The effect of broadband internet on children's weight: Evidence from China

Weisong Cheng[†,1] **and Hao Xu**[‡,*,1]

Abstract: This study employs ten-wave data from the China Health and Nutrition Survey (CHNS), covering the period from 1989 to 2015. It leverages the nationwide internet speed upgrading project launched in the early 21st century as an exogenous shock. Using this variation, we construct a difference-in-differences model to identify the causal effect of broadband internet access on children's weight outcomes. The results show that broadband internet significantly increases the probability of children being overweight. Robustness tests support these results. The heterogeneity analysis reveals that the weights of children who are older and in urban are more affected by broadband internet. Mechanism analysis reveals that broadband internet increases children's sedentary game activities time, decreases their physical activities time, and increases their snack intake and total energy intake. This study underscores the significance of coordinated regulation of children's gaming activities by parents, schools, communities, and the government, in order to effectively reduce children's online game time, mitigate the risk of overweight, and alleviate the economic burden associated with childhood overweight.

Keywords: Broadband internet; Children's weight; Health

JEL Classification Codes: I12; I18; D80

[†] Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai, China

[‡] Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai, China

[*] Corresponding author at: Antai College of Economics and Management, Shanghai Jiao Tong University, No.1954 Huashan Road, 200030, Shanghai, China.

[1] All authors contributed equally and are listed alphabetically.

1 Introduction

Obesity is a disease stemming from excessive fat accumulation, frequently resulting in abnormal weight gain and associated health risks. In China, one-fifth of children are overweight or obese (Wang et al., 2021). According to estimates of the Global Burden of Disease Study, the number of overweight and obese children in China ranked first in the world as early as 2015 (Collaborators, 2017). As an early onset of obesity, childhood obesity directly increases the likelihood of developing various diseases, such as adult obesity, early atherosclerosis, hypertension, type 2 diabetes, and fatty liver (Bass & Eneli, 2015; Kotani et al., 1997). It also harms children's social skills and mental health (Förster et al., 2023) and has serious adverse effects on children's education level, skill development, and their adult income (Cawley & Spiess, 2008; Fan et al., 2023; Hamilton et al., 2018).

Therefore, many studies have focused on and tried to discuss the causes of childhood obesity. Physiologically, obesity arises from an increase in energy intake and a decrease in physical activity, leading to a positive energy balance (Hall et al., 2022), a process that results from individual behavior. In recent years, the issue of childhood overweight and obesity has evolved into a societal epidemic, prompting researchers to shift their focus to rapidly changing economic, social, and familial determinants (Dolton & Tafesse, 2022; Nieto & Suhrcke, 2021; Zhang et al., 2020), such as the penetration of the broadband internet into households (Chen & Liu, 2022; DiNardi et al., 2019). The broadband internet represents a significant technological innovation, with numerous studies investigating its impact on productivity and the labor market (Akerman et al., 2015; Hjort & Poulsen, 2019), as well as its potential effects on children's mental health (McDool et al., 2020). However, to the best of our knowledge, few studies have examined the causal effects of the broadband internet on children's weight.

Broadband internet has had a major impact on production and lifestyle. On the one hand, broadband internet has expanded the sources of information access and improved the efficiency of information acquisition, thereby enhancing overall social welfare. On the other hand, the widespread use of broadband internet has led to an increase in computer usage time, which may raise the risk of developing diseases associated with prolonged sedentary behavior, such as obesity, thereby increasing health costs. Existing studies on the effect of broadband internet on body weight have focused mainly on adults but have not reached consistent conclusions (Chen & Liu, 2022; DiNardi et al., 2019). Fewer studies have focused on the causal effect of broadband internet on children's weight. Unlike adults, who primarily use the internet for information acquisition and learning assistance, children are more likely to engage in recreational activities online, spending considerable time playing online games (Malamud & Pop-Eleches, 2011; McDool et al., 2020), and may even develop internet gaming disorder as a result (Paulus et al., 2018). This implies that the time children spend sitting in front of computers will significantly increase, potentially displacing physical activity time and thereby increasing the risk of weight gain. Additionally, experimental studies have shown that the competitive nature of online games can increase players' stress levels, and individuals may consume more sugary snacks to alleviate this stress (Siervo et al., 2018), potentially leading to excessive energy intake and increasing the risk of being overweight.

However, broadband internet may also enhance parents' access to health information and influence their health behaviors, potentially leading to restrictions on children's activities and dietary content, thereby reducing the risk of being overweight. Consequently, the direction of broadband internet's impact on children's weight remains indeterminate. While numerous studies have found a correlation between internet usage and children's weight (Aghasi et al., 2020; Bozkurt et al., 2018), few have delved into the causal impact of the internet on children's weight and the mechanisms behind it. This paper uses the exogenous shock of the internet speed upgrading project in China to identify the causal effect of broadband internet on the weight of children.

The potential endogeneity of internet use poses challenges in identifying the causal impact of broadband internet on children's weight. Cities with higher levels of economic development have more opportunities to be early adopters of the internet, and the existence of the income-health gradient may lead to biased estimation results. To address this potential challenge, this study uses the exogenous impact of the internet speed upgrading project in China to overcome potential endogeneity. The main content of the internet speed upgrading project was the construction of three national internet exchange (IX) centers between 2000 and 2001. The establishment of these IX centers enabled interconnection among the six major backbone networks nationwide and increased the bandwidth between these backbone networks from less than 10 Mbps to 100 Mbps. The significant improvement in the connectivity and transmission efficiency between the backbone networks has greatly stimulated residents, especially teenagers, in their interest and usage of the internet and computers. Between 2000 and 2002, China's internet user base grew from 8.9 million to 33.7 million. The share of users aged 18 or younger within this population increased from 2.4% in 2000 to 15.3% in 2002. Simultaneously, China's online gaming industry experienced rapid growth, with its market value rising from $37 million in 2001 to $708 million in 2005 (Kim & Kang, 2021).

Concurrently, the widespread adoption of Asymmetric Digital Subscriber Line (ADSL) technology has bridged the final mile for broadband internet usage. This technology leverages digital coding to extract maximum data transmission capacity from copper telephone lines, boosting download speeds for internet users from 10kb/s to 512kb/s, and has also led to a sharp decline in internet prices (Yu et al., 2023). ADSL technology uses frequencies outside of those used for voice transmission to transmit data, allowing users to browse the internet and make phone calls or send faxes simultaneously without reducing the speed of downloading content. Since the network transmission medium is the existing landline telephone line, this paper constructs an identification strategy based on the fact that areas with a higher number of landline telephones are more affected by the internet speed upgrading project in China. Similar identification strategies have been widely used in numerous studies (Chen & Liu, 2022; Chen et al., 2020; Czernich et al., 2011; Falck et al., 2014). Accordingly, this paper employs a difference-in-differences model to examine the changes in children's weight in areas more significantly impacted by the project compared to those less affected after the project's implementation.

According to the results of the analysis, we find that broadband internet significantly increased children's weight. After the implementation of the internet speed upgrading project, a one standard deviation increase in the level of internet infrastructure development will lead to a significant 14.14 percentage point increase in the probability of children being overweight. Our conclusions may be more applicable to urban areas due to the significant gap in internet infrastructure between urban and rural regions. We further discuss the causal mechanisms through which broadband internet affects children's weight from the perspectives of physical activities and dietary intake: The results show that, on one hand, broadband internet increases the time children spend on sedentary gaming activities and reduces their time spent on physical activities, which lower their energy expenditure levels and disrupt the balance between energy expenditure and intake; on the other hand, broadband internet increases children's snack intake and total energy intake, which widen the positive energy balance gap and further increase the risk of children becoming overweight. Additionally, we do not find empirical evidence to support the notion that broadband internet increases parents' access to health information and influences their health behaviors. Our heterogeneity analysis indicates that children in urban areas and those who are older are more likely to become overweight due to broadband internet, providing additional evidence for the relationship between children's health and income levels.

Our paper contributes to the literature on the relationship between the internet and health, particularly supplementing the literature on the impact of the internet on children's weight. Two closely related studies are Chen and Liu (2022) and DiNardi et al. (2019). Compared to these studies, our research offers the following contributions: Firstly, Chen and Liu (2022) employed a similar identification strategy to examine the impact of broadband internet on adult body weight in China. They found that broadband internet reduced the probability of being overweight among adults by increasing income and health information. Contrary to their findings, our research indicates that broadband internet increases both the probability and duration of children's engagement in online gaming activities, thereby escalating the risk of childhood overweight. This may be related to immature brain development and weaker self-control in children (Casey, 2015; Casey & Caudle, 2013), making them more susceptible to the adverse impacts of the internet.

Secondly, DiNardi et al. (2019) examined the impact of internet access on adult body weight in the United States by leveraging changes in county-level broadband coverage. In their analysis of mechanisms, they found changes in health behaviors, such as increases in physical exercise, excessive drinking, and smoking. However, the authors did not specify the exact reasons for these changes in health behaviors. They only suggestively pointed to factors such as prolonged sedentary time in front of computers, exposure to low-quality health information, and expanded social networks as potential influences on adults' health behavior changes. Contrary to their study, we explicitly identify children's engagement in online gaming as the primary mechanism through which the internet affects children's body weight. We further examine the behavioral changes, including increased sedentary game time, decreased physical activity time, and increased snack consumption, thereby enriching the literature on the internet's impact on children's body weight.

