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ABSTRACT

Internet Use and Fertility Behavior among Reproductive-Age Women in China

Using longitudinal data from the 2014–2018 China Family Panel Studies, we investigate the impact of internet use (IU) on fertility among reproductive-age women. We find that IU reduces the number of children born, with more pronounced effects among those with a moderate level of education, those aged 16–19, rural residents, and those who are married. These results are robust to alternative IU measures and a series of estimation approaches that control for endogeneity. IU participation affects the number of children born through decreased marital satisfaction, changed attitudes toward traditional gender roles, a reduction in the importance placed on ancestral lines, deteriorated health and reduced fertility preferences.

JEL Classification: D13, D91, J13, J16, R20
Keywords: internet use, fertility, reproductive-age women, China

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1. Introduction

China outstripped the US and became the country with the largest population of internet users globally in 2008 (Wang & Li, 2012), with 1.032 billion Chinese "netizens" in 2021 (China Internet Network Information Center, 2022). The internet penetration rate (the ratio of internet users to the total population) increased substantially from 8.5% in 2005 to 73.0% in 2021 (China Internet Network Information Center, 2022). It is thus not surprising that such rapid growth of internet use (IU) in China – combined with the use of other information and communication technologies (ICTs), such as personal computers and mobile devices – has fundamentally transformed lifestyles and well-being (Nie et al., 2017). As the world's most populous country, China's total fertility rate (TFR) is of global significance (Guo et al., 2019). It has plummeted below the replacement level (2.1), from 6.11 in 1950 to 1.66 in 2015 (World Health Organization, 2015) and to 1.3 in 2020 (National Bureau of Statistics of China, 2021). Furthermore, with the popularization of the internet, most childbearing women are increasingly accessing the online environment, particularly social media groups, to connect with other childbearing women as an important source of childbearing information and interpersonal communication (Sparud-Lundin et al., 2011), thereby affecting women's childbearing decisions (Gleeson et al., 2019).

The effects of IU on individual behaviors and outcomes have been amply documented in the contexts of crime (Bhuller et al., 2013; Lindo et al., 2022), employment (Forman et al., 2012; Hjort & Poulsen, 2019) and unemployment (Czernich, 2014), sleep duration and satisfaction (Billari et al., 2018), marriage (Tong et al., 2021), happiness (Nie, Ma, et al., 2021; Nie et al., 2017), social capital (Bauernschuster et al., 2014; Geraci et al., 2022) and electoral outcomes (Falck et al., 2014; Gavazza et al., 2019; Miner, 2015). However, the relatively small body of extant literature focuses exclusively on the effect of IU on fertility behavior in Western countries, and to the best of our knowledge, there are no studies in developing and transitional economies, such as China. The purpose of this study, therefore, is to narrow this gap in the literature by investigating how IU affects the fertility behaviors of reproductive-age Chinese women using data from the 2014–2018 China Family Panel Studies (CFPS). Our study contributes to the literature on the IU–fertility nexus in several ways. First, by focusing on China, we extend the limited number of nationally representative studies beyond the Western setting. China's dramatically declining fertility during the past few decades reflects its citizens' low-fertility culture and intentions in the current socioeconomic context rather than governmental fertility policies (Gu et al., 2007; Hou et al., 2020). This expansion is also important because the different attitudes toward and perceptions of IU among those from different sociocultural backgrounds (Brosnan & Lee, 1998; Li & Kirkup, 2007) make it difficult to generalize the results from developed countries. Additionally, IU is more prevalent among reproductive-age Chinese women than among members of other age groups (Liu et al., 2020). Second, because the mixed results from prior research are often attributable to various definitions of IU, we adopt two different measures of IU, including IU participation (the first-level digital divide) and IU intensity (the second-level digital divide).[1] Especially with regard to the second-level digital divide, we further employ two methods: a macro approach that assesses IU as a whole and a micro approach that focuses on specific online activities (Nie et al., 2017). Thus, our study provides a more differentiated picture of the IU–fertility nexus. Third, using the sociodemographic characteristics of education, gender of the first child and region to explore the heterogeneous effects of IU on fertility offers useful guidance for policies intended to boost (below-replacement) fertility rates. Last, by including several major fertility-related outcomes (i.e., marital satisfaction, importance placed on the ancestral line, gender role attitudes, health, and fertility intentions), this study goes beyond a sole focus on IU's impact on fertility to examine the underlying pathways through which this effect occurs. In doing so, it provides useful insights into the linkage between IU and fertility in China and other economies, especially East and Southeast Asia, which have experienced a precipitous transition to ultralow fertility.

The fixed-effects (FE) IV results show that IU participation generates substantial fertility-decreasing effects by 28.6 percentage points (20.8% of the average fertility rate). We also find interesting heterogeneity in the effects, which is more pronounced among women with a moderate level of education, those aged 16–19, rural residents, and those who are married. The effects of IU may operate through multiple channels. We provide suggestive evidence that IU participation affects the number of children born (NCB) through decreased marital satisfaction and changed attitudes toward traditional gender roles. Moreover, the importance placed on ancestral lines has declined. Deteriorated health and decreased fertility preferences are also

[1] Our study adopts the Organization for Economic Cooperation and Development (OECD)'s broad definition of the digital divide: "*the gap between individuals, households, businesses and geographic areas at different socio-economic levels with regard both to their opportunities to access ICTs and to their use of the internet for a wide variety of activities*" (OECD, 2003, p.4). Thus, the first-level digital divide defines the gap between those who use digital technologies and those who do not ("haves" vs. "have nots"), suggesting that the first-level digital divide focuses on an access gap (Hargittai, 2003). However, the second-level digital divide commonly refers to the gap in actual ICT use, implying that it focuses on a use gap (van Dijk & Hacker, 2003). Accordingly, we introduce internet use participation as the proxy of the first-level digital divide and internet use intensity as the measure of the second-level digital divide. These measures have been used in other studies related to the impact of the internet on economic outcomes (Billari et al., 2018; Dettling, 2016; Hjort & Poulsen, 2019) and routinely in the well-being literature (Nie, Ma, et al., 2021; Nie et al., 2017; Sabatini & Sarracino, 2017).

important mechanisms behind the drop in the NCB. In particular, the purpose of entertainment online enhances the negative impact of IU intensity on fertility.

The remainder of this paper proceeds as follows. Section 2 documents the institutional background on the dynamics of China's TFR over the period 1950–2020 and the related literature on the effect of IU on fertility, and Section 3 documents the possible heuristic mechanisms underlying the impact of IU on fertility in China. Section 4 describes the data and empirical strategy, and Section 5 reports the results. Section 6 discusses the possible underlying mechanisms linking IU participation with fertility, followed by Section 7, which provides concluding remarks.

2. Institutional background and related literature

2.1 Institutional background

Fig. 1 displays the dynamics in China's TFR from 1950–2020. It was relatively stable from 1950–1970, with approximately six children per woman, leading to a population increase from 540 million to more than 800 million over these two decades (Zeng & Hesketh, 2016). In response to such rapid population growth – nearly 3% annually – the Chinese government implemented the mostly voluntary "later-longer-fewer" policy (later childbearing, longer spacing between children, and fewer children), along with the free provision of modern contraceptives to all citizens (Gu, 2021), thereby generating a dramatic decline in the TFR from an estimated 5.9 births per women in 1970 to 2.9 births by 1979 (Nie, Wang, et al., 2021). Due to the fear of persistent overpopulation, in 1979, the government introduced the one-child policy (OCP), which imposed a quota of one birth per couple among urban residents and up to two births for rural residents if the first child was a daughter. This policy led to a continued decline in the TFR but at a less precipitous and relatively stable rate. In particular, from 1995–2020, the TFR fluctuated between 1.3 and 1.7.[2]

The reasons for the decline in the TFR, however, have varied during different periods. The early fertility decline was primarily due to socioeconomic developments and access to contraceptive services (Zheng et al., 2018). The OCP then led to a continued drop in fertility, especially in less economically developed areas in terms of industrialization, employment

[2] To shed more light on China's period fertility and (completed) cohort fertility, we also calculate TFR as a proxy of period fertility measure and cohort fertility rate (CFR) as one measure of cohort fertility during our study period (2014–2018). We show that the fertility rate of reproductive-age women aged 16–49 declined from 2014–2016 and then increased from 2016–2018, whether TFR or CFR is used. The latter increase in the fertility rate is partially attributable to the universal two-child policy implemented since the beginning of 2016. However, China's census data are the most reliable and suitable basis for quantifying China's period and cohort fertility to analyze fertility and its trends over time. A detailed discussion on China's fertility and its trends using the 1995–2015 census data and various measures of period and cohort fertility is available in Yang et al. (2022).

structure, urbanization, education and women's employment status. Rural-to-urban migration has served as another important driver of the TFR drop since the 1990s. In addition, later marriage for both sexes and nonagricultural employment are negative predictors of childbearing (Jia & Dong, 2013). Even the two-child policy, which was enacted on January 1, 2016, and allows all Chinese couples to have two children, is unlikely to increase fertility remarkably (Wang et al., 2016; Zheng et al., 2018). Unexpectedly, the number of births in China has been declining continuously since 2016. According to the 2020 Census in China, approximately 12 million children were born in 2020, which is much lower than that in 2016 (18 million) (Tatum, 2021). This decline is attributable to the rising costs of childbearing and childrearing (e.g., housing, education and living) (Zheng et al., 2018) as well as changes in Chinese attitudes toward childbirth (Li et al., 2019). This suggests that the implementation of China's family planning policy played a vital role in the early stage of the fertility decline, while subsequent socioeconomic developments and changes in people's attitudes toward fertility have become increasingly important (Peng, 2021).

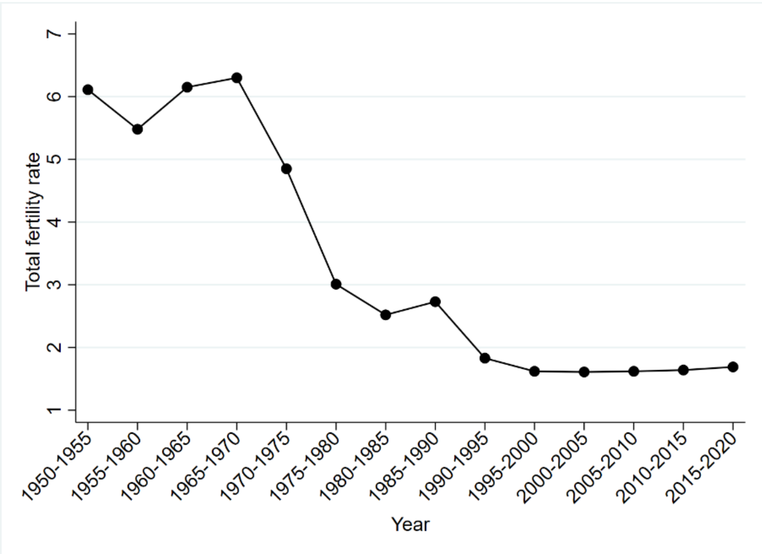

Fig. 1 Total fertility rate in China: 1950–2020

Source: United Nations (2019).

