability	49224	0.145	0.894	-2.044	1.948

Notes: The unit for Active Users per Capita is parts per million (ppm). The unit for Active Users per Child is parts per ten thousand (pptt). The unit for Share of Active Users is parts per thousand (ppt).

A.2 Six Parenting App Categories

We classify six types of applications as parenting apps, broadly ordered according to stages of child development. These categories include: Pregnancy and Childbirth Assistance, Maternal and Infant Health, Baby E-Commerce, Parenting Communities, Children's Education, and Primary and Secondary Education Tools. We further examine which categories attract a higher proportion of female users. Specifically, we plot the average share of female users across apps in each category. As shown in Figure A.1, all six categories exhibit female user shares exceeding 50%. In particular, Pregnancy and Childbirth Assistance, Baby E-Commerce, and Parenting Communities show extremely skewed gender compositions, with more than 80% female users. In contrast, Children's Education and Primary and Secondary Education Tools exhibit relatively lower proportions of female users, suggesting greater paternal involvement during later stages of child development.

Table A.3 presents regression results using parenting app categories as explanatory variables, where each category is represented by a dummy variable equal to one if the app belongs to that category. The regression compares the proportion of female users for apps in each category to that of all other apps excluding the focal category, while controlling for observable covariates. We find that all six parenting app categories attract disproportionately more female users compared to non-parenting apps, with particularly pronounced differences for those predominantly used during early stages of childrearing.

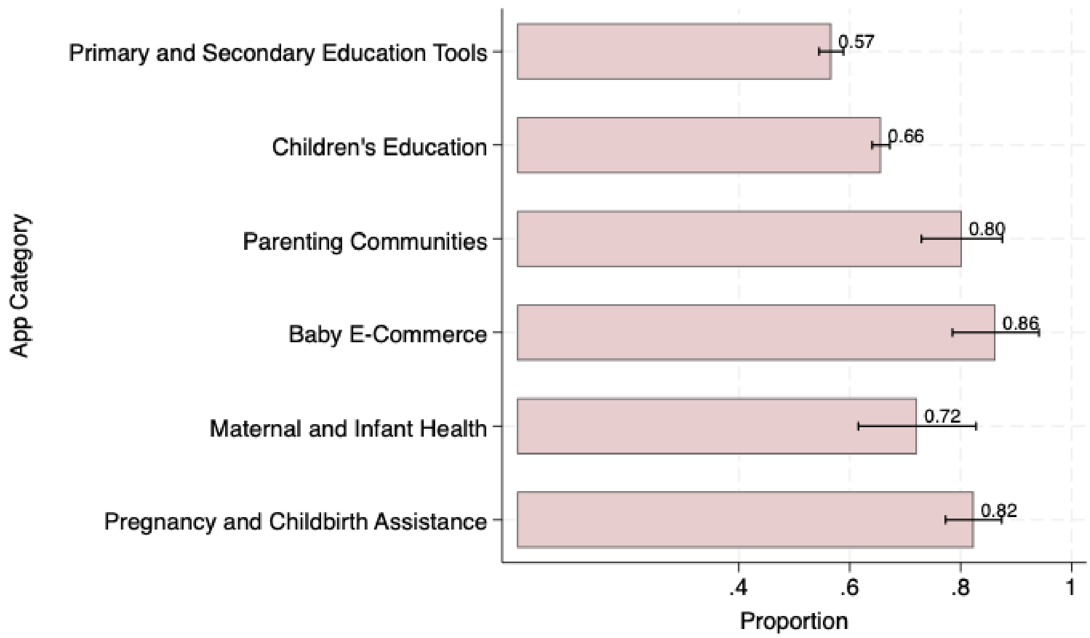

Figure A.1: The proportion of female users by parenting app category

Table A.3: Gender Disparity by Parenting App Type

Dependent Variable:	Proportion of Female Users					
	(1)	(2)	(3)	(4)	(5)	(6)
Pregnancy and Childbirth Assistance	0.2237***					
	(0.0553)					
Maternal and Infant Health		0.2800***				
		(0.0175)				
Baby E-Commerce			0.3336***			
			(0.0670)			
Parenting Communities				0.4413***		
				(0.0301)		
Children's Education					0.2020***	
					(0.0297)	
Primary and Secondary Education Tools						0.0866***
						(0.0166)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
adj. R^2	0.1610	0.1609	0.1595	0.1783	0.1676	0.1630
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each parenting app category is represented by a dummy variable indicating whether App_i belongs to that category. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