This paper also contributes to the literature on the health behavioral factors associated with childhood overweight. Many studies have found a positive correlation between the internet and children's weight, but due to endogeneity issues, they failed to provide strong causal evidence (Aghasi et al., 2020). Therefore, this paper uses the internet speed upgrading project as an exogenous shock to provide causal evidence on the impact of broadband internet on children's weight. It explores the causal mechanisms from the perspectives of changes in physical activities and dietary patterns. The observed actual changes in reduced physical activities, increased snack intake, and higher energy consumption among children provide empirical evidence for the energy balance model of obesity, thereby contributing theoretically to this body of literature.

The rest of this paper is organized as follows. Section 2 provides an overview of the institutional background and a literature review. Section 3 outlines the conceptual framework. Section 4 presents the empirical strategy and data used in this study. Section 5 reports the baseline results, while Section 6 discusses the robustness checks. Section 7 explores the results of the heterogeneity analysis, and Section 8 examines the potential mechanisms. Section 9 assesses the economic burden associated with increased childhood overweight rates due to broadband internet access. Finally, Section 10 concludes the paper.

2 Institutional background and literature review

2.1 Institutional background

As early as 1989, China began the construction of its internet infrastructure. By 2000, China had six backbone networks, within which users could quickly search for and exchange information. However, between these backbone networks, the speed of information transmission was significantly low. A reliable way to enhance the connections between backbone networks was to construct internet exchange (IX) centers, which, as physical nodes between networks, could reduce the portion of internet traffic that had to be transmitted through upstream providers, thereby reducing latency and increasing the speed of information transmission between networks. Although the Chinese government proposed the establishment of information exchange centers nationwide as early as 1997, the plan was not implemented promptly due to disagreements over the distribution of interests.

In 2000, Premier Zhu Rongji's personal supervision led to the operation of the first national IX in Beijing, which immediately significantly increased the speed of information exchange between backbone networks. By the end of 2001, the Chinese government had completed the construction of two more national IX centers in Shanghai and Guangzhou. The completion and operation of these three IX centers were the main components of the internet speed upgrading project in China at the beginning of the 21st century. The implementation of this project increased the bandwidth between backbone networks from less than 10 Mbps to 100 Mbps, greatly improving the efficiency of information transmission between networks.

Although the construction of internet exchange centers has overall improved internet access speeds in China, different cities have experienced varying impacts from the speed enhancement project due to differing internet infrastructure conditions. During the same period that the internet speed upgrading project was being implemented, Asymmetric Digital Subscriber Line (ADSL) technology was gaining widespread use. ADSL technology is a type of broadband internet technology that is referred to as "asymmetric" because its download speeds are faster than its upload speeds. This technology utilized digital encoding techniques to maximize data transmission capacity over copper landline telephone lines, increasing the download speed for network users from 10 kb/s to 512 kb/s, thereby bridging the last mile for broadband internet usage.

ADSL technology uses frequencies outside the range of voice transmission to transfer data, allowing users to browse the internet while simultaneously making phone calls or sending faxes. This not only ensures the full utilization of the telephone line but also enhances internet speeds. It is worth noting that ADSL technology is still built on existing landline telephone infrastructure. Given that the network transmission medium during this period was the existing copper landline telephone lines, we use the landline telephone penetration rate from 1999, the year before the implementation of the internet speed upgrading project in China, to represent the internet infrastructure conditions at the city level in our empirical analysis. This indicator is calculated as the ratio of landline telephone users to the total population of a city. Figure 1 shows the geographical distribution of landline telephone penetration rates in mainland Chinese cities in 1999. Similar strategies have been widely employed in numerous studies (Chen & Liu, 2022; Chen et al., 2020).

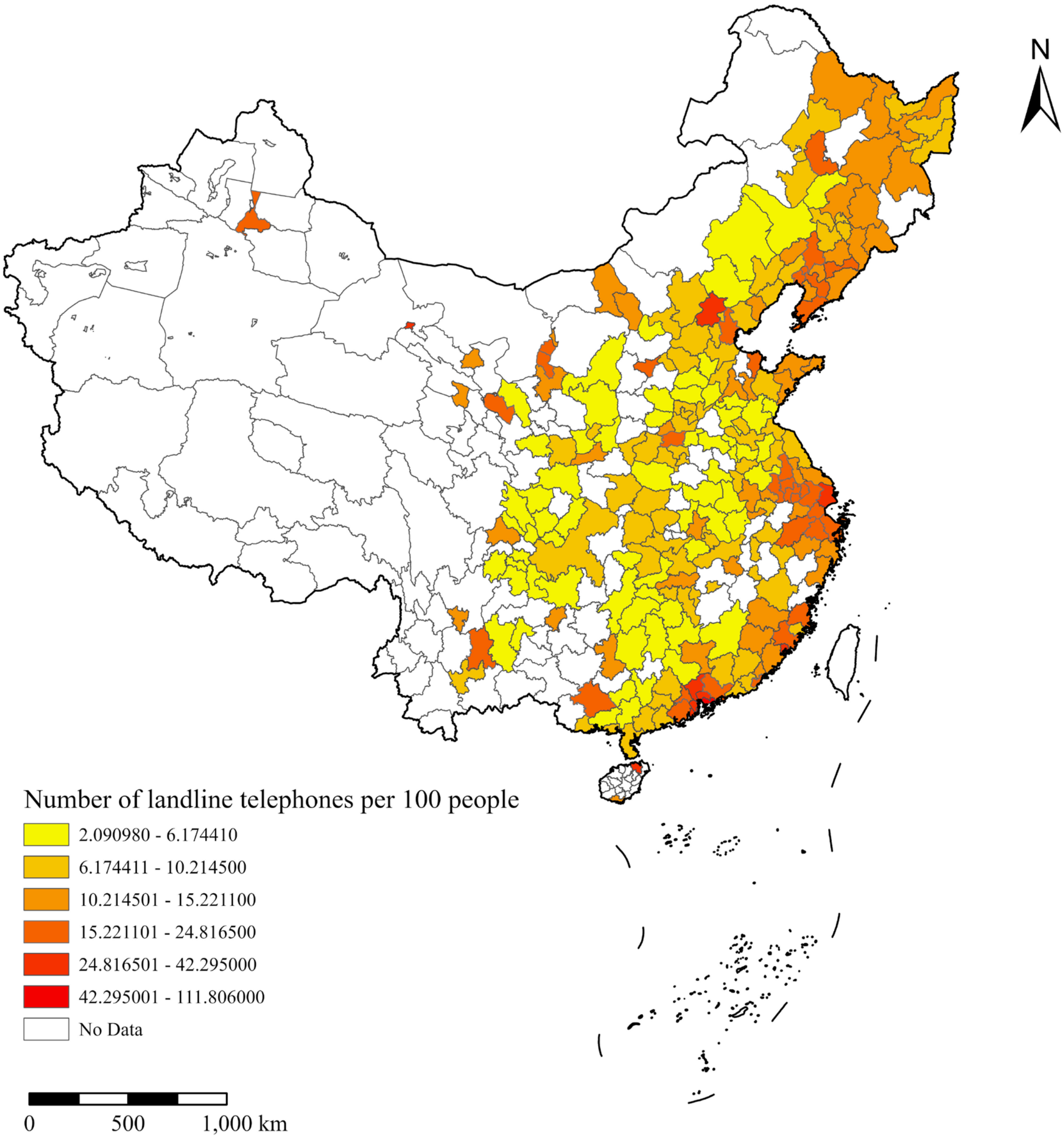

Figure 1. Landline telephone penetration rates by cities in 1999

Notes: This figure illustrates the geographical distribution of landline telephone penetration rates in 1999 for cities in mainland China. Darker colors indicate higher landline telephone penetration rates. Data source: The China City Statistical Yearbook 2000.

2.2 Literature review

Broadband internet is one of the most significant transformations of the 21st century. Extensive research has focused on the impact of broadband internet on productivity, employment, and income (Akerman et al., 2015; Hjort & Poulsen, 2019). It has been found that broadband internet not only increases productivity but also boosts people's incomes (Zuo, 2021). However, little is known about the impact of broadband internet on health. Some studies have found potential adverse effects of broadband internet on health, suggesting that it may lead to unfavorable social comparisons, thereby increasing depression and anxiety (McNamee et al., 2021; Russell-Mayhew et al., 2012). It may also increase sedentary time, thereby promoting obesity (DiNardi et al., 2019). Despite this, other studies have found contrary evidence, showing that internet access can improve overweight conditions through increased income and health information (Chen & Liu, 2022). However, most of these studies have focused on adults, and research on children's health is still scarce. Unlike adults, children are more likely to engage in online entertainment activities, such as playing online games, rather than acquiring information. This could have serious adverse effects on children's health, such as overweight, obesity, and internet addiction.

Compared to other traditionally recognized factors causing childhood overweight and obesity, broadband internet is the latest risk factor to gain attention. Previous studies have attributed childhood overweight and obesity to maternal employment, the introduction of fast food, ultra-processed foods, and the advent of television (Asirvatham et al., 2019; Gwozdz et al., 2013; MacInnis & Rausser, 2005; Nieto & Suhrcke, 2021). Among these, television is similar in nature to broadband internet, as both are major factors influencing children's screen time. However, unlike television, which only allows passive information reception, computers connected to broadband internet enable children to interact with screen devices, making broadband internet far more attractive to children than television.