Due to falling mortality and the subsequent decreasing fertility, China already has the world's largest aging population and is one of the most rapidly aging societies worldwide (Nie, Li, et al., 2021; Zhao et al., 2014). The number of adults aged 60 or over in 2021 was approximately 267 million (18.9% of the total population) (National Bureau of Statistics of China, 2022) and is projected to reach 491.5 million (36.5% of the total population) by 2050 (United Nations, 2020). China's OCP boosted economic development by slowing population growth (Li & Wu, 2013; Nie, Wang, et al., 2021; Zeng & Hesketh, 2016); however, it resulted in myriad unintended problems, such as gender imbalances, an aging population and a shrinking labor force (Hesketh et al., 2005; Zeng & Hesketh, 2016). Given both China's culture of low fertility and massive socioeconomic transformations, even today's three-child policy (TCP, implemented on May 31, 2021) will do little to address the financial, social and cultural factors that encourage startlingly low fertility rates (Tatum, 2021). In addition to China, other East Asian societies (Japan, South Korea, Taiwan, Hong Kong and Singapore) have attempted to implement policies to boost their low fertility rates. Nevertheless, those policies have not been notably successful in raising fertility (Jones, 2019).

2.2 Related literature

Motivated by the global concern surrounding low fertility rates, a handful of recent studies in economics have investigated the effects of IU on fertility behaviors in Western nations, including Germany (Billari et al., 2019) and the US (Guldi & Herbst, 2017; Jaeger et al., 2019; Kearney & Levine, 2015; Trudeau, 2016). For instance, Kearney and Levine (2015) find that MTV's "*16 and Pregnant"* resulted in a 4.3 percent reduction in US teen births. This observation is confirmed by Trudeau (2016), who indicates that such fertility-depressing impacts are stronger among young teens in US states without sex education mandates and higher viewership. Likewise, Guldi and Herbst (2017) suggest that increased broadband internet access accounted for at least 7% of the decline in the US teen birth rate between 1999 and 2007. By replicating Kearney and Levine (2015), Jaeger et al. (2019) find that there is little or even a positive association between "*16 and Pregnant"* and tweets about birth control and abortion. A recent study by Billari et al. (2019), using the 2008–2012 German Socio-Economic Panel, shows that a one-standard deviation increase in broadband access raised the total fertility of women aged 25–45 by 23%. Such positive impacts are attributable to an increased share of women reporting home- or part-time work and increased life satisfaction, as well as more time spent with children.

Overall, several aspects of this prior research are worth emphasizing. First, not only is the empirical evidence on the IU–fertility relation confined mostly to the US and other Western countries, but conclusions are mixed, and no such research exists for China. Thus, it is difficult to generalize those conclusions from Western countries to developing and transitional economies such as China. Second, most studies are based on cross-sectional data, thereby rendering causality impossible. Third, most such research has focused on the effects of IU on teen fertility behaviors rather than on those of reproductive-age women in developing and low-fertility societies, which are as yet poorly understood. However, as one of the key indicators for global monitoring (especially reproductive health) in the Millennium Development Goals (MDGs), TFRs are generally based on women of reproductive age (World Health Organization, 2006), who are particularly vulnerable to the damage caused by disease (e.g., anemia and micronutrient deficiency) and are important for reducing maternal deaths and accelerating progress toward achieving the 2030 sustainable development goals related to maternal health. Fourth, the existing research overall pays little attention to the underlying pathways through which IU may affect fertility behavior. To address these shortcomings, we perform a longitudinal analysis of the 2014–2018 CFPS data to assess the impact of IU (including IU participation, intensity and specific online activities) on the fertility behavior of Chinese reproductive-age women aged 16–49. In doing so, we use two-way fixed effects (FE) and instrumental variable (IV) approaches to shed more light on the causal IU–fertility relationship. Last, drawing on several major fertility-related outcomes, including marital satisfaction, importance placed on the ancestral line, gender role attitudes, health, and fertility intentions, we conduct a comprehensive exploration of possible mechanisms through which IU may operate on fertility behavior.

3. Possible mechanisms for the impact of IU on fertility

There are several main underlying pathways through which IU might act on fertility. We consider each mechanism in turn.

The first mechanism operates through the impact of IU on marital satisfaction. With its anonymity and convenience, the internet may decrease search costs and increase the set of partnership offers outside marriage (Bellou, 2015; Billari et al., 2019). For example, it allows people to pursue online interactions outside marriage, thereby resulting in acts of infidelity (Whitty, 2003). In addition, as Tong et al. (2021) highlight, idealized images of a better partner behind the screen may lead to a lower level of satisfaction in the current marriage. Marital dissatisfaction is in turn likely to lower marital investment. For instance, interacting with an online mate could be more attractive than mundane interactions within a family. Consequently, a marriage will end in divorce, especially when a lack of marital investment occurs or a partner finds a better match (Weiss & Willis, 1997). Prior studies confirm the negative impact of IU on family cohesion and marital satisfaction (Chesley, 2005; Tong et al., 2021; Valenzuela et al., 2014; Zheng et al., 2019). For instance, Chesley (2005) finds that communications technology use (cell phones and pagers) is linked with increased distress and lower family satisfaction among US employees. This finding is echoed by Valenzuela et al. (2014), who indicate that internet access is positively correlated with divorce and negatively associated with marital satisfaction in the US. In the context of China, Zheng et al. (2019) use province-level data and find that broadband internet access has contributed to an increase in the number of divorces. Similarly, a recent study by Tong et al. (2021), using data from the 2014 and 2018 CFPS, confirms the negative impact of IU on overall marital satisfaction. In addition, high marital satisfaction has a positive impact on the desire for or intention to have additional children; therefore, children are more likely to be born to satisfying marriages (Beaujot & Tong, 1985; Nitsche & Hayford, 2020).

The second channel focuses on the important role of the ancestral line in Chinese society. China has a strong tradition of extended family (coresidence of adult parents and descendants with grandparents) (Chen et al., 2011; Chen & Short, 2008). This tradition emphasizes children's filial obligation to their parents, particularly that of sons, and creates expectations that parents will live with at least one of their adult sons and depend on them for old age support (Duan et al., 2020). Thus, an adult son's responsibility is to carry on the family lineage (i.e., the importance of ancestral lines) and take care of older parents, while the adult daughter's responsibility lies with her husband's family (Lei et al., 2012). Although the nuclear family (coresidence of adult parents with their children) is the dominant family type in China, the majority of the older population still coresides with their adult children (Zhao et al., 2021). The literature shows that in China and other developing societies, cultural norms continue to emphasize the importance of ancestral lines and childbearing (Wu & Penning, 2019; Yao et al., 2018). As noted by Liu et al. (2020), IU is more prevalent among Chinese women of reproductive age than among members of other age groups. Importantly, mothers' understanding of childbearing norms is found to be shaped by digital interactions (Gleeson et al., 2019). As a result, IU may thus change norms about or perceptions of the importance of childbearing and ancestral lines. Thus, we argue that the importance placed on the ancestral line is closely linked to the number of children born and that the proliferation of false and exaggerated information online, such as on induced abortion, fear of childbirth and the extremely high cost of childrearing, will weaken the importance placed on ancestral lines and therefore diminish the actual fertility behaviors of reproductive-age women.

A third mechanism may operate through changed attitudes toward gender roles. In traditional Chinese culture, ingrained Confucian social norms regarding gender roles highlight distinct roles for men and women (Adamczyk & Cheng, 2015). Consequently, although women participate in the labor force, they are still seen as responsible for the majority of housework and childrearing, and men are viewed as the primary breadwinners and leaders (Tong et al., 2021; Xu & Lai, 2004). Such traditional norms regarding family and marriage seem to be in conflict with modernity and individualism (Ye et al., 2014). Nevertheless, as China's economy continues to grow rapidly, more widespread IU has narrowed the gender differences in resources, skills, and knowledge and provided women with more opportunities for jobs and education (Tong et al., 2021). As suggested by Zhou et al. (2020), the internet can cultivate an equal-gender ideology and influence traditional gender norms through its educational and informative functions. Consequently, demands for individuality and independence are increasing, while the traditional division of labor within the Chinese family is weakening, thereby discouraging actual fertility.

A fourth possible avenue may be the effect of IU on individual health. IU may be detrimental to psychological well-being for several reasons. One possibility is that too much time spent in online interactions (i.e., excessive IU) crowds out in-person interactions (Tong et al., 2021). Another possibility is that the information, empathy and other types of emotional support people receive from strangers they meet in online support groups may be less valuable than those they receive from offline interactions with their families and friends (Bessière et al., 2010). Especially for reproductive-age women, online advice on childbearing often consists of personal anecdotes that may not be as helpful as health professionals offline. Additionally, reading online information about possible health symptoms or health risks regarding pregnancy may induce reproductive-age women to visualize being ill and enhance their perceptions of health risks. Online interactions and discussions of health problems or risks will also make them ruminate and increase their psychological problems (Stone & Sharpe, 2003). IU also affects physical health, such as overweight and obesity. Possible explanations include physical inactivity due to excessive IU and unhealthy behaviors such as overeating and high snack consumption (Aghasi et al., 2020). In addition, psychological disorders such as depression and anxiety because of internet overuse could severely affect weight control and eating disorder syndromes (Aghasi et al., 2020). A large body of literature confirms the negative linkage between IU and both psychological well-being (Bessière et al., 2010; Nie, Ma, et al., 2021; Nie et al., 2017) and physical health (Aghasi et al., 2020; Billari et al., 2018; Kelley & Gruber, 2013). For example, Nie et al. (2017) find that IU is associated with lower happiness and higher levels of depression among Chinese individuals aged 16–60. IU has also been confirmed to be associated with objective health problems such as overweight and obesity (Aghasi et al., 2020), shorter sleep duration and reduced sleep satisfaction (Billari et al., 2018). The deterioration of the health status of childbearing women could lead not only to an increased risk of pregnancy-related complications (Li & Deng, 2017) but also to worries about maternal and perinatal safety (Liu et al., 2020).