A.3 Mechanism

Table A.4: Gender Disparities in the Use of Beauty Apps and Shopping Apps

Dependent Var.:	Proportion of Female Users	
	(1)	(2)
Beauty App	0.2628***	0.2553***
	(0.0578)	(0.0512)
Shopping APP	0.1764***	0.2234***
	(0.0603)	(0.0622)
Controls:	No	Yes
Observations:	6067	6067
Adjusted R^2:	0.0026	0.1634
Mean Dependent Var.:	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Beauty App is a binary indicator equal to one if the app is beauty-related. Shopping App is a binary indicator equal to one if the app is shopping-related. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, the earliest release year of the app, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.5: Heterogeneous Effects on Beauty App Usage

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Beauty App × Ratio	−0.4322	0.4096	−0.0208	0.8052	−0.1250	−0.7041
	(0.2809)	(0.7854)	(0.5885)	(0.5388)	(1.3347)	(0.5289)
Beauty App	0.3080***	0.1526	0.2548	0.0803	0.2877	0.3443***
	(0.0659)	(0.1521)	(0.1585)	(0.1092)	(0.1905)	(0.0949)
Adjusted. R^2	0.1646	0.1866	0.1732	0.1689	0.1705	0.1772
Panel B: Intervals Based on Female Education						
Beauty App × Ratio	−0.1725	1.3663	1.1585	−2.0197**	0.4036	0.3073
	(0.3216)	(0.9154)	(0.7390)	(0.8231)	(1.0642)	(1.0108)
Beauty App	0.3052***	−0.0234	0.1178	0.5373***	0.1868	0.1872*
	(0.1105)	(0.1864)	(0.1114)	(0.1321)	(0.1343)	(0.1063)
Adjusted. R^2	0.1898	0.1691	0.1593	0.1778	0.2092	0.2005
Panel C: Intervals Based on Female Income						
Beauty App × Ratio	0.0438	−0.5575	0.6817	0.3603	−0.7145	−0.1907
	(0.3427)	(0.6557)	(0.6115)	(1.0494)	(0.8192)	(1.5625)
Beauty App	0.2316	0.3558**	0.1614**	0.2078**	0.3032***	0.2788***
	(0.1613)	(0.1423)	(0.0773)	(0.0906)	(0.1122)	(0.1012)
Adjusted. R^2	0.1783	0.1665	0.1685	0.1797	0.1942	0.1928
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a beauty app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.6: Heterogeneous Effects on Shopping App Usage

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Shopping App× Ratio	−0.2278	−0.5237	0.6518	0.3477	−0.8805	−1.5829
	(0.8825)	(1.0804)	(1.2731)	(0.7673)	(1.3992)	(1.0206)
Shopping App	0.2572*	0.3314	0.0600	0.1417	0.3641	0.3731***
	(0.1427)	(0.2565)	(0.2904)	(0.1668)	(0.2683)	(0.1387)
Adjusted. R^2	0.1689	0.1906	0.1778	0.1729	0.1750	0.1822
Panel B: Intervals Based on Female Education						
Shopping App × Ratio	−3.0093	1.8224	0.5733	1.5664	−0.4938	−0.8341*
	(2.1558)	(1.1206)	(0.7812)	(1.0095)	(1.0863)	(0.4490)
Shopping App	0.3744**	−0.0127	0.1289	−0.0241	0.3083	0.4971***
	(0.1603)	(0.1118)	(0.1484)	(0.1566)	(0.2274)	(0.1810)
Adjusted. R^2	0.2048	0.2129	0.1818	0.1638	0.1732	0.1939
Panel C: Intervals Based on Female Income						
Shopping App × Ratio	−0.9263	−2.5965	−0.9112	−0.6918	0.7473	0.2787
	(1.6677)	(1.9458)	(2.3301)	(1.0032)	(1.3923)	(0.5456)
Shopping App	0.2768**	0.4193**	0.2947	0.3085*	0.0811	0.0902
	(0.1083)	(0.1992)	(0.2285)	(0.1712)	(0.2670)	(0.2373)
Adjusted. R^2	0.1976	0.1985	0.1839	0.1729	0.1707	0.1828
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a shopping app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.7: Gender Disparities in the Usage of Other Important Apps