Numerous studies have already found a close correlation between broadband internet or computers and children's weight (Bozkurt et al., 2018; Ning et al., 2024; Vandelanotte et al., 2009). Increased computer time, particularly time spent on computer games, strongly predicts weight gain in children. After the introduction of broadband internet, the increased computer time led to a reallocation of various activities for children, thereby encroaching on their physical exercise time and reducing their energy expenditure. Additionally, children may experience tension and stress while playing computer games, prompting them to consume more food, especially high-sugar snacks and drinks, to alleviate this stress. As a result, children's weight increased significantly after the introduction of broadband internet. Although numerous studies have found a correlation between broadband internet and children's weight, research on the causality between the two is still scarce. Therefore, this paper utilizes the exogenous shock of the internet speed upgrading project in China, which began in 2000, to identify the causal impact of broadband internet on the weight of Chinese children.

3 Conceptual framework

In recent years, broadband internet has significantly transformed the ways in which children and families access information, allocate their time, and participate in social activities. These transformations in the external environment may influence children's weight status through multiple behavioral and economic channels, including altered daily activity patterns, changes in dietary intake, access to health-related information, and increases in household income. To systematically analyze these potential mechanisms, we develop a conceptual framework to clarify the effect of broadband internet on children's weight and its underlying transmission pathways. Specifically, we first propose a general hypothesis concerning the effect based on conceptual analysis. We then examine potential heterogeneity in this effect across age groups and between urban and rural areas. Finally, we focus on four key mechanisms: time use, dietary intake, information access, and income channels.

3.1 The effect of broadband internet access on children's body weight

Broadband internet access may influence children's body weight through multiple mechanisms operating in opposite directions, leading to theoretical ambiguity regarding its effect. On the one hand, access to highly engaging digital entertainment content encourages children to spend extended periods in front of screens, reducing the time available for physical activity and promoting sedentary behavior. This reduction in physical activity and daily energy expenditure increases the likelihood of weight gain (DiNardi et al., 2019). Moreover, extended screen exposure may trigger mindless eating and emotional eating behaviors, resulting in higher caloric intake and further elevating the risk of overweight (Luo et al., 2018).

On the other hand, broadband internet also provides families with greater access to health and economic information (Chen & Liu, 2022). Parents who are better informed about health-related knowledge are more likely to adopt improved parenting practices, including the use of nutritional guidance and health management tools, thereby reducing the risk of childhood overweight (Ullmann et al., 2018). In addition, access to economic information may help parents expand income sources and increase their capacity to invest in health-related goods, which in turn supports healthier weight outcomes for their children (DiNardi et al., 2019).

Although the above mechanisms may work in opposite directions and lead to uncertainty about the theoretical effect of broadband internet on children's weight, the impact is likely shaped by contextual factors. In the early stages of broadband rollout in developing countries, limited parental education and low levels of digital literacy often constrain families' ability to access and effectively utilize health and economic information (Lou et al., 2024). In contrast, the highly engaging nature of digital entertainment rapidly alters children's daily activity patterns. Existing studies have shown that, in the absence of proper guidance and supervision, internet use is closely associated with unhealthy eating habits and sedentary behavior among children (Ning et al., 2024; Phelps et al., 2024). Therefore, under such conditions, the influence of broadband internet on childhood overweight is likely to be more pronounced and potentially dominant.

Accordingly, we propose the following general hypothesis:

H1: Broadband internet access leads to an increase in children's body weight.

3.2 The heterogeneity effect of broadband internet access on children's body weight

Given that children's ability to use the internet varies by age (Yan, 2005), and that the quality of internet infrastructure differs significantly between urban and rural areas (Nie & Wan, 2023), the impact of broadband internet on children's body weight is likely to be heterogeneous across age groups and between urban and rural areas.

First, as children grow older, their ability to use the internet and their behavioral autonomy increase significantly. Younger children, due to cognitive and operational limitations, often have restricted and supervised access to online content, making their daily routines less responsive to internet availability (Paulus et al., 2018). In contrast, older children are not only more proficient in using digital devices but also enjoy greater autonomy in their internet use, making them more likely to develop immersive usage habits. As a result, they are more susceptible to increased sedentary time and food intake following internet access, which in turn elevates their risk of becoming overweight.

Second, there are significant disparities in infrastructure quality between urban and rural areas. Urban regions typically enjoy higher-quality broadband services and more advanced digital devices, enabling faster and more stable internet connections. These conditions are more conducive to prolonged online entertainment activities such as gaming and video streaming. As a result, internet access is more likely to trigger excessive screen time, sedentary behavior, and overeating among urban children, thereby increasing their risk of becoming overweight. In contrast, limited hardware availability and insufficient network coverage in rural areas impose greater constraints on children's internet use. Consequently, their behavioral responses to internet access are weaker, and the associated increase in overweight risk is comparatively smaller.

Building on these differences, we further propose two hypotheses regarding heterogeneity:

H1a: The impact of broadband internet access on children's body weight is more pronounced among older children.

H1b: The effect of broadband internet access on children's body weight is more pronounced in urban areas.

3.3 The mechanisms of broadband internet access on children's body weight

3.3.1 Time use patterns

Existing literature on the impact of broadband internet on body weight has predominantly focused on adults, building on the rational decision-making framework (DiNardi et al., 2019). These studies generally assume that adults, under budget constraints and information asymmetries, are capable of optimizing their utility through cost-benefit analysis and rational choices. Under this paradigm, broadband access is expected to promote welfare-enhancing behaviors, such as maintaining a healthy weight, by expanding access to health-related information (Chen & Liu, 2022). However, this analytical framework does not readily apply to children due to fundamental differences in cognitive development. Children are in a developmental trajectory from infancy to adulthood, with incomplete rationality, patience, and independence. They still rely on parental guidance and support (Lundberg et al., 2009). Assuming children as fully rational decision-makers would be misleading. A substantial body of experimental economics literature suggests that, compared to adults, children are more egocentric, less patient, and more risk-tolerant (Sutter et al., 2019). This makes them more susceptible to addictive behaviors, such as internet gaming. Following broadband internet access, many children substitute their prior activities—such as watching television or outdoor exercise—with internet use and online gaming. When online gaming merely substitutes for other sedentary activities such as television viewing, the effect on physical activity intensity may be negligible. However, if internet use displaces more vigorous activities such as running or swimming, the overall intensity of physical activity declines. Holding other factors constant, this behavioral substitution is expected to significantly increase the risk of weight gain among children.

H2: Broadband internet access increases children’s body weight by substituting physical activity with online gaming.

3.3.2 Dietary intake

Beyond time use patterns, increased food consumption is another key channel through which broadband internet access may contribute to childhood weight gain. First, internet access may lead to prolonged sedentary behavior among children. Experimental evidence suggests that sedentary activities enhance the brain's responsiveness to food-related cues, which in turn induces higher food intake (Luo et al., 2018). Further, Siervo et al. (2018) find that playing video games significantly elevates heart rate and blood pressure. To meet the body's additional energy demands under stress, children may exhibit an adaptive eating response, increasing their consumption of high-energy-dense foods such as sweets and sugary beverages.

Additionally, research suggests that screen-based activities can distract individuals (Marsh et al., 2013). While browsing websites or playing online games, children may become less attentive to their habitual control over food intake. This implies that eating while engaged in digital activities may reduce satiety, leading to unintentional overeating.

Beyond sedentary behavior, broadband internet also increases children's exposure to food advertisements, which have been shown to influence dietary consumption and preferences. Food advertising is not only positively associated with higher food intake (Russell et al., 2019) but also linked to lower fruit and vegetable consumption (Boynton-Jarrett et al., 2003). Therefore, broadband internet access may also increase children’s food intake, which in turn elevates the risk of overweight and obesity.

H3: Broadband internet access increases children’s body weight by raising their food consumption.

3.3.3 Information channels

Broadband internet access significantly expands the avenues for health information dissemination, allowing individuals to search for a wealth of health-related knowledge at minimal cost. While it is reasonable to assume that greater access to health information improves overall health outcomes (Chen & Liu, 2022), children, who remain under parental supervision, have limited autonomy in their health-related behaviors. Consequently, the primary impact of broadband internet on children's health is mediated through parental influence.

First, parents who gain access to more health information are likely to improve their own health behaviors, serving as role models for their children. Take dietary habits as an example: while diverse food choices provide greater nutritional opportunities, they also pose dietary risks. Given these complexities, children rely on observational learning to assess potential food-related risks. The most straightforward approach is imitation—children develop their dietary patterns by observing parental food choices and consumption behaviors, which establish implicit dietary norms (Larsen et al., 2015). Thus, if parents modify their dietary habits, their children are likely to follow suit.

Second, parents may actively seek out child-specific health information, directly influencing their children's well-being by optimizing caregiving practices. A meta-analysis found that the majority of parents have searched for general health information online at least once on behalf of their children and have used the retrieved information to make health-related decisions (Kubb & Foran, 2020).

Third, broadband internet access enables parents to engage with various health intervention programs and digital health management tools, enhancing their ability to oversee their children's health. A study examining web-based tools designed to help parents assess their children's obesity risk found that these online platforms and applications quickly gained widespread adoption and had a significant impact within local communities (Ullmann et al., 2018). Therefore, we hypothesize that broadband Internet access enables parents to obtain more health-related information and knowledge, which in turn has a significant positive effect on maintaining a healthy body weight in children.

H4: Broadband internet access mitigates the potential negative impact on children's body weight gain by enhancing parental access to health information and knowledge.