With regard to the final mechanism, actual fertility is a realization of individual childbearing preferences or intentions (Nie, Wang, et al., 2021). This means that individuals' fertility preferences or intentions reflect their attitudes toward and views of childbearing behaviors and have long been considered a meaningful predictor of the actual number of children born (Nie, Wang, et al., 2021). A growing body of literature confirms that fertility intentions are a significant predictor of actual fertility behaviors in China (Luo & Mao, 2014) and other societies (Schoen et al., 1999; Tan & Tey, 1994). In addition, as previously stated, IU is more pervasive among Chinese women of reproductive age than among members of other age groups (Liu et al., 2020), and mothers' understanding of childbearing norms has been found to be shaped by digital interactions (Gleeson et al., 2019).

4. Data and methods

4.1 Study design and population

We take our dataset from the CFPS, which is administered by Peking University's Institute of Social Science Survey. The CFPS currently includes five waves: 2010, 2012, 2014, 2016, and 2018. We use data from the latest three waves due primarily to the availability of information on fertility, IU and other sociodemographic characteristics. Since the survey covers 25 provinces and administrative equivalents representing 94.5% of the total population in China (excluding Hong Kong, Macao and Taiwan), it constitutes a nationally representative sample that captures both the socioeconomic development and the economic and noneconomic well-being of Chinese households (Xie & Hu, 2014). We restrict the study sample to women of reproductive age, i.e., women aged 16–49, who have detailed information on fertility behavior, IU, and demographic and socioeconomic characteristics. Women of reproductive age refers to all women aged 15–49 years old (WHO, 2006). The CFPS defines adults as those aged 16 years or older. Thus, we include reproductive-age women aged 16–49 in our study sample. Our analysis sample is an unbalanced panel of 11,726 reproductive-age women with 23,051 observations.

4.2 Fertility behavior

Following Chen (2022) and Yang and Spencer (2022), we employ the NCB as a proxy for the actual fertility behavior of reproductive-age women. In the CFPS, the NCB is measured by asking reproductive-age women who have ever given birth how many children they have had at the time of the survey. This indicator incorporates information on the total number of children born up to the survey date, and the NCB quantifies all the live births a woman has experienced in her lifetime (Kiser & Hossain, 2018), thereby representing the actual occurrence of childbirth among members of the relevant age group and the present and past fertility behavior of women (Chouhan et al., 2020).

4.3 Measures of IU

To measure IU, we employ two different approaches to explore the first-level and second-level digital divides. Specifically, we capture the first-level digital divide by using IU participation (1=yes, 0=no), which is constructed based on the question: "*Do you surf the internet with a mobile electronic device or computer?*" Additionally, following Nie et al. (2017), we use two methods to measure the second-level digital divide, namely, IU intensity in hours/day and frequency of use measured on a 7-point scale (1 = never, 2 = once every few months, 3 = once a month, 4 = twice or thrice a month, 5 = once or twice a week, 6 = three or four times a week, 7 = almost every day) for different online functions, including study, work, social interactions, entertainment and commercial-related activities (such as online banking and online shopping).[3]

4.4 Control variables

We control for individual and household demographic and socioeconomic characteristics, including age, marital status, education, employment status, household size and logged household income. Age is an important determinant of fertility behavior (Liu et al., 2021). To capture the possible nonlinearity in the relation between age and fertility behavior (Billari et al., 2019; Liu et al., 2021), we introduce age and its squared term. Given that marital status has been found to be associated with reproductive behavior (Nitsche & Hayford, 2020; Schultz, 1994), we also include it as a dummy (1 = married/living together, 0 = otherwise). In addition, we control for education because it is one of the most well-established socioeconomic predictors of childbearing behavior (Liu et al., 2021; McElroy & Yang, 2000; Nitsche & Hayford, 2020). After coding education on a 3-point scale in which 1 = low (not literate/primary school), 2 = moderate (middle school/high school) and 3 = high (vocational school/university or higher), we convert education into a dummy variable with low as the reference. Because employment status is an important predictor of fertility behavior (Del Boca & Sauer, 2009; Nie, Wang, et al., 2021), we use one dummy to indicate whether the woman is

[3] Here, IU intensity is a macrolevel measure, while the use of different online functions is a microlevel proxy for the second-level digital divide (Nie et al., 2017).

employed (1 = yes, 0 = no). Given that household income determines the household's financial capacity to raise children and therefore positively influences actual fertility behavior, we include household income as well as household size (Huang et al., 2021; Nie, Wang, et al., 2021). Last, in addition to year dummies (with 2014 as the reference year), to address the existence of spatial heterogeneity in fertility (Zheng et al., 2018), we also construct an urban dummy (1=urban, 0=rural) and provincial dummies (with Beijing as the reference).

4.5 Empirical strategies

4.5.1 Ordinary least squares (OLS) regressions

We adopt the standard OLS regression approach to investigate the correlation between IU participation and the NCB. More specifically, we apply OLS estimation to the following model:

$$NCB_{ijt} = \alpha_0 + \alpha_1 IUP_{ijt} + \alpha_2 X_{ijt} + \alpha_3 F_{ijt} + \alpha_4 P_j + \alpha_5 W_t + \tau_j^1 t + \varepsilon_{ijt} \quad (1)$$

where NCB_{ijt} denotes the total NCB for individual *i* residing in province *j* at time *t* and IUP_{ijt} represents individual *i*'s IU participation (yes or no). X_{ijt} is a vector of individual *i*'s characteristics in province *j* at time *t*, F_{ijt} is a vector of household characteristics, P_j is a vector of provincial dummies (with Beijing as the reference), W_t is a vector of wave dummies (with 2014 as the reference), and $\tau_j^1 t$ denotes a set of province-specific time trends. Such province-specific time trends will account for unobserved, time-varying differences in fertility over time. This is important in the case of China due primarily to its large geographic area and imbalanced economic development levels across provinces. The introduction of province-year effects will also capture provincial policy changes that may affect both IU and fertility. ε_{ijt} is an error term. The linkage between fertility behavior and IU participation is captured by α_1.

To assess the effect of IU intensity on women's fertility behaviors, we also estimate the following model:

$$NCB_{ijt} = \beta_0 + \beta_1 IUI_{ijt} + \beta_2 X_{ijt} + \beta_3 F_{ijt} + \beta_4 P_j + \beta_5 W_t + \tau_j^1 t + \omega_{it} \quad (2)$$

where IUI_{it} represents the second-level digital divide measure (IU intensity in our case) for individual *i* residing in province *j* at time *t*, and other specifications are similar to Equation 1. β_1 is the coefficient representing the association between IU intensity and fertility behavior.

4.5.2 Two-way fixed effects (FE) estimation

Because of potential biases from individual-level time-invariant unobservables, we investigate the relationship between IU participation and the NCB by estimating the following two-way FE model:

$$NCB_{ijt} = \theta_0 IU_{ijt} + \theta_1 X_{ijt} + \theta_2 P_j + \theta_3 W_t + \mu_i + \tau_j^1 t + \delta_{ijt} \quad (3)$$

where NCB_{ijt} is the total NCB for individual i residing in province j at time t, IU_{ijt} represents individual i's internet use participation/intensity residing in province j at time t, and X_{ijt} denotes a set of time-variant individual and household controls. P_j and W_t are provincial and wave fixed effects, respectively. P_j controls for unobservable, time-invariant differences across provinces that may affect fertility. W_t captures possible trends in fertility behavior. The unobservable time-invariant individual-level effects are captured by μ_i. δ_{ijt} is the disturbance error.

4.5.3 Two-stage least squares (2SLS)

In our baseline model, however, the use of OLS and FE estimators creates a potential for endogeneity in IU. In particular, one key limitation of the FE estimate is that it cannot address certain time-varying unobserved factors that may simultaneously impact IU participation and the NCB. For instance, some unobserved personal traits, such as differences in timing preferences, may affect not only IU participation but also the NCB. Another concern is reverse causality, such as when women with more or fewer children have a greater preference for using the internet to communicate about and obtain useful information on parenting. The inclusion of a set of control variables could reduce the possible impact of omitted variables. However, it is impossible to avoid the possible bias stemming from reverse causality. For instance, women with more children may want to share their feelings or certain information about childbearing with their spouses, relatives or friends online. On the other hand, those with fewer children may also want to communicate with people who are important to them to share their feelings. To identify a causal relationship between IU participation and fertility behavior, we turn to an FE two-stage IV model to address concerns regarding the endogeneity of IU participation. In doing so, similar to Bhuller et al. (2013) and Falck et al. (2014), we use one instrument that can be readily shown to be exogenous to individual fertility behavior (i.e., satisfies the orthogonality condition) but closely linked with IU (i.e., satisfies the relevance condition), namely, the preexisting population-adjusted number of internet broadband access terminals (IBAT) measured at the provincial or municipality level. ICT facilities are likely to increase access to the internet and therefore boost the probability of surfing the internet (Nie et al., 2017). However, it is impossible to link them with actual fertility behavior. However, our IV strategy depends on an exclusion restriction: that there are no other channels through which fertility is affected other than the use of the internet. While this exclusion restriction is ultimately untestable, we run a falsification test using data on fertility behavior before 2000 (i.e., before the introduction of upgraded internet speed) and provide reassurance that the exclusion restriction is reasonable. As stated before, we have introduced a set of province-specific time trends to account for unobserved, time-varying differences in fertility over time. More economically developed provinces or municipalities may be more likely to be equipped with better internet access, and therefore local economic development levels may be associated with fertility behavior. Consequently, we should treat our results as associations. Although IU participation is binary, we employ a linear probability model in the first-stage regression and then estimate the second-stage regression using an FE model in which the dependent variable is *NCB*. Model 1 is estimated with 2SLS, and the first-stage regression model is given by:

$$IUP_{ijt} = \gamma_0 + \gamma_1 Z_{jt-1} + \gamma_2 X_{ijt} + \gamma_3 P_j + \gamma_4 W_t + \vartheta_{ijt} \quad (4)$$

where IUP_{ijt} indicates whether individual i surfs the internet with a computer/mobile electronic device (1 = yes; 0 = no) at time t. X_{ijt} is a vector of individual and household controls, and Z_{jt-1} represents the instrumental variable IBCT at *t-1*.

5. Results

5.1 Descriptive statistics

Table A1 in the Appendix shows that the NCB is approximately 1.38. IU participation is 59.6%, and IU intensity is 1.9 hours per day. We also observe heterogeneity in the frequency with which different online functions are used, and the top two most frequently used functions are social interactions (5.9) and entertainment (5.5), followed by work (3.6), study (3.4) and commercial-related activities (3.3). These results highlight the importance of combining macro- and microlevel approaches when assessing the second-level digital divide. Our sample is composed of relatively young women, with an average age of 33. The majority are employed (78%), married (86%), and have a low or moderate level of education (83%). Approximately half of the sample resides in urban areas.