Dependent Var.:	Proportion of Female Users	
	(1)	(2)
Office App	-0.0187	-0.0504**
	(0.0209)	(0.0243)
News App	-0.1363***	-0.1907***
	(0.0357)	(0.0311)
Game App	-0.0681***	-0.0848**
	(0.0158)	(0.0349)
Controls	No	Yes
Observations:	6067	6067
Adjusted R^2:	0.0992	0.3208
Mean Dependent Var.:	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Office App is a dummy variable indicating whether the app is a business office or a work-related app. News App is a dummy variable indicating whether the app is an informational or news app. Game App is a dummy variable indicating whether the app is used for playing games. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Heterogeneous Effects on Office App Usage

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Office App× Ratio	0.3536	0.3831	0.1920	−0.1222	−0.3773	−0.7744
	(0.3120)	(0.3623)	(0.2762)	(0.3890)	(0.3382)	(0.5295)
Office App	−0.0941	−0.1314	−0.0827	−0.0157	0.0274	0.0476
	(0.0584)	(0.0993)	(0.0784)	(0.0745)	(0.0542)	(0.0506)
Adjusted. R^2	0.1677	0.1894	0.1748	0.1710	0.1727	0.1801
Panel B: Intervals Based on Female Education						
Office App × Ratio	−1.1484	−1.5059***	−1.0182**	0.0727	−0.0653	0.5232*
	(1.0317)	(0.4969)	(0.4517)	(0.4956)	(0.7822)	(0.2781)
Office App	0.0248	0.1209**	0.1039	−0.0590	−0.0306	−0.2163**
	(0.0456)	(0.0490)	(0.0654)	(0.0888)	(0.1595)	(0.1070)
Adjusted. R^2	0.2022	0.2126	0.1814	0.1624	0.1717	0.1929
Panel C: Intervals Based on Female Income						
Office App × Ratio	−1.2059	−0.4457	−1.1522*	−0.4961	0.3205	0.2392
	(0.7795)	(0.8283)	(0.6385)	(0.5429)	(0.3691)	(0.1655)
Office App	0.0395	0.0084	0.0589	0.0201	−0.1120	−0.1437
	(0.0425)	(0.0543)	(0.0514)	(0.0567)	(0.0707)	(0.0925)
Adjusted. R^2	0.1950	0.1951	0.1817	0.1707	0.1699	0.1802
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between an office app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.9: Heterogeneous Effects on News App Usage

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
News App× Ratio	−0.6868	0.4586*	0.3520*	0.1426	0.6070	0.1174
	(0.5215)	(0.2462)	(0.1935)	(0.4833)	(0.6179)	(0.6436)
News App	−0.1003	−0.2943***	−0.2700***	−0.2199**	−0.3055**	−0.2006**
	(0.0755)	(0.0596)	(0.0570)	(0.0960)	(0.1194)	(0.0815)
Adjusted. R^2	0.3235	0.3406	0.3228	0.3239	0.3267	0.3287
Panel B: Intervals Based on Female Education						
News App × Ratio	−0.8361	0.1680	−0.0826	−0.0844	0.8773***	−0.1796
	(0.5407)	(0.4731)	(0.3590)	(0.3406)	(0.2963)	(0.2644)
News App	−0.1383***	−0.2010***	−0.1772***	−0.1752***	−0.3596***	−0.1262
	(0.0433)	(0.0587)	(0.0651)	(0.0561)	(0.0584)	(0.0938)
Adjusted. R^2	0.3429	0.3540	0.3319	0.3133	0.3236	0.3406
Panel C: Intervals Based on Female Income						
News App × Ratio	1.2444	0.3616	0.0735	−0.4414	0.0482	−0.0010
	(1.4350)	(1.0500)	(0.5956)	(0.5143)	(0.4139)	(0.2604)
News App	−0.2637***	−0.2165**	−0.1940***	−0.1317*	−0.1968***	−0.1879
	(0.0930)	(0.0930)	(0.0589)	(0.0686)	(0.0674)	(0.1202)
Adjusted. R^2	0.3434	0.3431	0.3309	0.3217	0.3169	0.3311
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a news app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Heterogeneous Effects on Game App Usage