3.3.4 Income channels

Extensive research has demonstrated the significant positive effects of broadband internet access on productivity, employment, and income growth (Akerman et al., 2015; Hjort & Poulsen, 2019; Zuo, 2021). The increased availability of information following broadband adoption not only improves job matching for workers and optimizes production decisions, but also expands markets for goods and services, thereby contributing to higher levels of wage, business, and property income at the household level. A substantial body of economic literature has also documented the positive correlation between income and health (DiNardi et al., 2019), arguing that as income rises and budget constraints loosen, individuals tend to spend more on health-related goods and services, thereby achieving higher levels of well-being for both themselves and their children. For instance, with rising income, households tend to consume more nutritious food, fitness services, and regular medical checkups, all of which help maintain a healthy body weight. Consequently, increased household income resulting from broadband internet access may help children maintain a healthy weight.

H5: Broadband internet access mitigates the potential negative impact on children's body weight gain by increasing household income.

3.4 Summary

In sum, broadband internet access exerts a significant influence on children's body weight. Moreover, this impact is likely to be heterogeneous across age groups and between urban and rural areas, reflecting differences in internet usage ability and infrastructure quality. Furthermore, the effect may operate through four primary mechanisms: time allocation, dietary intake, information access, and income channels. These mechanisms may work in opposing directions, potentially offsetting one another and complicating theoretical predictions. To identify the effect of broadband internet and explore the underlying mechanisms, we exploit the exogenous variation introduced by the internet speed upgrading project in China to systematically test the proposed hypotheses.

4 Empirical strategy and data sources

4.1 Empirical strategy

In the early 21st century, ADSL technology replaced dial-up as the most commonly used home broadband internet technology, significantly enhancing data transmission speeds compared to the latter. Within the internet speed upgrading project in China, the construction of internet exchange centers greatly increased the bandwidth between backbone networks, while the 'last mile' of home networks determined the intensity of the project's impact. In other words, since ADSL technology uses landline telephone lines for internet access, cities with higher landline telephone penetration rates experienced stronger impacts after the project. Additionally, as the China Internet Network Information Center (CNNIC) reported in 2000 that only 3.49% of users accessed the internet via mobile devices, we do not need to worry about confounding effects from other internet tools.

Our empirical strategy leverages the basic fact that cities with higher landline telephone penetration rates were more affected by the internet speed upgrading project to observe the causal impact of broadband internet on children's weight. In our empirical analysis, we use the landline telephone penetration rate in 1999 as the treatment variable at the city level. Specifically, landline telephone penetration rate refers to the number of landline telephones per 100 people. We use the landline telephone penetration rate to measure the intensity of the project impact and construct a difference-in-differences model, with the baseline specification as follows:

$$Y_{i,c,t} = \alpha + \beta Landline_{c,1999} \times After_t + X'_{i,c,t}\gamma + \delta_i + \theta_t + (\mathrm{W}_{\mathrm{c},1999} \times After_{\mathrm{t}})'\eta + \epsilon_{i,c,t} \tag{1}$$

where i, c, and t represent the individual, city, and survey wave, respectively. $Y_{i,c,t}$ indicates the outcome variable for child i in city c at wave t. $Landline_{c,1999}$ represents the level of the internet infrastructure, which is measured by the landline telephone penetration rate in city c. $After_t$ is a dummy variable representing the implementation of the project, coded as 1 if the survey wave is in 2001 or later, and 0 otherwise. β is the coefficient of interest, which captures the causal effect of broadband internet on the outcome variable. $X'_{i,c,t}$ is a vector containing control variables at the individual level and family level, including age and family size. δ_i and θ_t represent the individual fixed effects and wave fixed effects, respectively, absorbing non-time-varying individual characteristics and time-varying macroeconomic shocks. Considering that the landline telephone penetration rate may be influenced by urban socioeconomic factors, we also control for the initial socioeconomic characteristics of cities, following the approach of Li et al. (2016). $W_{c,1999}$ is a vector containing socioeconomic characteristics at the city level, and its interaction with $After_t$ is used to control for the impact of initial urban socioeconomic characteristics. $\epsilon_{i,c,t}$ is a random error term clustered at the city-wave level.

Additionally, we have undertaken a series of measures to test the validity of our identification strategy. These include event analysis, substituting alternative measures of children's weight, replacing internet infrastructure conditions, controlling for city characteristics, and conducting placebo tests. The specific results of these tests will be detailed in Section 5 and Section 6.

4.2 Data sources

This study utilizes two primary data sources: the China City Statistical Yearbook and the China Health and Nutrition Survey (CHNS). City-level socioeconomic characteristics are derived from the

China City Statistical Yearbook, compiled by the National Bureau of Statistics of China. This dataset offers comprehensive information on the socioeconomic conditions of all prefecture-level cities across China since 1985.

Data on children's health are drawn from the CHNS, a collaborative longitudinal survey conducted by the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Center for Disease Control and Prevention. The survey has been carried out in ten waves (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015), covering provinces with diverse economic, social, and health profiles. The sample expanded from 9 provinces in 1989 to 15 provinces in 2015.

The CHNS employs a multistage, random cluster sampling strategy. In each selected province, four counties and two cities are randomly chosen, followed by the random selection of villages and urban communities within them. From each village or community, 20 households are randomly sampled. By the 2015 wave, the CHNS covered over 30,000 individuals across approximately 7,200 households. The sample used in this study includes all children aged 2 to 17 years.

4.3 Variable definition

4.3.1. Outcome Variables

Our primary outcome of interest is the incidence of overweight. Overweight and obesity are typically defined as having excessive body fat, but body fat is difficult to measure directly. Based on existing studies (Gwozdz et al., 2013; Zhang et al., 2020), we use anthropometric methods to measure obesity. Specifically, according to the World Health Organization's Child Growth Standards (Organization, 2006), we define children whose Body Mass Index (BMI) is greater than or equal to 1 standard deviation above the reference for their age and sex as overweight and those whose BMI is greater than or equal to 2 standard deviations above the reference as obese. This allows us to construct binary variables for overweight and obesity. Surveyors from the China Health and Nutrition Survey used professional portable equipment to measure the height and weight of each member of the surveyed households. Using these measurements, we can calculate each child's BMI, which is defined as BMI = weight/height squared. Additionally, we consider two alternative indicators of children's weight: the BMI-for-age Z-score (BMIAZ) and the weight-for-age Z-score (WAZ). The calculation of these two indicators is specified below.

Based on the body mass index, we use the LMS method to calculate each child's BMI Z-score (BMIAZ) as an additional measure of obesity (Tim et al., 2000). Simply put, the BMI Z-score is obtained by comparing each child's BMI to the reference BMI median in the World Health Organization's child growth charts. Children with a BMI above the median have a BMI Z-score greater than 0, and those below have a score less than 0. Specifically, the BMI Z-score is calculated using the following formula:

$$BMIAZ = [(BMI/M)^L - 1] \div (L \times S) \tag{2}$$

where BMI refers to each child's body mass index, M refers to the reference BMI median in the child growth charts, L refers to the distribution skewness of BMI for each age group in the child growth charts, and S refers to the coefficient of variation of BMI for each age group in the child growth charts. If a child's BMI is significantly larger than the reference BMI median in the child growth charts, then $(BMI/M)^L$ approaches 0, and the maximum value of BMIAZ could be $(-1) \div (L \times S)$.

We also use the same method to calculate the weight-for-age Z-score (WAZ) as another additional measure of obesity. Essentially, it refers to the number of standard deviations a child's weight deviates from the median weight of healthy children of the same age and gender. Simply put, the weight-for-age Z-score is obtained by comparing each child's weight to the reference weight median in the child growth charts, grouped by age. Children with a weight above the median have a weight-for-age Z-score greater than 0, and those below have a score less than 0. Specifically, the weight-for-age Z-score is calculated using the following formula:

$$WAZ_i = [(\text{ Weight } /M)^L - 1] \div (L \times S) = \frac{(w - w_m)}{\sigma} \tag{3}$$

where WAZ refers to the weight-for-age Z-score, Weight refers to each child's weight, M refers to the reference weight median in the child growth charts, L refers to the distribution skewness of weight for each age group in the child growth charts, and S refers to the coefficient of variation of weight for each age group in the child growth charts. w refers to the child's weight, w_m refers to the reference weight median in the child growth charts, and σ refers to the reference weight standard deviation in the child growth charts.

These indicators and calculation methods have been widely used in numerous studies (Carneiro et al., 2021; Guo et al., 2022; Zhang et al., 2020).

4.3.2. Treatment Variable

We extract data on landline telephone penetration in 1999 from the China City Statistical Yearbook to serve as a proxy for city-level internet infrastructure. Specifically, landline telephone penetration is defined as the number of landline telephones per 100 residents.

4.3.3. Control Variables

Children's weight is significantly influenced by both individual and family factors. The growth of children exhibits changes with age, and the size of the family affects the allocation of resources to each child by parents (Dasgupta & Solomon, 2018). Therefore, we include the child's age as a control variable at the individual level and the family size as a control variable at the family level.

To account for potential confounding effects arising from other city-level characteristics, we include three categories of control variables in the baseline specification: per capita GDP, industrial structure (measured as the ratio of tertiary industry output to secondary industry output), and population density.

It is worth noting that gender is not included as a control variable, as the baseline specification incorporates individual fixed effects, which absorb all time-invariant individual characteristics.