Fig. 2 shows the change in the internet penetration rate. The rate has increased over time, growing from approximately 48% in 2014 to 65% in 2016 and to 77% in 2018. Those percentages are much higher than the corresponding statistics at the national level, especially for the latter two waves (2014: 48%; 2016: 53% and 2018: 60%) (China Internet Network Information Center, 2020). One possible explanation is that we focus on reproductive-age women, and IU is more prevalent in that group than in other age groups (Liu et al., 2020). Furthermore, interestingly, the average number of children is consistently lower among mothers who use the internet than among those without IU participation over all three waves of the CFPS (Fig. 3).

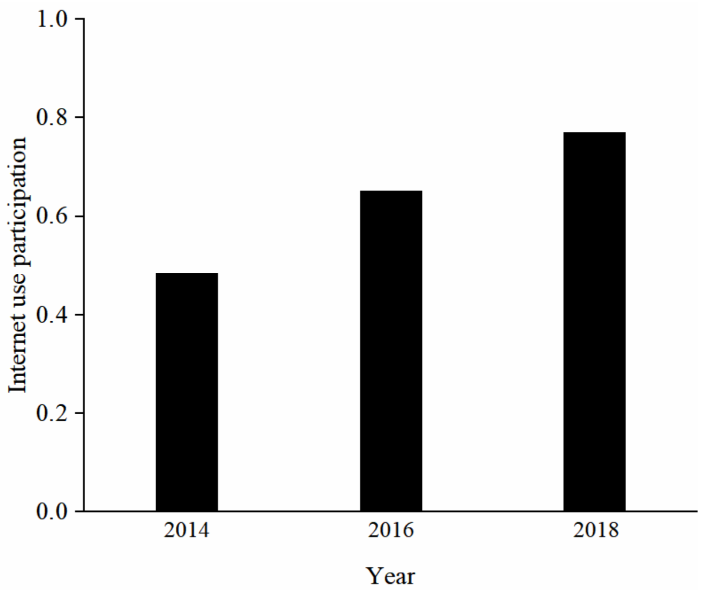

Fig. 2 Internet penetration rate: CFPS 2014–2018

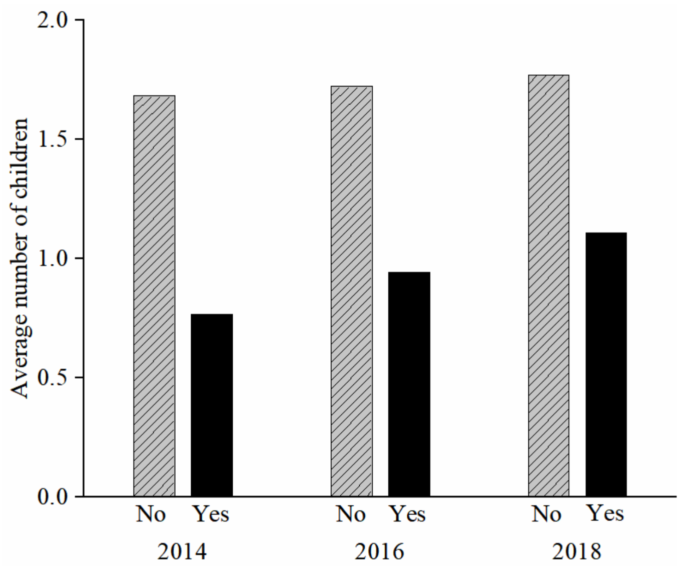

Fig. 3 Number of children born by internet use participation: CFPS 2014–2018
Note: Internet use participation is a dummy (1=yes, 0=no).

5.2 Impact of internet use on fertility

5.2.1 IU participation and fertility

Table 1 shows the results of the OLS/FE estimates of the impact of IU participation/intensity on the NCB. Since the dependent variable in Panel A is IU participation, the study sample includes both internet users and nonusers. However, for Panels B and C, we focus on IU intensity, and this information is available only for internet users in the CFPS. Thus, observations for Panels B and C (obs.=13628) are fewer than those for Panel A (obs.= 23051). We find that IU participation is negatively and significantly associated with the NCB for reproductive-age women, irrespective of whether OLS or FE is used for estimation (Panel A), which is consistent with the observation from Figure 2. Nevertheless, the estimated coefficient from the FE estimation is substantially smaller than that from the OLS estimation (-0.014 vs. -0.111). This difference in the size of the effect on the NCB is attributable to the fact that the FE estimation addresses individual time-invariant heterogeneity. For the FE estimation, IU participation decreases the NCEB by 1.4 percentage points, or 1.0% of the average rate (0.014/1.376 = 1.0%). Our results are consistent with those of Kearney and Levine (2015) and Guldi and Herbst (2017) for the US. Kearney and Levine (2015), for instance, find that the MTV show "*16 and Pregnant*" contributed to a 4.3% decline in teen births in the 18 months after the show's debut. Guldi and Herbst (2017) suggest a smaller effect – approximately 0.67% over 8 years.

Table 1 OLS/FE estimates on the effect of internet use participation/intensity on the NCB, CFPS 2014–2018

	(1) OLS	(2) FE
Panel A: Internet use participation		
Internet use participation	-0.111***	-0.014*
	(0.013)	(0.008)
Mean of dep. var.	1.376	1.376
N	23051	23051
Adjusted R^2	0.514	
Panel B: Internet use intensity (continuous variable)		
Internet use intensity	-0.021***	-0.008***
	(0.003)	(0.003)
Mean of dep. var.	1.108	1.108
N	13628	13628
Adjusted R^2	0.540	
Panel C: Internet use intensity (categorical variable)		
1 ≤ IU intensity < 2	-0.040***	-0.016
	(0.013)	(0.011)
2 ≤ IU intensity < 3	-0.077***	-0.016
	(0.015)	(0.013)
IU intensity ≥ 3	-0.098***	-0.044***
	(0.016)	(0.014)
Mean of dep. var.	1.108	1.108
N	13628	13628
Adjusted R^2	0.550	

Notes: The dependent variable is the number of children ever born. The controls are internet use participation (1 = yes, 0 = no)/internet use intensity (hours/day)/dummies for internet use intensity, age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = not literate/primary school, moderate = middle school/high school, high = vocational school/university or higher, with low as the reference), household net income, household size, urban (1 = urban, 0 = rural), year (with 2014 as the reference), province dummies (with Beijing as the reference) and province-specific time trends. For Panel C, the reference group for IU intensity is IU intensity < 1. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.2.2 IU intensity and fertility

We next examine how IU intensity affects the fertility behavior of reproductive-age women. Panel B of Table 1 shows that IU intensity has a dampening effect on the NCB when it is used as a continuous variable. Similar to the results from Panel A of Table 1, the FE regression still estimates smaller effects of IU intensity on the NCB than does the OLS estimate. In addition, to detect a possible nonlinear IU-NCB relationship, we redefine the dummy variable for IU intensity by recoding it into four categories: IU intensity < 1 h/day, 1 ≤ IU intensity < 2 h/day, 2 ≤ IU intensity < 3 h/day, and IU intensity ≥ 3 h/day, with IU intensity < 1 h/day as our reference group. We also find that, relative to those who use the internet for < 1 h per day, IU intensity, especially IU intensity ≥ 3 h/day, is uniformly and negatively linked with the NCB of reproductive-age women (see Table 1, Panel C). Furthermore, such effects become stronger with an increase in IU intensity, which echoes the estimate obtained when we employ the continuous IU intensity variable.

5.2.2 Online function use and fertility

In addition to our macro approach to the second-level digital divide, we employ a micro approach to analyze how the use of various online functions affects the NCB (see Table 2). To capture the possible heterogeneity of different online functions by various age groups, we also control for the interaction terms of frequency of online function use with three age groups (16–29, 30–39 and 40–49). The results of the OLS estimation show that the use of different online functions, irrespective of whether those functions are study-, work-, social interaction-, entertainment- or commercial-related activities, is uniformly and negatively associated with the NCB (column 1). Nevertheless, based on the results of the FE estimation, we only find that a higher frequency of work online is negatively associated with fertility, implying that, given a certain time constraint, the internet, which is used as a means for attaining a valuable goal (e.g., work), reduces fertility. The results, once again, underscore the importance of introducing both macro- and microlevel approaches when assessing the second-level digital divide. Furthermore, the interaction term between the frequency of online work and the age group of 30–39 is positively and statistically significantly linked with fertility, suggesting that this age group attenuates the negative impact of internet use intensity on fertility. This may mean that compared to those aged 16–29 years, those aged 30–39 years are more likely to have children, possibly due to delayed marriage. The mean age at childbearing in 2015 was 28.5 years (Yang et al., 2022).

Table 2 OLS/FE estimates of the effect of online function use on the NCB, CFPS 2014–2018

Online function	(1) OLS	(2) FE
Panel A: Study	-0.011***	-0.003

	(0.003)	(0.003)
Study x aged 30–39	0.010***	0.008**
	(0.003)	(0.004)
Study x aged 40–49	-0.007	0.000
	(0.005)	(0.004)
Mean of dep. var.	1.107	1.107
N	13558	13558
Adjusted R^2	0.538	
Panel B: Work	-0.023***	-0.007**
	(0.003)	(0.003)
Work x aged 30–39	0.009***	0.009***
	(0.003)	(0.003)
Work x aged 40–49	-0.005	0.006
	(0.005)	(0.004)
Mean of dep. var.	1.084	1.084
N	12334	12334
Adjusted R^2	0.546	
Panel C: Social interactions	-0.010***	-0.002
	(0.004)	(0.004)
Social interactions x aged 30–39	0.013***	0.008***
	(0.003)	(0.003)
Social interactions x aged 40–49	0.001	0.000
	(0.005)	(0.004)
Mean of dep. var.	1.107	1.107
N	13557	13557
Adjusted R^2	0.539	
Panel D: Entertainment	-0.016***	-0.000
	(0.004)	(0.003)
Entertainment x aged 30–39	0.010***	0.005*
	(0.003)	(0.003)
Entertainment x aged 40–49	-0.007	-0.004
	(0.005)	(0.004)
Mean of dep. var.	1.107	1.107
N	13558	13558
Adjusted R^2	0.538	
Panel E: Commercial-related activities	-0.022***	-0.001
	(0.004)	(0.004)
Commercial-related activities x aged 30–39	0.008**	0.005
	(0.004)	(0.004)
Commercial-related activities x aged 40–49	-0.014**	-0.004
	(0.006)	(0.005)
Mean of dep. var.	1.107	1.107
N	13554	13554
Adjusted R^2	0.540	

Notes: The dependent variable is the number of children ever born. The controls are the frequency (1 = never, 2 = once every few months, 3 = once a month, 4 = twice or thrice a month, 5 = once or twice a week, 6 = three or four times a week, 7 = almost every day) of different online functions (study, work, social interaction, entertainment and commercial-related activities) interacted with three age groups (16–29, 30–39, 40–49), married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = not literate/primary school, moderate = middle school/high school, high = vocational school/university or higher, with low as the reference), household net income, household size, urban (1 = urban, 0 = rural), year (2014 as the reference), and province dummies (with Beijing as the reference), and province-specific time trend (quadratic). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.3 A note on endogeneity

As Table 3 shows, the first-stage IV estimates indicate a significant and positive association between the instrument and individual IU participation (Panel B), validating our assumption that individuals are more likely to use the internet if telecommunication facilities boost internet access. The first-stage *F* test results (*F*-statistic = 19.2) reject the possibility of a weak instrument. The second-stage results then confirm that IU participation reduces the NCB (Panel A). Specifically, the results of the FE-IV estimate reveal that IU participation reduces the NCB by 28.6 percentage points, equivalent to approximately 20.8% of the average NCB in the full sample. However, these IV results are much larger than the FE results in Table 1. This observation is attributable to the fact that our IV estimate should be interpreted as local average treatment effects (LATEs).