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Game App× Ratio	−1.1286***	−0.0946	−0.3154	0.0191	0.4427	0.3035
	(0.3887)	(0.3432)	(0.2596)	(0.2870)	(0.2799)	(0.4486)
Game App	0.0676	−0.0489	0.0009	−0.0617	−0.1656**	−0.1091
	(0.0475)	(0.0683)	(0.0593)	(0.0745)	(0.0783)	(0.0814)
Adjusted. R^2	0.1690	0.1897	0.1761	0.1710	0.1739	0.1803
Panel B: Intervals Based on Female Education						
Game App × Ratio	−0.4874	−0.1493	0.1657	0.7077	0.0079	−0.2775
	(0.5654)	(0.4365)	(0.4341)	(0.4463)	(0.2859)	(0.2256)
Game App	−0.0355	−0.0439	−0.0815	−0.1834**	−0.0674	0.0259
	(0.0563)	(0.0742)	(0.0806)	(0.0779)	(0.0657)	(0.0642)
Adjusted. R^2	0.2038	0.2118	0.1799	0.1619	0.1719	0.1924
Panel C: Intervals Based on Female Income						
Game App × Ratio	0.3718	0.2056	0.4287	0.3845	0.0998	−0.3600*
	(0.6159)	(0.6342)	(0.5247)	(0.4846)	(0.3115)	(0.2134)
Game App	−0.0987	−0.0846	−0.1119	−0.1206	−0.0793	0.0651
	(0.0677)	(0.0801)	(0.0749)	(0.0901)	(0.0686)	(0.0761)
Adjusted. R^2	0.1959	0.1969	0.1827	0.1714	0.1688	0.1821
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a game app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.11: Intensive Parenting Norms: Evidence from CFPS

Dependent Variable:	**Supervising Homework**			**Academic Expectations**		
	(1)	(2)	(3)	(4)	(5)	(6)
Mother	0.9049**	−0.1744	0.5375	1.0878**	−0.7813	0.8624**
	(0.2436)	(0.6721)	(0.3393)	(0.4123)	(0.7343)	(0.4149)
Education×Mother		0.3169*			0.6531*	
		(0.1704)			(0.2282)	
Education		−0.3488**			−0.1397	
		(0.1559)			(0.1816)	
Income×Mother			0.0825*			0.2794*
			(0.0475)			(0.1555)
Income			−0.0667*			−0.3670**
			(0.0388)			(0.1385)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Hukou FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	2889	2889	2889	3279	3279	3038
Adjusted R^2	0.0630	0.0645	0.0634	0.0577	0.0604	0.0610
Mean Dependent Var.:	6.2085	6.2085	6.2085	90.3732	90.3732	90.3732

Notes: The dependent variables are weekly hours spent assisting with homework and expected academic performance, both reported by parents. The variable Mother is a binary indicator equal to 1 if the respondent is the mother and 0 if the respondent is the father. Education refers to the highest level of educational attainment, and Income is measured as annual labor income (in CNY). Control variables include the number of children and the number of boys in the household. All regressions include county and hukou fixed effects. Standard errors are clustered at the county level. *p<0.1, **p<0.05, ***p<0.01.