4.3.4. Mechanism Variables

To explore the potential mechanisms through which broadband internet affects children's weight, we focus on four key areas: time allocation, food consumption, access to health information, and household income. Specifically, broadband internet may influence children's weight by altering their activity patterns, dietary habits, parents' health information, and family income levels. The following sections detail the variables used to test each mechanism and their respective measurement methods.

Time Allocation. In terms of time allocation, we are primarily concerned with the overall changes in sedentary and physical activities following broadband internet access. We summarize all types of sedentary and physical activities to examine changes in these variables: (1) whether the child engaged in sedentary activities during a typical week and the total time spent on sedentary activities per week, and (2) whether the child engaged in physical activities during a typical week and the total time spent on physical activities per week. We also examine the changes in specific types of sedentary activities, focusing on three key variables: (1) whether the child engaged in TV watching during a typical week and the total time spent on watching TV per week; (2) whether the child engaged in reading and doing homework during a typical week and the total time spent on these activities per week; and (3) whether the child engaged in sedentary game activities during a typical week and the total time spent on such activities per week. Notably, sedentary game activities include playing video games, playing with toy cars, and playing board games. We expect broadband internet to significantly increase children's engagement in online gaming activities while reducing their physical activities. We provide evidence by comparing changes before and after the broadband program. To measure children's activity time, we rely on self-reported data. Respondents (children aged 10 and above, or their parents for children under 10) are asked, "How much time do you spend on each activity during a typical day?" Respondents report their activity times separately for weekdays (Monday to Friday) and weekends (Saturday and Sunday). We calculate weekly activity time by multiplying the weekday activity time by 5 and the weekend time by 2. Given that these measures rely on self-reports, they may be subject to measurement error.

Food Consumption. Regarding food intake, we primarily focus on two sets of results: snack intake and intake of vegetables and fruits. Firstly, considering the potential correlation between playing online games and children's snack intake (Siervo et al., 2018), we consider two sets of variables regarding snack intake: (1) Whether snacks were consumed daily, the frequency of snack intake daily, and the total energy intake daily. (2) The average daily intake of Ethnic food and cake and the average daily intake of beverages. Secondly, considering that internet use might also increase the likelihood of children adopting a healthy diet through parental knowledge of nutrition, we also examine the changes in the average daily intake of vegetables and fruits by children (Loewenstein et al., 2016). To measure food consumption, data is collected through interviews with respondents (children aged 10 and above, or their parents for younger children). Interviewers visit the household for three consecutive days, recording the respondent's food consumption using the 24-hour recall method. The average daily food intake over the three days is calculated. Additionally, we match children's food consumption data with the "Chinese Food Composition Table" to calculate the caloric content of each food item, enabling us to determine the total average daily caloric intake over the three-day period. Since these data are self-reported, measurement error is also a possibility.[1]

[1] It should be noted that although data on children's activity time and food intake are derived from survey questionnaires and may be subject to measurement error, these variables serve as dependent variables in this study. As such, their

Parental Health Information. To assess the influence of parental health information, we also examine whether the health behaviors of children's fathers and mothers have changed. Following the approach of Chen and Liu (2022), by examining changes in adults' health behaviors, we can verify changes in their health information. Specifically, we investigate the following parental variables: (1) smoking behaviors and quantity, (2) alcohol consumption and frequency, (3) participation in physical activities and the variety of activities, (4) enrollment in health insurance, and (5) participation in regular health check-ups. These variables are derived from interview responses to questionnaires conducted by the interviewers.

Household Income. Regarding household income, we examine whether there is an increase in household income following broadband internet access. Specifically, we track changes in household annual income post-broadband installation. This variable is also collected through interviews with respondents, with responses recorded by interviewers.

Table 1 presents the descriptive statistical results of the main variables used in the analysis. Detailed definitions and measurement units for each variable are provided in the table notes.

Table 1. Summary statistics.

Variable	N	Mean	SD	Min	Max
Individual Variables					
Overweight	15413	0.17	0.38	0	1
Obesity	15413	0.06	0.23	0	1
BMIAZ	15413	-0.12	1.25	-4.94	4.83
WAZ	8985	-0.11	1.23	-6.47	5.38
Age	15413	9.27	4.25	2	17
Gender	15413	0.53	0.50	0	1
Rural	15413	0.71	0.45	0	1
Physical activity	7825	0.78	0.42	0	1
Physical activity time	7825	131.53	259.69	0	4050
Sedentary activity	7825	0.93	0.25	0	1
Sedentary activity time	7825	1145.34	931.15	0	5640
Sedentary game activity	7825	0.34	0.47	0	1
Sedentary game activity time	7825	162.52	388.21	0	4473
TV watching	7825	0.87	0.34	0	1
TV watching time	7825	498.35	493.43	0	4370
Reading and homework	7825	0.75	0.43	0	1
Reading and homework time	7825	487.29	566.80	0	4410

measurement errors are unlikely to cause bias or inconsistency in parameter estimates but may reduce estimation efficiency. This property has been well established in the econometric literature (Bound et al., 2001).

Eating snack	13700	0.15	0.36	0	1
Eating snack frequency	13700	0.40	0.99	0	3
Energy intake	12419	1771	668.30	111.00	12090
Ethnic food and cake intake	7600	52.89	132.10	0	1900
Beverage intake	7600	24.10	129.60	0	2655
Vegetable intake	7600	253.60	188.90	0	4457
Fruit intake	7600	38.10	91.06	0	1818
Household Variables					
Screen activity rule	6567	0.64	0.69	0	2
Household size	11624	4.31	1.32	1	14
Household income	11624	28000.88	43561.43	6.94	1427292
City Variables					
Landlines per 100 people	45	10.65	7.07	2.71	36.86
Log of Population Density	45	6.02	0.67	4.19	7.64
Log of GDP per capita	45	8.84	0.56	7.86	10.33
Output share of services/manufacturing industry	45	0.90	0.30	0.52	1.87
Hospitals per 10,000 people	45	0.48	0.20	0.27	1.37
Hospital beds per 10,000 people	45	28.28	12.49	10.44	59.08
Doctors per 10,000 people	45	16.50	7.46	5.99	42.12

Notes: Individual Variables include characteristics of the child, such as whether the child is overweight, obese, BMI-for-age Z-score (BMIAZ), weight-for-age Z-score (WAZ), age, gender, whether they are rural residents, whether they participate in physical activities weekly, the time spent on physical activities per week (minutes), whether they engage in sedentary activities weekly, the time spent on sedentary activities per week (minutes), whether they participate in sedentary game activities weekly, the time spent on sedentary game activities per week (minutes), whether they watch TV weekly, the time spent watching TV per week (minutes), whether they engage in reading and homework activities weekly, the time spent on reading and homework activities per week (minutes), whether they eat snacks daily, the frequency of snack intake per day, daily total energy intake (kilocalories), daily intake of ethnic food and cake (grams), daily intake of beverages (grams), daily intake of vegetables (grams), and daily intake of fruits (grams). Family-level characteristics include whether parents restrict TV watching (2=Strict, 1=Moderate, 0=No Restriction), family size (number of people), and the family's annual income (China yuan). City-level characteristics include the number of landline telephones per hundred people, the logarithm of population density, the logarithm of per capita GDP, the ratio of tertiary industry output to secondary industry output, the number of hospitals per 10,000 people, the number of hospital beds per 10,000 people, and the number of doctors per 10,000 people.

5 Baseline results

5.1 Overweight

We first report the regression results using the baseline specification.

Table 2 presents the impact of broadband internet on child overweight. Column 1 shows the regression results without adding any control variables, which are positive. Column 2 shows the regression results after adding individual age and family size, which remain significantly positive with little change in coefficient size.[2] Column 3 shows the regression results of the baseline specification after adding the interaction terms of city characteristics and post-project indicators as control variables, with the coefficient becoming larger and significant at the 1% level. As shown in Table 2, broadband internet significantly increases the probability of childhood overweight. Specifically, for every one standard deviation increase (7.07) in pre-project internet infrastructure conditions, the probability of childhood overweight post-project increases by 14.14 percentage points, equivalent to an increase of 0.37 (0.1414/0.38) standard deviations.

Table 2. The effect of broadband internet on children's overweight.

	(1)	(2)	(3)
	Overweight	Overweight	Overweight
$Landline_{c,1999} \times After_t$	0.007**	0.007**	0.020***
	(0.003)	(0.003)	(0.006)
Age		0.067***	0.067***
		(0.019)	(0.019)
Household size		-0.004	-0.005
		(0.005)	(0.005)
Log of Population Density $\times After_t$			-0.052**
			(0.024)
Log of GDP per capita $\times After_t$			-0.126**
			(0.056)
Output share of services/manufacturing industry $\times After_t$			-0.145***
			(0.050)
Wave FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	15413	15413	15413
R^2	0.554	0.555	0.556

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000.

5.2 Other measures of weight

Alternative measures of children's weight include child obesity, the BMI-for-age Z-score

[2] Given that the child's age was not fully absorbed by the fixed effects, to eliminate the potential interference of age on the regression results, we re-estimated the baseline regression after excluding the age variable, as shown in Appendix Table A1.

(BMIAZ), and the weight-for-age Z-score (WAZ). Based on this, we use the baseline specification to test the impact of broadband internet on child obesity, the BMI-for-age Z-score, and the weight-for-age Z-score, which are commonly used anthropometric indicators for measuring children's weight in the literature. As shown in Table 3, Column 1 indicates a positive impact of broadband internet on child obesity, with the regression results being positively significant at the 10% level, suggesting that broadband internet may increase the risk of child obesity, albeit with weak evidence. Columns 2 and 3 separately show the impact of broadband internet on children's BMI-for-age Z-score (BMIAZ) and weight-for-age Z-score (WAZ), both results are positive, but WAZ lacks significance. It is noteworthy that the WAZ indicator is only applicable to children under 11 years old, which implies that the impact of broadband internet on younger children might be smaller.