Table 3 FE-IV estimates of the effect of internet use participation on the NCB

Panel A: Second-stage estimation	(2)
Internet use participation	-0.286***
	(0.101)
Mean of dep. var.	1.376
Panel B: First-stage estimation	
Internet broadband access terminals (IBAT) at t-1	0.654***
	(0.064)
Kleibergen–Paap *F* statistic	19.22
N	23051

Notes: The dependent variable is the number of children ever born. The instrumental variable is the one-year lagged number of internet broadband access terminals per capita at the provincial/municipality level. Controls include internet use participation, age and age squared, married/living together, employment status, education, translog household net income, household size, urban, year, province dummies (with Beijing as the reference) and province-specific time trends. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.4 Robustness checks

Using alternative estimation methods. Given that the NCB might be highly skewed, we introduce FE Poisson and zero-inflated Poisson models. We find that IU participation is still negatively and significantly associated with the NCB, regardless of whether FE Poisson or zero-inflated Poisson estimation is used (Table A2). In addition, we reestimate the model with an ordered probit, multinomial logit and FE multinomial logit regression and, once again, find that IU participation reduces the NCB (Table A3).

Using an alternative IV candidate. In addition to the one-year lagged IBAT, we use the two-year lagged IBAT as the IV candidate and reestimate the FE-IV regression. The main results (see Appendix Table A4) are similar to those in Table 3, in which the one-year lagged IBAT is used as the instrument.

Using an alternative fertility measure. We also employ an alternative fertility measure indicating whether a reproductive-age woman gives birth at year *t* (1=yes, 0=no) and rerun the

FE estimates for both internet use participation and intensity. The results in Appendix Table A5 indicate that our baseline results are persistent, although insignificant for IU participation.

Attrition bias. The panels in the CFPS dataset are unbalanced, which may lead to concerns regarding attrition bias. To address this possible concern, we employ a three-year balanced panel and rerun the estimates. Reassuringly, the results presented in column 1 of Appendix Table A6 are consistent with the main results.[4]

Adding province-level house prices. Prior literature provides evidence linking rocketing housing prices to the declining fertility rate in China (Liu et al., 2021). Consequently, we introduce province-level house prices and reestimate the model (see Appendix Table A6, column 2). As in the baseline results from Table 1, we still find a statistically negative impact of IU participation on the NCB (-0.024). We also confirm that increasing housing prices reduce the NCB (although statistically insignificantly), which is well in line with the results of existing studies in the Chinese context (Liu et al., 2021; Liu et al., 2020). One possible explanation for this finding is that increased house prices may enhance the housing costs of having an additional child, thereby reducing the actual fertility behavior of childbearing women (Liu et al., 2021).

Adding personality traits. Given that personality influences reproductive behavior (Alvergne et al., 2010; Skirbekk & Blekesaune, 2014), we also control for personality traits. The Big Five personality framework divides personality characteristics into five dimensions: conscientiousness, agreeableness, extroversion, openness and neuroticism (Costa & McCrae, 1988). In the CFPS, the measurement of the Big Five personality traits is available only in the 2018 wave, and each dimension encompasses three specific questions, with the responses ranging from 1= fully disagree to 5 = fully agree (see Table A7 for detailed definitions of the Big Five personality traits). We then introduce those five dimensions into the model and rerun the estimates. The results in Table A8, irrespective of whether IU participation or intensity is used, remain similar to the main results (in Table 1). Additionally, we find that conscientiousness, extraversion and neuroticism are related to having more children, but agreeableness and openness are linked with having fewer children, albeit with an insignificant coefficient for agreeableness when regressing on IU participation. Our findings are in accordance with those for Senegal (Alvergne et al., 2010).

[4] We perform another robustness check and rerun the estimates with the adjustment of sampling weights. The results, available on request, are similar to those in Table 1.

Specific wave/period. Although the two-child policy is unlikely to have increased fertility substantially, especially given the rising costs of childbearing and childrearing, we speculate that it might have attenuated the negative impact of IU participation on fertility. To test this possibility, we reestimate the model for each specific wave. Interestingly, the results in Appendix Table A9 show that the effects are uniformly negative and significant, but the effect size decreases over time (2014: -0.138; 2016: -0.104 and 2018: -0.072). In addition, we split the whole period into two phases (2014–2016 and 2016–2018) and reestimate the FE model. Once again, our main results are persistent (2014-2016: -0.019; 2016-2018: -0.006; see Table A10).

Using reproductive-age women aged 16–44. As highlighted by the WHO (2006), in some estimates from censuses and surveys, the upper age for reproductive-age women is also taken as 44 years. As a result, we have also restricted our sample of reproductive-age women aged 16–44 and rerun the estimates. The results, shown in Appendix Table A11, are similar to those in Panels A and B of Table 1.

Falsification test. We perform a falsification test to provide an indirect assessment of the exclusion restriction assumption. Specifically, following Chen and Liu (2022), we use data on fertility behavior before 2000.[5] Since there was no internet speed upgrade before this period, IU should not have any significant effect on fertility behavior. The results show that there is no significant association between IU and fertility behavior, regardless of IU participation or intensity (see Appendix Table A12).

Excluding migration. One possible concern is that individuals migrate across provinces in response to better access to the internet in given areas, thereby leading to biased estimates of IU. For instance, women who plan to give birth may move to areas with better access to high-speed internet. To address this concern, we restrict our sample to those without migration (defined as whether the respondent's current residence is the same as the residence at birth, 1=nonmigration, 0=migration) and then rerun the estimates. From Appendix Table A13, we confirm that our main findings are robust, irrespective of IU participation or intensity.

5.5 Heterogeneity analysis

To provide more pragmatic guidance for IU and fertility, using FE-IV estimates, we perform heterogeneity analyses by extensive margin (the probability of having children or not) versus

[5] A detailed discussion on the development of China's internet networks is available in Chen and Liu (2022).

intensive margin (number of children born), residence (urban versus rural), gender of the first child, age groups, marital status, region and education level.

Extensive margin versus *intensive margin*. Following Aaronson et al. (2014), we define extensive margin as a dummy of whether having at least one child (1=yes, 0=no) and intensive margin as the number of children conditional on at least one child. Although we only observe the negative and significant impact of IU participation on intensive margins (see Table 4, column 2 of Panel A), this implies that IU participation reduces the number of children conditional on at least one child, which, to some extent, is in line with the results in Table 3.

Table 4 FE-IV estimates for the effect of internet use participation on the NCB by various sociodemographic characteristics, CFPS 2014–2018

	(1)	(2)	(3)	(4)
Panel A: By extensive vs. intensive margin	Extensive	Intensive		
Internet use participation	0.077	-0.347***		
	(0.064)	(0.080)		
Mean of dep. var.	0.821	1.676		
Kleibergen–Paap *F* statistic	19.22	17.38		
N	23051	18918		
Panel B: By residence	Rural	Urban		
Internet use participation	-0.472***	-0.189		
	(0.148)	(0.139)		
Mean of dep. var.	1.568	1.188		
Kleibergen–Paap *F* statistic	11.53	12.64		
N	11376	11675		
Panel C: By gender	Girls	Boys		
Internet use participation	-0.270***	-0.446***		
	(0.098)	(0.130)		
Mean of dep. var.	1.807	1.547		
Kleibergen–Paap *F* statistic	9.40	9.92		
N	9330	9598		
Panel D: By age groups	16-19	20-29	30-39	40-49
Internet use participation	-2.240	-1.150	-0.628***	0.055
	(1.487)	(0.771)	(0.234)	(0.051)
Mean of dep. var.	0.102	0.789	1.548	1.769
Kleibergen–Paap *F* statistic	1.12	1.56	6.60	28.07
N	537	6805	6796	8913
	16-29	30-39	40-49	
Internet use participation	-1.014*	-0.628***	0.055	
	(0.604)	(0.234)	(0.051)	
Mean of dep. var.	0.739	1.548	1.769	
Kleibergen–Paap *F* statistic	2.08	6.60	28.07	
N	7342	6796	8913	
Panel E: Marital status	Married	Unmarried		
Internet use participation	-0.310***	-0.149		
	(0.097)	(0.223)		
Mean of dep. var.	1.553	0.275		
Kleibergen–Paap *F* statistic	19.09	3.05		
N	7205	5896		
Panel F: By region	East	Central	West	Northeast
Internet use participation	-0.042	-0.511	0.121	0.116
	(0.171)	(0.366)	(0.351)	(0.184)
Mean of dep. var.	1.293	1.435	1.569	0.999

Kleibergen–Paap *F* statistic	10.20	6.03	16.46	7.56
N	7205	5896	7015	2935
Panel G: By education	Low	Moderate	High	
Internet use participation	-0.049	-0.362***	-0.687	
	(0.135)	(0.122)	(0.891)	
Mean of dep. var.	1.830	1.248	0.784	
Kleibergen–Paap *F* statistic	10.00	31.66	1.55	
N	8778	10450	3823	

Notes: The dependent variable is the number of children ever born. The controls are internet use participation; age and age squared; married/living together; employment status; education; translog household net income; household size; urban, year, and province dummies; and province-specific time trends. Individual-level adjusted standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

By residence (urban versus *rural)*. The negative effect of IU participation is only observed among rural women of reproductive age (see Table 4, Panel B), which we attribute to the fact that due to the urban–rural digital divide, the Chinese government has launched an informatization strategy that aims to develop ICT infrastructure such as village-to-village electricity, gas and telecommunication networks to boost the rural economy (Nie, Ma, et al., 2021; Yan & Schroeder, 2019). Additionally, government-led construction of 4G and 5G networks serves as a stimulus for mobile IU in rural China. Consequently, rural women satisfy more of their informational needs and social needs via online interactions than urban women do (Yan & Schroeder, 2019). For instance, rural women of reproductive age are more likely to interact with other women of reproductive age for childbearing information and communication; therefore, they are more likely to be affected by using the internet.