A.4 Robustness Tests

Table A.12: Gender Disparity in Parenting App Usage with free app

Dependent Variable:	Proportion of Female Users	
	(1)	(2)
Parenting App	0.1626***	0.1697***
	(0.0386)	(0.0403)
Controls	No	Yes
Observations	6022	6022
Adjusted R^2	0.0253	0.1849
Mean Dependent Var.:	0.4457	0.4457

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Control variables include: whether the app usage data is from 2023, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.13: Robustness Test with a Larger Sample Size

	Proportion of Female Users
Parenting App	0.1686***
	(0.0325)
Controls	No
Observations	18121
Adjusted R^2	0.0281
Mean Dependent Var.:	0.4529

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.14: Robustness Test with Only 2022 Sample

Dependent Variable:	Proportion of Female Users	
	(2)	(3)
Parenting App	0.1457***	0.1474***
	(0.0422)	(0.0429)
Controls	No	Yes
Observations	6067	6067
Adjusted R^2	0.0252	0.1504
Mean Dependent Var.:	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Control variables include: the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.15: Robustness Test with Only 2023 Sample

Dependent Variable:	Proportion of Female Users	
	(1)	(2)
Parenting App	0.1843***	0.1990***
	(0.0330)	(0.0362)
Controls	No	Yes
Observations	6067	6067
Adjusted R^2	0.0253	0.2174
Mean Dependent Var.:	0.4369	0.4369

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Control variables include: the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.16: Robustness Test Without Weighting by User Scale

Dependent Variable:	Proportion of Female Users	
	(1)	(2)
Parenting App	0.1945***	0.1852***
	(0.0107)	(0.0113)
Controls	No	Yes
Observations	6067	6067
Adjusted R^2	0.0654	0.0829
Mean Dependent Var.:	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Standard errors are clustered at the app level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.17: Robustness Test with Outcome Variable Winsorized at 1% and 99%

Dependent Variable:	Proportion of Female Users	
	(1)	(2)
Parenting App	0.1616***	0.1687***
	(0.0380)	(0.0397)
Controls	No	Yes
Observations	6067	6067
Adjusted R^2	0.0252	0.1882
Mean Dependent Var.:	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.18: Robustness Test with Standard Errors Clustered at the Company Level

Dependent Variable:	Proportion of Female Users	
	(1)	(2)
Parenting App	0.1626***	0.1697***
	(0.0391)	(0.0408)
Controls	No	Yes
Observations	6067	6067
Adjusted R^2	0.0253	0.1848
Mean Dependent Var.:	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the company level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.19: Gender Disparity in Parenting App Usage Using Fractional Logit Model

Dependent Variable:	Proportion of Female Users	
	(1)	(2)
Parenting App	0.1629***	0.1692***
	(0.0397)	(0.0416)
Controls	No	Yes
Observations	6067	6067
pseudo R^2	0.0012	0.0089
Mean Dependent Var.:	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. *Parenting App* is a dummy indicating whether the app is parenting-related. Control variables include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.20: Robustness Test with a Large Sample Size

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Parenting App × Ratio	0.9457***	0.8104***	0.6143*	-0.9252***	-0.9482***	-1.0467***
	(0.3137)	(0.2660)	(0.3136)	(0.2771)	(0.2885)	(0.3952)
Parenting App	0.0904**	0.0048	0.0407	0.3893***	0.3957***	0.3154***
	(0.0380)	(0.0649)	(0.0777)	(0.0729)	(0.0739)	(0.0547)
Adjusted. R^2	0.0370	0.0588	0.0399	0.0411	0.0416	0.0451
Panel B: Intervals Based on Female Education						
Parenting App × Ratio	0.8827***	0.2629	-1.3354***	-0.6108*	-1.2786***	-1.7090**
	(0.2177)	(0.5029)	(0.3426)	(0.3673)	(0.4876)	(0.6810)
Parenting App	0.1136	0.4136***	0.2777***	0.2768***	0.3258***	0.3241***
	(0.1043)	(0.0608)	(0.0470)	(0.0501)	(0.0515)	(0.0518)
Adjusted. R^2	0.0398	0.0313	0.0667	0.0384	0.0570	0.0539
Panel C: Intervals Based on Female Income						
Parenting App × Ratio	0.5532***	0.2232	-0.7710**	-1.0734**	-1.4841***	-1.8148***
	(0.1946)	(0.2912)	(0.3507)	(0.4604)	(0.4530)	(0.5519)
Parenting App	0.1242*	0.2579***	0.4282***	0.6204***	0.8432***	0.8373***
	(0.0715)	(0.0597)	(0.1428)	(0.1639)	(0.1874)	(0.2033)
Adjusted. R^2	0.0341	0.0479	0.0481	0.0452	0.0540	0.0539
Controls	No	No	No	No	No	No
Observations	18121	18121	18121	18121	18121	18121
Mean Dependent Var.:	0.4529	0.4529	0.4529	0.4529	0.4529	0.4529