Table 3. The effect of broadband internet on children's obesity, BMIAZ, and WAZ.

	(1) Obesity	(2) BMIAZ	(3) WAZ
$Landline_{c,1999} \times After_t$	0.008^{*}	0.067^{***}	0.041
	(0.004)	(0.017)	(0.029)
Control Variables	Yes	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	15413	15413	8985
R^2	0.485	0.641	0.829

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. BMIAZ is the BMI-for-age Z-score. WAZ is the weight-for-age Z-score, which only covers children under 11 years old. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

5.3 Event study

The identification strategy of the difference-in-differences method requires that the groups adhere to the parallel trends assumption. This implies that, prior to the project implementation, the outcome variable should not show significant differences among different cities. To test this assumption, we employed the following specification for an event study analysis to empirically test the parallel trends of the outcome variable.

$$Y_{i,c,t} = \alpha + \sum_{k=-4}^{k=5} \beta_k Landline_{c,1999} \times wave_{\mathrm{k}} + X'_{i,c,t}\gamma + \delta_i + \theta_t + (\mathrm{W}_{\mathrm{c},1999} \times After_{\mathrm{t}})'\eta + \epsilon_{i,c,t} \qquad (4)$$

where $Y_{i,c,t}$ is the outcome variable, which includes the overweight prevalence, the obesity prevalence, the BMI-for-age Z-score, and the weight-for-age Z-score. $wave_{\mathrm{k}}$ is a group of dummy variables representing the CHNS survey waves.[3] The coefficient β_k captures the impact of broadband internet on children's weight before and after the project implementation. Figure 2 displays the estimated coefficients for four outcome variables. The base period is the survey wave conducted in the year 2000. It shows that the coefficients before the project are not significantly different from zero, which validates the parallel trends assumption. Additionally, the estimated coefficients are significantly different from zero after the project implementation, indicating that the internet speed upgrading project has a persistent effect on the incidence of overweight and obesity. This suggests a clear long-term positive impact of the internet on children's weight.

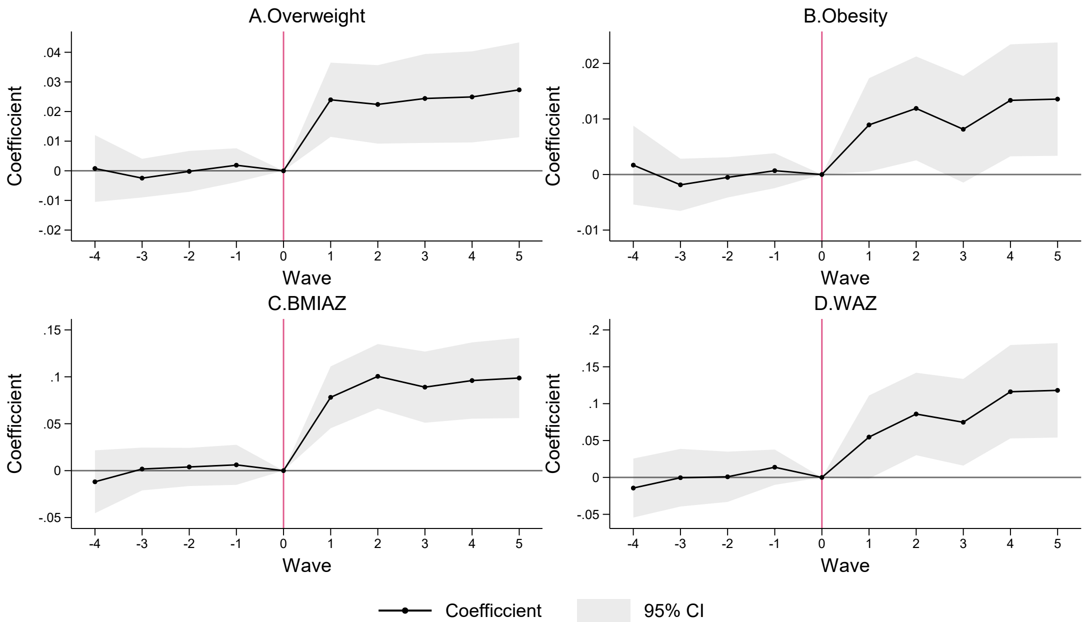

Figure 2. The effect of broadband internet on overweight prevalence, obesity prevalence, BMIAZ, and WAZ of children.

Notes: This figure demonstrates the effect of broadband internet on the prevalence of overweight and obesity, BMIAZ, and WAZ both preceding and subsequent to the implementation of the internet speed upgrading project. The plotted estimated coefficients reflect a 95% confidence interval.

[3] In the wave of 1989, k=-4; in the wave of 1991, k=-3; in the wave of 1993, k=-2; in the wave of 1997, k=-1; in the wave of 2000, k=0; in the wave of 2004, k=1; in the wave of 2006, k=2; in the wave of 2009, k=3; in the wave of 2011, k=4; and in the wave of 2015, k=5.

6 Robustness checks

In this section, we will conduct a series of robustness checks to verify the robustness of our baseline results. We will alter the measurement of the treatment variable, further account for the influence of urban characteristics, exclude the impact of concurrent policies, and perform placebo tests to validate the robustness of the baseline results presented in this paper.

6.1 The measurement of the treatment variable

In the previous section, we have examined multiple anthropometric indicators of children's weight and found that our results are relatively consistent. Here, we again alter the measurement of the treatment variable to test the robustness of the results. Firstly, we consider using the average landline telephone penetration rate from 1995 to 1999 as a proxy for internet infrastructure conditions and re-run the regression, with the results shown in column 1 of Table 4. It is found that the results in column 1 are essentially consistent with the baseline results, which validates the robustness of the internet infrastructure conditions used in the baseline specification. Secondly, we define cities that are above the median of landline telephone penetration rates as the treatment group and those below the median as the control group, and re-run the regression, with the results shown in column 2 of Table 4. We find that the regression results remain significantly positive, and overall, the post-project overweight rate for children in the treatment group is 9.4 percentage points higher than that in the control group.

6.2 Urban characteristics

Further, we consider the potential threat of urban characteristics to the regression results. Firstly, we interact urban characteristics with wave dummy variables to allow for varying impacts of urban characteristics on children's weight across different waves, with the results shown in column 3 of Table 4. These results remain largely consistent with the baseline results. Secondly, we separately add the city-level children overweight rate in 1997 and the supply level of healthcare services[4] at the city level in 1999 as control variables, and interact them with post-project indicators before incorporating them into the baseline specification. The results are shown in columns 4 and 5 of Table

[4] We use four variables at the city level—hospital beds per capita, hospitals per capita, doctors per capita, and the proportion of health service expenditure in total fiscal expenditure—as measures of the supply level of healthcare services. The robustness test results, controlling for each of these variables individually, are presented in Appendix Table A2.

4, respectively. We find that our results remain robust.

6.3 Excluding regions affected by China's Western Development Policy

Additionally, we consider the impact of the China Western Development Policy. Alongside the implementation of the internet speed upgrading project, the China Western Development Policy, aimed at economic development in China's western provinces, began in March 2000. In May 2003, the Northeast Area Revitalization Plan, focused on the industrial development of China's three northeastern provinces, was initiated. These policies involve four provinces in our sample: Liaoning, Heilongjiang, Guizhou, and Guangxi. To eliminate the potential confounding effects of these policies on our results, we exclude these four provinces from the sample. The regression results are shown in column 6 of Table 4, and we find that our results remain robust.

Table 4. Robustness checks.

	Changing measures of treatment variables		Urban Characteristics			Subsample
	(1)	(2)	(3)	(4)	(5)	(6)
	Overweight	Overweight	Overweight	Overweight	Overweight	Overweight
$Landline_{c,1995\text{-}1999} \times After_t$	0.015**					
	(0.008)					
$Landline_{higher} \times After_t$		0.094**				
		(0.039)				
$Landline_{c,1999} \times After_t$			0.020***	0.020***	0.024***	0.031***
			(0.006)	(0.007)	(0.008)	(0.010)
$W_{c,1999} \times After_t$	Yes	Yes	No	Yes	Yes	Yes
$W_{c,1999} \times$ Wave Dummy	No	No	Yes	No	No	No
Childhood Overweight Prevalence at the city-level in 1997 $\times After_t$	No	No	No	Yes	No	No
Healthcare Accessibility at the city-level in 1999 $\times After_t$	No	No	No	No	Yes	No
Excluding concurrent policies	No	No	No	No	No	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15413	15413	15413	13333	15413	9871
R^2	0.555	0.555	0.558	0.536	0.556	0.555

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1995\text{-}1999}$ refers to the average city-level landline telephone penetration rates from 1995 through 1999. $Landline_{higher}$ is a dummy variable that equals 1 for cities where the landline telephone penetration rates are higher than the median. $\text{Landline}_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. After_t is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is the city-level variables that contain the log of population density, the log of GDP per capita, and the output share of services/manufacturing industry. Healthcare Accessibility contains city-level hospitals per capita, doctors per capita, hospital beds per capita, and the proportion of health service expenditures to total fiscal expenditures. Excluding concurrent policies implies the exclusion of four provinces: Liaoning, Heilongjiang, Guizhou, and Guangxi.