By gender of the first child. Regarding the heterogeneity by the gender of the first child, we find negative and statistically significant effects among both girls and boys; however, the observed impacts are more pronounced among boys than girls (see Table 4, Panel C). One possible explanation for this discrepancy is the preference for sons in China. Thus, compared to girls, boys are more affected by IU participation.

By age group. In terms of the heterogeneity by age group (16–19, 20–29, 30–39 and 40–49), we show that IU participation is negatively and statistically significantly associated with fertility behavior among those aged 16–19 (see Table 4, Panel D). One possible explanation is that IU is more prevalent among adolescents than among other age groups, and in 2020, 98.3% of Chinese adolescents aged 15–19 used the internet (China Internet Network Information Center, 2021), which was much higher than the percentage of adults (70.4%) (China Internet Network Information Center, 2022). Although we observe a negative impact of IU participation on fertility for women aged 20–29 and 30–39 years, it is statistically insignificant. We also recategorize age into three groups (16–29, 30–39 and 40–49), and once again, the results demonstrate that IU participation negatively affects fertility among women aged 16–29 and 30–39.

By marital status. For the split analysis by marital status, IU participation reduces fertility behavior only among married women of reproductive age and not among those who are unmarried/widowed/divorced (see Table 4, Panel E). Not surprisingly, childbearing is relatively common among married women, and reproductive-age women are generally encouraged to give birth after marriage in China to carry on the family lineage.

By region. The need to examine the heterogeneity by region stems from the remarkable geographic differences in economic development and fertility behavior across China. Those residing in the eastern and central regions are more vulnerable to the negative impact of IU participation on the NCEB, although these impacts are statistically insignificant (see Table 4, Panel F).

By education. For the heterogeneity by education level (see Table 4, Panel G), the effect is significant and negative among only those with a moderate level of education. This may suggest that middle-level education is an important determinant of fertility decline in many developing countries (Cohen, 2008), and this could be particularly important for Asian nations such as China (James et al., 2012).

Overall, Table 4 implies the presence of heterogeneity effects by residence, gender of the first child, age group, marital status, education and intensive margin (the number of children conditional on at least one child). However, given the large standard errors and the relative weakness for age groups and gender based on the FE-IV approach, the magnitudes of those estimates should be interpreted with caution.[6]

6. Underlying mechanisms

To identify the pathways through which IU may affect fertility, we detect the effect of IU on five important dimensions: (i) marital satisfaction, (ii) importance placed on the ancestral line, (iii) gender role attitudes, (iv) health and (v) fertility preferences.

Marital satisfaction. To identify marital satisfaction as a possible mechanism, we introduce a variable for it based on the following question: "*How satisfied are you with your marriage?*" (measured on a 5-point scale ranging from 1 = very unsatisfied to 5 = very satisfied).[7] Panel A

[6] We also check how IU participation affects first births using FE-IV estimation. The results of the second-stage estimate, available on request, show that the impact of IU participation on first births is negative (-0.071) but statistically insignificant, although the first-stage F test result (*F*-statistic = 17.38) eliminates the possibility of a weak instrument.

[7] The information on marital satisfaction is available only in the 2014 and 2018 waves of the CFPS.

of Table 5 reveals that IU participation is significantly and negatively associated with marital satisfaction, although the effect is insignificant in the FE estimation, suggesting that internet users have lower marital satisfaction than internet nonusers. This observation is well in line with those of Tong et al. (2021) for China, confirming the negative impact of IU on overall marital satisfaction, satisfaction with spousal contributions to housework, and marital stability in China. There are several possible explanations for these results: The internet may substantially decrease search costs (Bellou, 2015; Billari et al., 2019) and raise the reservation values of partners (Tong et al., 2021), thereby contributing to lower marital satisfaction. Another possibility is that changes to gender ideology via the internet's educational function increase spousal dissatisfaction in China (Tong et al., 2021). In addition, excessive use of the internet crowds out time spent on housework and other investments in one's current marriage and thus has negative effects on marital satisfaction (Tong et al., 2021). Previous studies (e.g. Beaujot & Tong, 1985; Nitsche & Hayford, 2020) confirm that low marital satisfaction negatively affects the desire for or intention to have additional children; thus, children are less likely to be born to satisfying marriages. Therefore, the results here support our argument that IU participation reduces fertility behavior via low marital satisfaction.

Table 5 OLS/FE estimates for the effect of IU participation on marital satisfaction, importance placed on the ancestral line, gender role attitudes and health, CFPS 2014 and 2018

	(1)	(2)
Panel A: Marital satisfaction	OLS	FE
Internet use participation	-0.053**	-0.007
	(0.023)	(0.038)
N	13080	13080
Adjusted R^2	0.013	
Panel B: Importance placed on ancestral line	OLS	FE
Internet use participation	-0.378***	-0.108**
	(0.028)	(0.051)
N	15100	15100
Adjusted R^2	0.251	
	OLS	
Panel C: Gender role attitudes (GRAs)[a]	GRA1	GRA2
Internet use participation	-0.442***	-0.257***
	(0.038)	(0.040)
N	7884	7879
Adjusted R^2	0.182	
	GRA3	GRA4
Internet use participation	-0.023	0.028
	(0.034)	(0.033)
N	7885	7888
Adjusted R^2	0.048	
Panel D: Self-reported health (SRH)	Probit (marginal effects)	
Internet use participation	-0.042***	
	(0.009)	
N	23023	

Pseudo R^2	0.048

Notes: The dependent variables include marital satisfaction (measured on a 5-point scale ranging from 1 = very unsatisfied to 5 = very satisfied), the importance placed on the ancestral line (measured on a 5-point scale ranging from 1 = very unimportant to 5 = very important), women's gender role attitudes (GRAs) measured on a 5-point scale from 1 = strongly disagree to 5 = strongly agree (GRA1: "Men are career-oriented, while women are family-oriented"), (GRA2: "For women, a good marriage is better than a good career"), (GRA3: "Women should have children to be complete") and (GRA4: "Men should be responsible for half of the housework"), and self-reported health (SRH, 1 = good/very good/excellent, 0 otherwise). The controls include internet use participation; age and age squared; married/living together; employment status; education; translog household net income; household size; urban, year and province dummies; and province-specific time trends. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
[a] Information on gender role attitudes is available only in the 2014 wave.

Importance placed on ancestral lines. Next, we investigate the importance placed on the ancestral line as another possible channel. We exploit information on the importance placed on ancestral lines by reproductive-age women, which is measured on a 5-point scale ranging from 1 = very unimportant to 5 = very important.[8] We find that IU participation is negatively associated with the importance placed on the ancestral line (see Table 5, Panel B), suggesting that IU reduces the importance placed on childbearing. Thus, this finding supports our former argument that IU will weaken the importance placed on ancestral lines that are closely linked to the number of children born. In addition, as previously stated, the effect size for IU participation from the FE estimation is much smaller than that from the OLS estimation (0.108 vs. 0.378). Due to data limitations in the CFPS, we cannot directly test how IU participation affects the proliferation of false and exaggerated information online, such as induced abortion, fear of childbirth and the extremely high cost of childrearing; however, we can provide some suggestive evidence. In doing so, we attempt to introduce the Baidu (a search engine equivalent to Google) Index of induced abortion (ranging from 57–135, with a higher value indicating higher popularity)[9] in prefecture-level cities. We then sum the individual-level IU participation to the prefecture-level city. We use individual sociodemographic factors from the CFPS and aggregate them into the prefecture-level city level. Those sociodemographic characteristics include age groups (share of reproductive-age women aged 16–29, 30–39, and 40–49), marital status (share of those who are married), and education (share of those who are not literate/completed only primary school, completed middle school/high school, and completed vocational school/university or higher). We regress the Baidu Index of induced abortion in prefecture-level cities on aggregated IU participation using two-way FE estimation. The results

[8] We also redefine this variable to be a dummy equal to 1 if the response is "important" or "very important" and 0 otherwise. We reestimate the probit regression, and our results, reported in the Appendix Table A14, are quantitatively similar to those in Table 5.
[9] The annual Baidu Index of induced abortion in the prefecture-level cities is the average value aggregated from the daily index, which is available from https://index.baidu.com/v2/index.html#/.

in Appendix Table A15 show that IU participation at the city level increases the popularity of induced abortion, providing suggestive evidence that internet use boosts the prevalence of induced abortion, which will weaken the importance placed on ancestral lines and therefore may reduce actual fertility behaviors.

Gender role attitudes (GRAs). To capture GRAs, we follow Tong et al. (2021) and examine four statements: *GRA1:* "*Men are career-oriented, while women are family-oriented*"; *GRA2:* "*For women, a good marriage is better than a good career*"; *GRA3:* "*Women should have children to be complete*" and *GRA4:* "*Men should be responsible for half of the housework*" (with the responses ranging from 1 = strongly disagree to 5 = strongly agree). The first three (GRA1–GRA3) statements represent traditional gender roles, but the last one (GRA4) reflects a modern view on sharing housework (Tong et al., 2021). The results in Panel C of Table 5 show that relative to childbearing women who do not access the internet, internet users are less likely to agree with all of the statements that reflect traditional attitudes toward gender roles (although these results are insignificant for GRA3), which is consistent with Tong et al. (2021). However, IU participation is uncorrelated with having a modern view of gender roles: "*Men should be responsible for half of the housework.*" As stated before, more widespread IU has altered ideas about women's traditional gender roles (Zhou et al., 2020) and therefore weakened the traditional division of labor within the Chinese family (Tong et al., 2021). Women who are employed generally have difficulty balancing work and parenthood and thus spend less time with their families, which reduces actual fertility (Fang et al., 2013). Notably, those employed women with higher education prioritize their personal development (Zhou & Guo, 2020), and higher education increases the opportunity cost of having children (Musick et al., 2009). We thus take changed attitudes toward traditional gender roles as the third channel for the relationship between IU participation and fertility.