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.21: Robustness Test with Only 2022 Sample

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Parenting App × Ratio	1.2810***	1.0620**	0.8617*	-0.9763**	-1.1772***	-1.4117**
	(0.4786)	(0.4826)	(0.5138)	(0.4006)	(0.4259)	(0.5920)
Parenting App	0.0502	-0.0499	-0.0259	0.3900***	0.4397***	0.3562***
	(0.0510)	(0.1029)	(0.1212)	(0.1041)	(0.1097)	(0.0840)
Adjusted R^2	0.1569	0.1694	0.1606	0.1549	0.1590	0.1665
Panel B: Intervals Based on Female Education						
Parenting App × Ratio	1.1557***	0.1718	-1.6737***	-0.8405	-1.3622**	-2.0870*
	(0.3345)	(0.9341)	(0.5492)	(0.6830)	(0.6916)	(1.0827)
Parenting App	0.1112	0.4608***	0.2885***	0.3329***	0.3786***	0.3560***
	(0.1853)	(0.0970)	(0.0706)	(0.0994)	(0.0801)	(0.0736)
Adjusted R^2	0.1563	0.1532	0.1849	0.1560	0.1747	0.1779
Panel C: Intervals Based on Female Income						
Parenting App × Ratio	0.6778**	0.4243	-1.2661	-1.3561*	-2.0465***	-2.3418***
	(0.2795)	(0.3945)	(0.7748)	(0.7254)	(0.6809)	(0.7816)
Parenting App	0.0642	0.2827***	0.3535**	0.6226***	0.9305***	1.0048***
	(0.0979)	(0.1073)	(0.1682)	(0.2211)	(0.2709)	(0.2714)
Adjusted R^2	0.1629	0.1629	0.1621	0.1685	0.1808	0.1839
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3571	3571	3571	3571	3571	3571
Mean Dependent Var.:	0.4528	0.4528	0.4528	0.4528	0.4528	0.4528

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Controls include the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.22: Robustness Test with Only 2023 Sample

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Parenting App × Ratio	0.8936**	1.0269***	0.5696	-1.2808**	-1.1021***	-1.1063*
	(0.4181)	(0.3841)	(0.4527)	(0.5074)	(0.3395)	(0.5926)
Parenting App	0.1239**	0.0003	0.0761	0.5121***	0.4601***	0.3531***
	(0.0484)	(0.0865)	(0.1095)	(0.1371)	(0.0858)	(0.0743)
Adjusted R^2	0.2216	0.2410	0.2285	0.2252	0.2297	0.2333
Panel B: Intervals Based on Female Education						
Parenting App × Ratio	0.7552**	-0.2588	-1.8324***	-0.2423	-1.5281***	-1.5342
	(0.3354)	(0.8843)	(0.6591)	(0.6326)	(0.5588)	(1.2754)
Parenting App	0.2337	0.5368***	0.2880***	0.3251***	0.3971***	0.3582***
	(0.1756)	(0.1196)	(0.0840)	(0.1036)	(0.0673)	(0.0662)
Adjusted R^2	0.2265	0.2185	0.2538	0.2289	0.2483	0.2467
Panel C: Intervals Based on Female Income						
Parenting App × Ratio	0.5602**	0.0314	-0.9000	-1.3069**	-1.9094***	-1.9615***
	(0.2282)	(0.4550)	(0.8073)	(0.6391)	(0.6079)	(0.7355)
Parenting App	0.1935*	0.2223**	0.6059**	0.9554***	1.2436***	1.2207***
	(0.1106)	(0.0972)	(0.2402)	(0.3355)	(0.3696)	(0.3636)
Adjusted R^2	0.2335	0.2325	0.2335	0.2354	0.2559	0.2543
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2496	2496	2496	2496	2496	2496
Mean Dependent Var.:	0.4369	0.4369	0.4369	0.4369	0.4369	0.4369