6.4 Concurrent policy

Additionally, we considered the potential interference of concurrent policies such as state-owned enterprise reforms, higher education expansion, and China's accession to the WTO, as shown in Table 5. Column 1 considers the impact of the state-owned enterprise (SOE) reform policy, by interacting the proportion of SOE output to the total industrial output of the prefecture-level city in 1999 with the After variable and adding it to the regression. Column 2 considers the impact of the higher education expansion policy, by interacting the proportion of college students to the population of the prefecture-level city in 1999 with the After variable and adding it to the regression. Column 3 considers the impact of China's accession to the World Trade Organization (WTO), by interacting with the tariff level of the prefecture-level city[5] in 1999 with the After variable and adding it to the regression. Column 4 shows the robustness check results considering all three policies simultaneously. We found that the interference of these concurrent policies on the baseline results is not severe, thereby confirming the robustness of the baseline results presented in this paper.

Table 5. Considering the state-owned enterprise reform, higher education expansion, and China's WTO accession.

	(1)	(2)	(3)	(4)
	Overweight	Overweight	Overweight	Overweight
$\text{Landline}_{c,1999} \times \text{After}_t$	0.018^{***}	0.022^{***}	0.015^{***}	0.015^{**}
	(0.006)	(0.006)	(0.006)	(0.006)
$\text{SOE} \times \text{After}_t$	Yes	No	No	Yes
College Expansion $\times \text{After}_t$	No	Yes	No	Yes
Tariff at the city-level $\times \text{After}_t$	No	No	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
$W_{c,1999} \times \text{After}_t$	Yes	Yes	Yes	Yes

[5] Following the methodology of Chen and Liu (2022), the tariff levels of prefecture-level cities are calculated using the following formula: $\text{Tariff}_{c,1999} = \frac{\sum_i \text{Worker}_{c,i,199}\ \text{Tariff}_{i,1999}}{\text{Total worker}_{c,1999}}$

Wave FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	15267	15267	15267	15267
R^2	0.551	0.550	0.551	0.551

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $\text{Landline}_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. After_t is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

6.5 Placebo test

Lastly, we examine whether the project effects are due to random factors. To this end, we conduct a placebo test, where we randomly assign internet infrastructure conditions to different cities and then perform the regression according to the baseline specification. This process is repeated one thousand times, resulting in one thousand estimated coefficients, the distribution of which is shown in Figure 3. We find that the coefficient of our estimated project effect, 0.02, is well outside the range of the estimated coefficients from the placebo test. This suggests that our results are unlikely to be due to random factors.

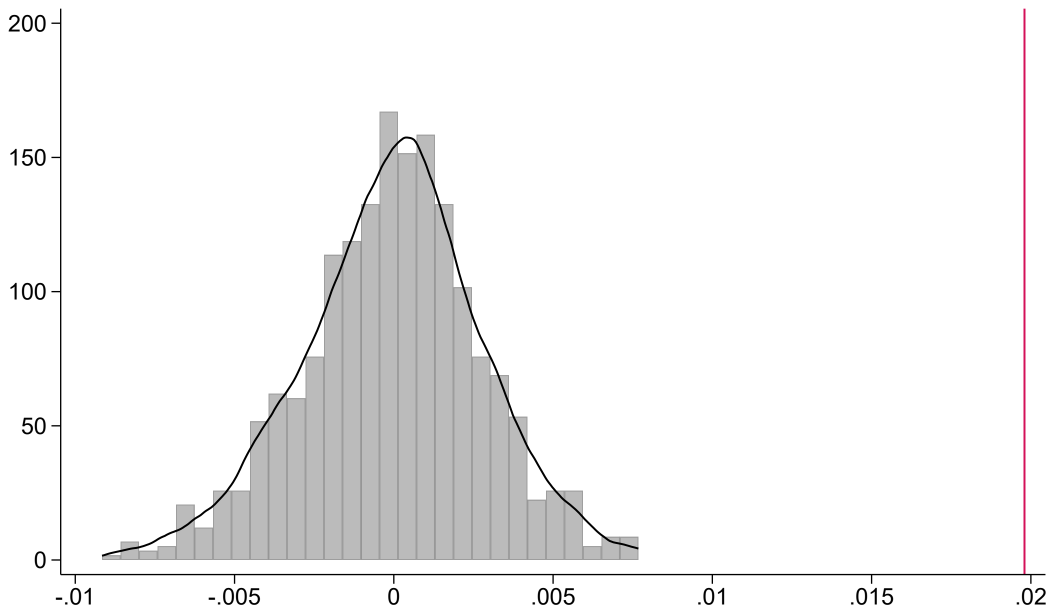

Figure 3. Distribution of estimated coefficients of placebo test

7 Heterogeneity effects

We will examine the heterogeneous effects of broadband internet on children's weight at both the individual and regional levels.

7.1 Heterogeneity at the individual level

We begin by conducting a heterogeneity analysis at the individual level. Given that children of different genders and ages have heterogeneous preferences for different leisure activities, the impact of broadband internet may vary by gender and age. Therefore, we first test for heterogeneity by gender and age in separate samples, as shown in Table 6. Column 1 shows the impact of broadband internet on boys, and Column 2 shows its impact on girls. We do not find a statistically significant difference in the coefficients, indicating that the effect of broadband internet on boys' and girls' weight does not differ significantly. Column 3 shows the impact of broadband internet on children under 11 years old, and Column 4 shows its impact on adolescents aged 11 and above. We find that broadband internet does not have a significant impact on children under 11, but significantly increases the overweight rate of adolescents aged 11 and above, which is consistent with the results obtained from the baseline regression using WAZ as the outcome variable in the previous section. A possible explanation is that younger children may lack sufficient cognitive skills, resulting in fewer opportunities to access the internet and online games (Jackson et al., 2006; Willett, 2016).

Table 6. Analysis of gender and age heterogeneity.

	Boys	Girls	Children under 11	Adolescents aged 11 and above
	(1)	(2)	(3)	(4)
	Overweight	Overweight	Overweight	Overweight
$Landline_{c,1999} \times After_t$	0.023***	0.017**	-0.006	0.019**
	(0.009)	(0.009)	(0.020)	(0.009)
Control Variables	Yes	Yes	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	8217	7196	7846	7567
R^2	0.559	0.546	0.646	0.796
p-value for the difference in treatment effect between groups	0.310		0.027	

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999. The Fisher permutation test is used to assess the statistical significance of the difference in estimated coefficients between the two groups.

7.2 Heterogeneity at the regional level

Subsequently, we conduct a heterogeneity analysis at the regional level. The impact of the internet may vary across regions with different levels of economic development. Therefore, we further examine the heterogeneity in the effect of broadband internet on children's weight living in urban and rural areas as well as in regions with different income levels, as shown in Table 7. Column 1 shows the impact of broadband internet on children in urban areas, and Column 2 shows its impact on children in rural areas. We find that broadband internet has a significant positive impact on children in urban areas but does not have a significant impact on children in rural areas. A possible explanation is that the internet infrastructure in rural areas is relatively weak (Meng et al., 2024), and internet usage has remained low (Ma et al., 2020), thus the impact of the internet speed upgrading project on rural children is also weaker. Column 3 shows the impact of broadband internet on regions with high-income levels, where income levels are defined by per capita GDP and cities with per capita GDP above the median are considered high-income regions. We find that broadband internet has a significant positive impact on children's weight in high-income regions. However, based on the test results of the differences in treatment effects between groups, the impact of broadband internet on children's weight in areas with different income levels shows no significant difference. This suggests that in the early stages of internet development, the income-health gradient may be negative across children's groups of different income levels.

Table 7. Analysis of residence and income heterogeneity.

	Urban area	Rural area	High-income regions	Low-income regions
	(1)	(2)	(3)	(4)
	Overweight	Overweight	Overweight	Overweight
$Landline_{c,1999} \times After_t$	0.045***	0.011	0.017**	0.022
	(0.011)	(0.008)	(0.008)	(0.014)
Control Variables	Yes	Yes	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	4488	10925	6899	8514
R^2	0.604	0.533	0.590	0.522
p-value for the difference in	0.029		0.320	

treatment effect between groups

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999. The Fisher permutation test is used to assess the statistical significance of the difference in estimated coefficients between the two groups.

8 Potential mechanisms

8.1 Children's activities channel

Broadband internet directly increases children's online activities and time spent online. Among children's online activities, online gaming is the primary content (Shen et al., 2013). Engaging in online gaming requires children to spend a significant amount of time sitting still, which will have a significant substitution effect on other activities. However, it is difficult to determine whether this substitutes for sedentary activities like watching TV or replaces physical activities like running. Therefore, we first examine the impact of broadband internet on children's overall physical activities and overall sedentary activities, as shown in Table 8.[6]

The results, as shown in Table 8, indicate that columns 1 and 3 reveal no significant impact of broadband internet on children's physical activities and sedentary activities. This suggests that broadband internet does not have a noticeable impact on the extensive margin of children's activities. However, the intensive margin of children's activities has significantly changed after the introduction of broadband internet, as shown in column 2. Broadband internet has significantly reduced the time children spend on physical activities. Specifically, a one standard deviation increase (7.07) in internet infrastructure conditions before the project results in a weekly reduction of 82.80 minutes in children's physical activities time after the project, equivalent to a decrease of 0.32 (82.80/259.69) standard deviations. Additionally, column 4 shows that broadband internet has also increased the time children spend on sedentary activities which may be due to the additional increase in time spent online. Therefore, we need to conduct further separate tests on the specific content of sedentary activities.