Self-reported health (SRH). We then investigate the effect of IU participation on the health of reproductive-age women. We measure individual health by using SRH based on the question "How would you rate your health status?", with the possible responses of 1 = poor, 2 = fair, 3 = good, 4 = very good and 5 = excellent. We then recode it as a dummy variable for good SRH, which is equal to 1 if the response is good/very good/excellent and 0 otherwise. Reassuringly, our probit estimation shows that IU participation reduces the probability of reporting good SRH by 4.2% (see Table 5, Panel D). This observation implies that IU is harmful for SRH, which captures not only physical and mental health but also acute and chronic diseases (Nie et al., 2015; Xie & Mo, 2014). Furthermore, prior research confirms that such deterioration of the health status of childbearing women would result in an increased risk of pregnancy-related complications (Li & Deng, 2017) and concerns about maternal and perinatal safety (Liu et al., 2020), thereby reducing actual fertility behavior. Therefore, we provide evidence that IU decreases fertility through poor health (the fourth channel).

Ideal number of children. To test whether childbearing preferences act as a possible mechanism, we analyze the impact of IU participation on fertility preferences. We base our measure of fertility preferences on responses to the following question: "What is your ideal number of children?" (with the responses ranging from 0–10). We report the results of this analysis in Table 6. In our sample period, information on the ideal number of children is available only for 2014 and 2018. Interestingly, we show that IU participation increases the preference for 0 or 1 child by 0.2% and 1.4% (columns 1 and 2), respectively, but decreases preferences for 2, 3, or 4 or more children by 0.7%, 0.7% and 0.3%, respectively (columns 3–5). This finding suggests that IU reduces preferences for having 2 or more children. Furthermore, individuals' fertility preferences or intentions reflect their attitudes toward and views of childbearing behaviors (Nie, Wang, et al., 2021) and have been found to be a significant predictor of the actual number of children born in China (Luo & Mao, 2014) and other societies (Schoen et al., 1999; Tan & Tey, 1994). Consequently, the results here support our final channel by which such an IU-depressing effect on fertility preferences translates into a decline in the actual number of children born.

Table 6 Ordered probit estimates for the effect of internet use participation on the ideal number of children, CFPS 2014 and 2018

	(1) Child=0	(2) Child=1	(3) Child=2	(4) Child=3	(5) Child≥4
Internet use participation	0.002**	0.014**	-0.007**	-0.007**	-0.003**
	(0.001)	(0.006)	(0.003)	(0.003)	(0.001)
N	15081	15081	15081	15081	15081
Pseudo R^2			0.120		

Notes: The dependent variable is the ideal number of children. The controls are internet use participation; age and age squared; married/living together; employment status; education; translog household net income; household size; urban, year and province dummies; and province-specific time trends. Marginal effects are reported for the ideal number of children. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

7. Discussion and conclusions

This study makes several important contributions to the literature on IU's role in fertility: it extends the focus to a non-Western developing country, employing a novel combination of measures for the first-level and second-level digital divides. In particular, regarding the second-level digital divide, this study incorporates macro- and microlevel approaches to measure IU intensity. By using the sociodemographic characteristics of age group, education, gender of the first child, marital status, extensive and intensive margins, residence (urban versus rural), and region to explore the heterogeneity in the effects of IU on fertility, it offers useful guidance for policies meant to boost (below-replacement) fertility rates. Last, it provides a thorough assessment of the possible mechanisms through which IU affects fertility behaviors, which sheds light on the relationship between IU and fertility in China and other developing economies.

In particular, this study finds a robust and negative impact of IU, irrespective of IU participation or intensity, on the NCEB among childbearing women in China. In addition, we estimate LATEs, and the results of the FE-IV estimation show that IU participation decreases the NCEB by 28.6 percentage points, equivalent to 20.8% of the average NCEB in the full sample.

Drawing on the literature, we also identify several major channels through which IU participation appears to operate on fertility: marital satisfaction, gender role attitudes, importance placed on ancestral lines, health, and fertility preferences. That is, IU reduces actual fertility behavior by reducing marital satisfaction, altering perceptions of traditional gender roles, reducing importance placed on the ancestral line, diminishing SRH, and decreasing the ideal number of children. This analysis also confirms that such negative impacts are much stronger among those with a moderate level of education, rural residents and those who are married or living together.

The strength of our analysis lies in its Chinese nationally representative longitudinal data with detailed information on internet use, which considerably extends the limited and mixed evidence for Western countries, and its comprehensive exploration of possible mechanisms through which IU exerts its effect. Its main limitation is that, although we attempt to identify causality by applying an IV approach, identification problems remain, and our results should be treated as associations. In addition, the endogeneity issue of IU intensity remains an open question. This calls for future research to generate more insights into the causal relation between IU and fertility.

Despite these limitations, our key findings have several important policy implications. Although China has recently implemented a TCP to reverse low fertility rates, a substantial increase in fertility might be unlikely. Given the negative impact of IU on women's actual fertility behavior, this study highlights the importance of IU in assessing the overall impacts of China's family planning policy adjustments on population growth. Specifically, when designing fertility-enhancing programs or policies, appropriate use of the internet is highly encouraged, which could be achieved via governmental education programs on health literacy. A good starting point for such health interventions is suggested in China's new *Basic Healthcare and Health Promotion Law* (enacted on June 1, 2020), which addresses health issues via information campaigns, the promotion of healthy lifestyles, and the integration of health education into the national curriculum (Nie et al., 2022). Considering the negative impacts of IU on attitudes toward traditional gender roles, the government should create education programs or undertake other measures, such as encouraging men to engage more in homework and childrearing, to reduce possible conflicts between traditional and modern social norms and concepts (Tong et al., 2021), optimize the division of labor by gender within the family and promote marital satisfaction. Given that childbirth is of societal importance in all countries, including China, its associated costs should be borne by the whole society, not just women and their families (Li et al., 2019).

Declaration of interest statement

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Appendix:

Table A1 Descriptive Statistics

Dependent and key independent variables	Obs.	Mean	S.D.	Min.	Max.
The number of children born	23051	1.376	0.945	0	7
Internet use participation (1=yes,0=no)	23051	0.596	0.491	0	1
Internet use intensity (hours/day)	13628	1.902	1.679	0	10
Frequency of Internet use					
Study	12318	3.406	2.384	1	7
Work	12318	3.608	2.776	1	7
Social interactions	12318	5.962	1.804	1	7
Entertainment	12318	5.486	1.971	1	7
Commercial-related activities	12318	3.321	2.031	1	7
Control variables					
Married/living together	23051	0.861	0.346	0	1
Age	23051	35.359	8.888	16	49
Education					
Low	23051	0.381	0.486	0	1
Moderate	23051	0.453	0.498	0	1
High	23051	0.166	0.372	0	1
Employment status	23051	0.785	0.411	0	1
Household size	23051	4.576	1.953	1	21
Ln(household net income)	23051	10.504	1.492	0	15.22
Urban	23051	0.506	0.500	0	1
Wave					
2014	23051	0.350	0.477	0	1
2016	23051	0.336	0.472	0	1
2018	23051	0.314	0.464	0	1
Mechanism variables					
Marital satisfaction[a]	13080	4.345	0.935	1	5
Importance placed on ancestral lines[a]	15100	3.439	1.463	1	5
Gender role attitudes (GRAs)[a]					
GRA1	7884	3.769	1.290	1	5
GRA2	7879	3.497	1.343	1	5
GRA3	7885	4.210	1.108	1	5
GRA4	7888	4.139	1.060	1	5
Ideal number of children[a]	15081	1.906	0.670	0	10
Self-reported health (SRH)	23023	3.169	1.140	1	5

Notes: Internet use participation is a binary variable (1 = yes, 0 = no). Internet use intensity is measured in terms of hours per day. Frequency of Internet use (study; work; social interaction; entertainment; commercial related activities) is measured on a 7-point scale from 1 = never to 7 = every day. Importance for Internet use (study; work; social interaction; entertainment; commercial related activities) is measured on a 5-point scale from 1 = very unimportant to 5 = very important. Married/living together is a binary variable (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), urban resident (1 = urban, 0 = rural), dummies of age groups, dummies of education level. Marriage satisfaction is measured on a 5-point scale ranging from 1 = very unsatisfied to 5 = very satisfied. The self-reported importance of ancestral line is measured on a 5-point scale ranging from 1 = very unimportant to 5 = very important. Gender role attitudes (GRAs) measured on 5-point scale from 1 = strongly disagree to 5 = strongly agree (GRA1: "Men is career-oriented, while women is family-oriented"), (GRA2: "For women, a good marriage is better than a good career"), (GRA3: "Women should have children to be complete") and (GRA4: "Men should be responsible for half of housework"). Self-reported health is measured on a 5-point scale ranging from 1 = unhealth to 5 = very health.

[a] Information on marital satisfaction, importance placed on ancestral lines and the ideal number of children is available in waves of 2014 and 2018. Information on gender role attitudes is only available in the wave of 2014.

Table A2 FE Poisson/zero-inflated Poisson estimates of the effect of internet use on the number of children, CFPS 2014-2018

Panel A: FE Poisson	
Internet use participation	-0.022***
	(0.006)
Mean of dep. var.	1.614
N	16670
Panel B: Zero-inflated Poisson	
Internet use participation	-0.062***
	(0.009)
Mean of dep. var.	1.376
N	23051

Notes: The dependent variable is the number of children. Controls are internet use participation, age and age squared, married/living together, employment status, education, translog household net income, household size, urban, year and province dummies, and province-specific time trends. Individual level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A3 Order probit/multi-nominal logit/FE multi-nominal logit estimates of the effect of internet use participation on number of children, CFPS 2014-2018

Panel A: Ordered probit	(1)	(2)	(3)	(4)
	Child=0	Child=1	Child=2	Child≥3
Internet use participation	0.019***	0.021***	-0.020***	-0.019***
	(0.003)	(0.003)	(0.003)	(0.003)
Mean of dep. var.		1.376		
N	23051	23051	23051	23051
Panel B: Multi-nominal logit (base outcome: number of children = 1)				
Internet use participation	-0.169*		-0.355***	-0.571***
	(0.090)		(0.053)	(0.084)
Mean of dep. var.		1.376		
N	23051		23051	23051
Panel C: FE Multi-nominal logit (base outcome: number of children = 1)				
Internet use participation	0.167		-0.569**	-0.600
	(0.452)		(0.276)	(0.446)
Mean of dep. var.		1.281		
N	3596		3596	3596

Notes: The dependent variable is the number of children. Controls are internet use participation, age and age squared, married/living together, employment status, education, translog household net income, household size, urban, year and province dummies, and province-specific time trends. Marginal effects are reported for the number of children. Individual level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A4 FE-IV estimates effect of internet use participation on the number of children

Using two-year lagged IBAT as IV	
Panel A: Second-stage estimation	
Internet use participation	-0.176*
	(0.093)
Panel B: First-stage estimation	
IBAT at t-2	0.563***
	(0.051)
Mean of dep. var.	1.376
Kleibergen-Paap *F* statistic	27.26
N	23051