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Controls include the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.23: Robustness Test Without Weighting by User Scale

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Parenting App × Ratio	0.1870**	-0.0217	0.0365	-0.0229	-0.0758	-0.1509
	(0.0925)	(0.1172)	(0.0999)	(0.1029)	(0.1212)	(0.1333)
Parenting App	0.1636***	0.1869***	0.1760***	0.1882***	0.2004***	0.2028***
	(0.0144)	(0.0240)	(0.0232)	(0.0293)	(0.0285)	(0.0206)
Adjusted R^2	0.0861	0.0845	0.0846	0.0852	0.0838	0.0837
Panel B: Intervals Based on Female Education						
Parenting App × Ratio	0.1328*	0.0715	-0.2023*	-0.0634	-0.1815	-0.0430
	(0.0762)	(0.1342)	(0.1185)	(0.1416)	(0.1385)	(0.1603)
Parenting App	0.1440***	0.1720***	0.2205***	0.1951***	0.2058***	0.1864***
	(0.0232)	(0.0264)	(0.0236)	(0.0281)	(0.0216)	(0.0154)
Adjusted R^2	0.0874	0.0837	0.0855	0.0832	0.0856	0.0850
Panel C: Intervals Based on Female Income						
Parenting App × Ratio	0.2030***	-0.1747	0.1277	-0.4425***	-0.3006**	-0.1419
	(0.0596)	(0.1129)	(0.0943)	(0.1284)	(0.1188)	(0.2040)
Parenting App	0.1079***	0.2225***	0.1669***	0.2316***	0.2126***	0.1947***
	(0.0252)	(0.0236)	(0.0198)	(0.0190)	(0.0172)	(0.0195)
Adjusted R^2	0.0891	0.0835	0.0838	0.0872	0.0863	0.0845
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Controls include whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Standard errors are clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.24: Robustness Test with Outcome Variable Winsorized at 1% and 99%

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Parenting App × Ratio	1.1343**	1.0775**	0.7626	-1.1098***	-1.1703***	-1.3338**
	(0.4431)	(0.4261)	(0.4643)	(0.4264)	(0.3721)	(0.5663)
Parenting App	0.0793	-0.0344	0.0122	0.4422***	0.4541***	0.3624***
	(0.0500)	(0.0939)	(0.1132)	(0.1113)	(0.0930)	(0.0746)
Adjusted R^2	0.1903	0.2065	0.1956	0.1910	0.1951	0.2007
Panel B: Intervals Based on Female Education						
Parenting App × Ratio	0.9926***	0.0751	-1.7424***	-0.6024	-1.4798**	-1.9108*
	(0.3261)	(0.8695)	(0.5523)	(0.6439)	(0.6027)	(1.1228)
Parenting App	-0.0943	0.1478	0.4929***	0.2593***	0.3441***	0.2925***
	(0.0980)	(0.1740)	(0.0959)	(0.0989)	(0.0824)	(0.0721)
Adjusted R^2	0.2101	0.1924	0.1871	0.1989	0.2123	0.2131
Panel C: Intervals Based on Female Income						
Parenting App × Ratio	0.6465***	0.3211	-1.1451	-1.3716**	-2.0412***	-2.2244***
	(0.2475)	(0.3975)	(0.7616)	(0.6515)	(0.6230)	(0.7483)
Parenting App	-0.0437	0.1060	0.3341***	0.3177***	0.3926***	0.3605***
	(0.0913)	(0.0986)	(0.0957)	(0.0671)	(0.0695)	(0.0668)
Adjusted R^2	0.1996	0.1927	0.1931	0.1996	0.2123	0.2131
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Controls include whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors clustered at the app level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.25: Robustness Test with Standard Errors Clustered at the Company Level