Notes: The dependent variable is the number of children. The instrument variable is the number of Internet broadband access terminals (IBAT) per capita at the provincial/municipality level at time t-2. Controls include internet use participation, age and age squared, married/living together, employment status, education, translog household net income, household size, urban, year and province dummies, and province-specific time trends. Individual level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A5 FE estimates of the effect of internet use participation/intensity on having a child birth, CFPS 2014-2018

	(1)	(2)
Internet use participation	-0.004	
	(0.008)	
Internet use intensity		-0.009***
		(0.003)
Mean of dep. var.	1.376	1.108
N	23051	13628

Notes: The dependent variable is having a child birth at year *t* (1 = yes, 0 = no). The controls are internet use participation (1 = yes, 0 = no)/internet use intensity (hours/day), dummies for age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, moderate = middle school/high school, and high = vocational school/university or higher, with low as the reference), household net income, household size, urban (1 = urban, 0 = rural), year (with 2014 as the reference year) and province dummies (with Beijing as the reference) as well as province-specific time trends. Individual-level adjusted standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01

Table A6 FE estimates of the effect of internet use participation on the number of children, CFPS 2014-2018

	(1) Balanced panel	(2) Unbalanced panel
Internet use participation	-0.024***	-0.014*
	(0.009)	(0.008)
Ln(house price)		-0.172
		(0.114)
Mean of dep. var.	1.448	1.376
N	13927	23051

Notes: The dependent variable is the number of children. The controls are internet use participation, house price at province level, age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, moderate = middle school/high school, high = vocational school/university or higher, with low as the reference), household net income, household size, urban dummy (1 = urban, 0 = rural), year dummies (2014 as the reference year), province dummies (with Beijing as the reference) and province-specific time trends. Individual level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A7 Definition of Big Fiver personality

Big Five personality	Questions	Scale
Conscientiousness	I am rigorous and serious	1=totally disagree to 5=totally agree
	I do things efficiently	1=totally disagree to 5=totally agree
	I am lazy	1=totally agree to 5=totally disagree
Agreeableness	I am considerate and kind to almost everyone	1=totally disagree to 5=totally agree
	I have a forgiving nature	1=totally disagree to 5=totally agree
	I am sometimes rude to others	1=totally agree to 5=totally disagree
Extraversion	I am talkative	1=totally disagree to 5=totally agree
	I am outgoing and sociable	1=totally disagree to 5=totally agree
	I am conservative	1=totally agree to 5=totally disagree
Openness	I am original and come up with new ideas	1=totally disagree to 5=totally agree
	I value artistic experiences	1=totally disagree to 5=totally agree
	I have an active imagination	1=totally disagree to 5=totally agree
Neuroticism	I worry a lot	1=totally disagree to 5=totally agree
	I become nervous easily	1=totally disagree to 5=totally agree
	I can cope with pressure well	1=totally agree to 5=totally disagree

Source: CFPS 2018.

Table A8 OLS estimates of the effect of internet use participation/intensity on the number of children, CFPS 2018 (adding big-five personality)

	(1)	(2)
Internet use participation	-0.068***	
	(0.023)	
Internet use intensity		-0.030***
		(0.005)
Big five personality		
Conscientiousness	0.039***	0.047***
	(0.014)	(0.014)
Agreeableness	-0.022	-0.027*
	(0.014)	(0.015)
Extraversion	0.023**	0.030**
	(0.012)	(0.013)
Openness	-0.041***	-0.040***
	(0.011)	(0.011)
Neuroticism	0.040***	0.046***
	(0.011)	(0.012)
Mean of dep. var.	1.413	1.274
N	7215	5374
Adjusted R^2	0.498	0.533

Notes: The dependent variable is number of children. The controls are Internet use participation (1 = yes, 0 = no)/intensity (hours/day), big five personality measured 5-point scale (conscientiousness, agreeableness, extraversion, openness and neuroticism), age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, moderate = middle school/high school, high = vocational school/university or higher, with low as the reference), household net income, household size, urban dummy (1 = urban, 0 = rural), and province dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01

Table A9 OLS estimates of the effect of internet use participation on the number of children, CFPS 2014-2018

	(1) 2014	(2) 2016	(3) 2018
Internet use participation	-0.138***	-0.104***	-0.072***
	(0.018)	(0.021)	(0.022)
Age			
30-39	0.145***	0.166***	0.190***
	(0.008)	(0.009)	(0.009)
40-49	-0.148***	-0.180***	-0.225***
	(0.011)	(0.012)	(0.012)
Married/living together	0.493***	0.543***	0.587***
	(0.026)	(0.028)	(0.028)
Employment status	-0.002	0.008	-0.000
	(0.019)	(0.020)	(0.020)
Education			
Moderate	-0.233***	-0.211***	-0.246***
	(0.018)	(0.020)	(0.022)
High	-0.416***	-0.436***	-0.513***
	(0.025)	(0.025)	(0.027)
Ln(household net income)	-0.037***	-0.044***	-0.030***
	(0.007)	(0.008)	(0.004)
Household size	0.123***	0.110***	0.111***
	(0.006)	(0.006)	(0.006)
Urban	-0.128***	-0.113***	-0.091***
	(0.017)	(0.017)	(0.017)
Mean of dep. var.	1.363	1.355	1.412
N	8070	7747	7234
Adjusted R^2	0.534	0.513	0.495

Notes: The dependent variable is the number of children. The controls are internet use participation (1 = yes, 0 = no), age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, moderate = middle school/high school, high = vocational school/university or higher, with low as the reference), household net income, household size, urban dummy (1 = urban, 0 = rural), and province dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. **p*<0.1; ***p*<0.05; ****p*<0.01

Table A10 FE estimates of the effect of internet use participation on the number of children, CFPS 2014-2018

	(1) 2014-2016	(2) 2016-2018
Internet use participation	-0.019**	-0.006
	(0.010)	(0.012)
Age		
30-39	0.222***	0.256***
	(0.018)	(0.021)
40-49	-0.262***	-0.358***
	(0.013)	(0.019)
Married/living together	0.129***	0.159***
	(0.031)	(0.032)
Employment status	-0.051***	-0.050***
	(0.013)	(0.015)
Education		
Moderate	0.100**	0.018
	(0.049)	(0.027)
high	0.017	-0.057
	(0.064)	(0.045)
Ln(household net income)	-0.006*	-0.007*
	(0.004)	(0.004)
Household size	0.058***	0.054***
	(0.006)	(0.006)
Mean of dep. var.	1.359	1.383
N	15817	14981

Notes: The dependent variable is the number of children. The controls are Internet use participation (1 = yes, 0 = no), age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, moderate = middle school/high school, high = vocational school/university or higher, with low as the reference), household net income, household size, year dummies (2014 as the reference year), province dummies (with Beijing as the reference) and province-specific time trends. Individual-level adjusted standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A11 FE estimates effect of Internet use/Internet use intensity on the number of children age, CFPS 2014-2018 (using reproductive-age women aged 16-44)

	(1)	(2)
Internet use participation	-0.020*	
	(0.010)	
Internet use intensity		-0.009***
		(0.003)
Mean of dep. var.	1.258	1.062
N	18105	12159

The dependent variable is the number of children. The controls are internet use participation (1 = yes, 0 = no)/internet use intensity (hours/day), age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, medium = middle school/high school, high = vocational school/university or higher, low as the reference), household net income, household size, urban dummy (1 = urban, 0 = rural), year dummy (2014,2016,2018, 2014 as the reference group), province dummy (Beijing as the reference) and province-specific time trends. Individual-level adjusted standard errors are in parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$

Table A12 FE estimates of the effect of internet use participation/intensity on the number of children, CFPS 2014-2018 (falsification test)

	(1)	(2)
Internet use participation	0.018	
	(0.017)	
Internet use intensity		0.007
		(0.006)
Mean of dep. var.	1.451	1.260
N	6548	1992

The dependent variable is the number of children. The controls are internet use participation (1 = yes, 0 = no)/internet use intensity (hours/day), age and age squared, employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, medium = middle school/high school, high = vocational school/university or higher, low as the reference), household net income, household size, urban dummy (1 = urban, 0 = rural), year dummy (2014,2016,2018, 2014 as the reference group), province dummy (Beijing as the reference) and province-specific time trends. Individual-level adjusted standard errors are in parentheses. **p<0.1, **p<0.05, ***p<0.01*

Table A13 FE estimates of the effect of internet use participation/intensity on the number of children, CFPS 2014-2018 (excluding migration)

	(1)	(2)
Internet use participation	-0.017**	
	(0.008)	
Internet use intensity		-0.009***
		(0.003)
Mean of dep. var.	1.375	1.096
N	21383	12493

Notes: The dependent variable is the number of children born. The controls are internet use participation (1=yes, 0=no)/intensity (hours/day), age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, moderate = middle school/high school, high = vocational school/university or higher, with low as the reference), household net income, household size, year dummies (2014 as the reference year), province dummies (with Beijing as the reference) and province-specific time trends. Individual level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A14 Probit estimates of the effect of internet use participation on importance placed on ancestral lines, CFPS 2014 and 2018

	Probit
Internet use participation	-0.113***
	(0.010)
Age	-0.013***
	(0.004)
Age squared	0.020***
	(0.006)
Married/living together	0.085***
	(0.013)
Employment status	0.026***
	(0.010)
Education	
Moderate	-0.152***
	(0.009)
High	-0.213***
	(0.014)
Ln(household income)	-0.005**
	(0.002)
Household size	0.014***
	(0.002)
Urban	-0.034***
	(0.008)
N	15100
Pseudo R^2	0.144

Notes: The dependent variable is the importance of ancestral line (1=very important/important, 0=otherwise). The controls are internet use participation, age and age squared, married/living together (1 = yes, 0 = no), employment status (1 = employed, 0 = unemployed), education (low = illiterate/primary school, moderate = middle school/high school, high = vocational school/university or higher, with low as the reference), household net income, household size, urban dummy (1 = urban, 0 = rural), year dummies (2014 as the reference year), province dummies (with Beijing as the reference) and province-specific time trends. Marginal effects are reported for importance of ancestral line. Individual level adjusted standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A15 FE estimates of the effect of IU participation on the Baidu Index of induced abortion at the prefecture-level city, CFPS 2014-2018

	Induced abortion
Internet use participation	0.106*
	(0.055)
N	368

Notes: The dependent variable is the Baidu Index of induced abortion at the prefecture-level city. The controls are the share of internet use at the prefecture-level city, age groups (share of reproductive-age women aged 16-29, 30-39, and 40-49), marital status (share of being married), education (share of having illiterate/primary school, middle school/high school, and vocational school/university or higher), year dummies (2014 as the reference year), prefecture-level city dummies and prefecture-level city-specific time trends. Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$