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Parenting App × Ratio	1.1464**	1.0745**	0.7556	-1.1239***	-1.1755***	-1.3340**
	(0.4556)	(0.4546)	(0.4715)	(0.3638)	(0.3949)	(0.5749)
Parenting App	0.0794	-0.0330	0.0145	0.4468***	0.4564***	0.3634***
	(0.0506)	(0.1000)	(0.1146)	(0.0925)	(0.1005)	(0.0767)
Adjusted R^2	0.1903	0.2064	0.1955	0.1910	0.1950	0.2006
Panel B: Intervals Based on Female Education						
Parenting App × Ratio	0.9973***	0.0210	-1.7592***	-0.6031	-1.4560**	-1.8935*
	(0.3291)	(0.8745)	(0.5670)	(0.6755)	(0.6217)	(1.1097)
Parenting App	-0.0945	0.1582	0.4970***	0.2604**	0.3415***	0.2921***
	(0.0991)	(0.1760)	(0.1000)	(0.1037)	(0.0855)	(0.0707)
Adjusted R^2	0.2100	0.1923	0.1870	0.1988	0.2255	0.2203
Panel C: Intervals Based on Female Income						
Parenting App × Ratio	0.6476**	0.3127	-1.1525	-1.3541**	-2.0411***	-2.2374***
	(0.2572)	(0.3856)	(0.7765)	(0.6636)	(0.6439)	(0.7594)
Parenting App	-0.0430	0.1086	0.3362***	0.3164***	0.3935***	0.3628***
	(0.0933)	(0.0957)	(0.0979)	(0.0697)	(0.0739)	(0.0693)
Adjusted R^2	0.1995	0.1926	0.1930	0.1994	0.2123	0.2130
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Notes: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Controls include whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the company level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.26: Heterogeneous Effects on Parenting App Usage by Socioeconomic Context Using Fractional Logit Model

	Proportion of Female Users					
Intervals in Descending Order:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intervals Based on City Tier						
Parenting App × Ratio	1.4412**	1.1397**	0.8096	-1.1809**	-1.2402***	-1.3861**
	(0.5793)	(0.4731)	(0.4997)	(0.4752)	(0.4081)	(0.6037)
Parenting App	0.0600	-0.0453	0.0033	0.4614***	0.4737***	0.3709***
	(0.0537)	(0.1018)	(0.1206)	(0.1257)	(0.1049)	(0.0803)
pseudo R^2	0.0092	0.0100	0.0095	0.0092	0.0094	0.0097
Panel B: Intervals Based on Female Education						
Parenting App × Ratio	1.1258***	0.0434	-2.0849***	-0.6536	-1.5412**	-2.0350*
	(0.3713)	(0.9411)	(0.7082)	(0.6753)	(0.6556)	(1.1918)
Parenting App	-0.1243	0.1532	0.5585***	0.2677***	0.3509***	0.3002***
	(0.1075)	(0.1883)	(0.1252)	(0.1035)	(0.0896)	(0.0770)
pseudo R^2	0.0102	0.0093	0.0091	0.0096	0.0109	0.0107
Panel C: Intervals Based on Female Income						
Parenting App × Ratio	0.6879**	0.3374	-1.2185	-1.4077**	-2.1233***	-2.3277***
	(0.2707)	(0.4168)	(0.8329)	(0.6873)	(0.6597)	(0.7880)
Parenting App	-0.0548	0.1033	0.3455***	0.3221***	0.4032***	0.3711***
	(0.0968)	(0.1037)	(0.1061)	(0.0710)	(0.0751)	(0.0717)
pseudo R^2	0.0092	0.0100	0.0095	0.0092	0.0094	0.0097
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6067	6067	6067	6067	6067	6067
Mean Dependent Var.:	0.4463	0.4463	0.4463	0.4463	0.4463	0.4463

Note: The outcome variable is the proportion of female users for each app. Each column reports the coefficient on the interaction term between a parenting app indicator and the ratio of app *i*'s users residing in cities within each interval of the corresponding socioeconomic trait. Panels A, B, and C present analyses based on six ranked city intervals constructed according to city tier, average female education, and average female income, respectively. Controls include: whether the app usage data is from 2023, the app's price, the number of in-app purchases, the app's size, the app's age rating, user ratings, release year, the number of supported languages, and compatibility with both Android and iOS platforms. Regressions are weighted by active users. Standard errors are clustered at the app level. * p<0.10, ** p<0.05, *** p<0.01.