[6] Since some mechanism variables were only surveyed starting in 1997 and there is missing data for some respondents, the sample size in the mechanism analysis is inconsistent with the baseline regression. Considering the comparability issue between the sample used in the mechanism analysis and the baseline regression sample, we conducted the baseline regression using the sample from the mechanism analysis, as shown in Appendix Table A4.

In Table 9, we examine three components of sedentary activities: sedentary game activities, TV watching activities, and reading and homework activities.

Table 8. The effect of broadband internet on physical activities and sedentary activities.

	(1) Physical activity	(2) Physical activity time	(3) Sedentary activity	(4) Sedentary activity time
$Landline_{c,1999} \times After_t$	0.003	-11.711**	-0.001	53.239*
	(0.015)	(5.603)	(0.011)	(28.402)
Control Variables	Yes	Yes	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	7825	7825	7825	7825
R^2	0.551	0.486	0.567	0.586

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

In Table 9, columns 1 and 2 show that broadband internet significantly increases children's sedentary game activities and time. Specifically, for every one standard deviation increase (7.07) in pre-project internet infrastructure conditions, the probability of the child's sedentary game activities post-project increases by 0.23, equivalent to an increase of 0.48 (=0.23/0.47) standard deviations. The time spent on sedentary game activities increases by 129.28 minutes per week, equivalent to an increase of 0.33 (=129.28/388.21) standard deviations. Additionally, columns 3-6 of Table 9 show that broadband internet has no significant impact on children's TV watching activities and time or on their reading and homework activities and time.

This indicates two points: first, broadband internet increases children's sedentary game activities but does not have a noticeable substitution effect on other sedentary activities besides games. Second, combining this with Table 8, the reduction in children's physical activity time may be due to the increase in sedentary game activity time. The substitution of physical activities time with sedentary game activities time implies a reduction in children's energy expenditure, weakening the close relationship between energy intake and energy expenditure, which increases the risk of weight gain in children.

It is worth noting that sedentary game activities here include playing video games, playing with toy cars, and playing board games. Due to the high cost of gaming consoles and the ban on the sale of home game consoles in China from 2000 to 2014, computer-based online games gradually became the primary content of video games (Kshetri, 2009). To reveal the impact of broadband internet on video game activities, we conduct a sub-sample test on sedentary game activities, leveraging the heterogeneity in parental restrictions on children's screen time, as shown in Table 10.

Table 9. The effect of broadband internet on sedentary game activities, TV watching activities, and reading and homework activities.

	(1) Sedentary game activity	(2) Sedentary game activity time	(3) TV watching	(4) TV watching time	(5) Reading and homework	(6) Reading and homework time
$\text{Landline}_{c,1999} \times \text{After}_t$	0.032**	18.286**	-0.013	5.072	-0.000	29.950
	(0.013)	(9.143)	(0.013)	(14.973)	(0.014)	(19.780)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
$\text{W}_{c,1999} \times \text{After}_t$	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7825	7825	7825	7825	7825	7825
R^2	0.560	0.490	0.548	0.542	0.546	0.570

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $\text{Landline}_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. After_t is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $\text{W}_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

In Table 10, we use "whether parents limit the length of time children watch TV" as a proxy variable for parental restrictions on children's screen activities within the family. Columns 1-2, 3-4, and 5-6 of Table 10 refer to the impact of broadband internet on children's sedentary game activities under conditions where parents do not limit screen time, moderately limit screen time, and strictly limit screen time, respectively. Columns 1-2 show that broadband internet increases the likelihood and the time of children engaging in sedentary game activities when parents do not limit screen time. Columns 3-6 of Table 10 refer to broadband internet has no significant impact on children's sedentary game activities when parents limit children's screen time. This indicates that under conditions where parents do not limit screen time, broadband internet can have a significant impact on both children's sedentary game activities and time, with the main channel likely being an increase in video game activities, as other types of games such as playing with toys and board games are not related to electronic screens. This provides suggestive evidence for the direct mechanism by which broadband internet influences children's engagement in online games.

Table 10. The heterogeneity of the effect of broadband internet on sedentary game activities.

	No Restriction		Moderate		Strict	
	(1)	(2)	(3)	(4)	(5)	(6)
	Sedentary game activity	Sedentary game activity time	Sedentary game activity	Sedentary game activity time	Sedentary game activity	Sedentary game activity time
$Landline_{c,1999} \times After_t$	0.054**	57.618*	0.051	3.328	0.084	-0.007
	(0.027)	(29.712)	(0.042)	(18.371)	(0.080)	(10.044)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4065	4065	2489	2489	717	717
R^2	0.758	0.685	0.797	0.811	0.926	0.909

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

8.2 Children's dietary intake channel

In this section, we examine the impact of broadband internet on the dietary content of children. Physiological studies suggest that certain sedentary activities are closely associated with increased food intake (Chaput et al., 2008; Chaput et al., 2011). For example, engaging in video gaming activities can impair satiety signals, leading to increased food consumption (Siervo et al., 2013). Siervo et al. (2018) found that after playing video games, people experience a significant increase in heart rate and blood pressure. To meet the body's demand for additional energy during periods of stress, adaptive eating responses occur, leading to increased intake of snacks and beverages. Given that playing video games is the primary online activity for children, we hypothesize that broadband internet may increase children's snack intake and overall energy intake. First, we examine the impact of broadband internet on children's snacks and energy intake, as shown in Table 11.

In Table 11, columns 1 to 3 sequentially represent the effects of the broadband internet on whether children eat snacks daily, the frequency of snack intake per day, and daily total energy intake. We find that broadband internet increases the likelihood and frequency of children's snack intake. Specifically, a one standard deviation increase (7.07) in internet infrastructure conditions prior to the project results in a 0.14 increase in the probability of children consuming snacks post-project, equivalent to an increase of 0.39 (0.14/0.36) standard deviations. Column 3 shows that with the increase in children's snack intake, their daily total energy intake also increases, further raising the risk of childhood obesity.

Table 11. The effect of broadband internet on snacks and energy intake.

	(1)	(2)	(3)
	Eating snack	Eating Snack times	Energy intake
$\text{Landline}_{c,1999} \times \text{After}_t$	0.020*	0.057**	27.855**
	(0.011)	(0.028)	(13.724)
Control Variables	Yes	Yes	Yes
$W_{c,1999} \times \text{After}_t$	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	13700	13700	12419
R^2	0.546	0.524	0.676

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $\text{Landline}_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. After_t is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

Furthermore, we examine the impact of broadband internet on the consumption of different types of snacks. As shown in Table 12, columns 1 and 2 respectively test the effects of broadband internet on children's average daily intake of Ethnic food and cake, and beverages. Column 1 shows that broadband internet has a significant impact on children's intake of Ethnic food and cake. Specifically, for every one standard deviation (7.07) increase in pre-project internet infrastructure conditions, children's average daily intake of Ethnic food and cake increases by 60.05 grams post-project, equivalent to an increase of 0.45 (=60.05/132.10) standard deviations. Additionally, broadband internet has a positive, albeit not significant, impact on children's average daily beverage intake. This indicates that following the broadband internet rollout, Chinese children's snack consumption, particularly of Ethnic food and cake, has increased significantly.

Considering that broadband internet might increase parents' health knowledge, thereby promoting healthier dietary contents for children, we examined the impact of broadband internet on children's average daily vegetable and fruit intake, as shown in columns 3 and 4 in Table 12. However, the results indicate that broadband internet has a negative, although not significant, impact on children's vegetable and fruit intake. This suggests two things: first, broadband internet does not significantly influence children's consumption of healthy foods, and the effect on increasing parents' health knowledge is not evident. We will further examine the changes in parental health knowledge after the introduction of broadband internet in Section 6.3. Second, the increase in children's snack consumption may substitute for healthy foods, potentially further threatening children's health.

Table 12. The effect of broadband internet on ethnic food and cake intake, beverage intake, and vegetables and fruits intake.

	(1) Ethnic food and cake intake	(2) Beverage intake	(3) Vegetable intake	(4) Fruit intake
$Landline_{c,1999} \times After_t$	8.494**	2.192	-2.627	-1.212
	(3.516)	(1.536)	(6.933)	(2.760)
Control Variables	Yes	Yes	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	7600	7600	7600	7600
R^2	0.623	0.531	0.591	0.546

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

8.3 Parents' health knowledge channel

As children are under parental supervision, the parents' health knowledge directly determines the children's dietary and exercise behaviors, which have a strong impact on the children's weight (Cai et al., 2023; Variyam et al., 1999). Therefore, if broadband internet enhances parents' health knowledge, the trend of children's weight gain may be mitigated. In this section, we examine whether parents' health knowledge increased after the introduction of broadband internet. Following the approach of Chen and Liu (2022), we use parents' health behaviors as a proxy variable for health knowledge, as shown in Table 13 and Table 14.

As shown in Table 13, we find that broadband internet does not have a significant impact on various health behaviors of mothers. This indicates that broadband internet does not increase mothers' health knowledge. Similarly, the results in Table 14 also show that broadband internet does not significantly change fathers' health knowledge and behaviors. We compare our findings with those of Chen and Liu (2022), as presented in Appendix Table A6. Our results are largely consistent with theirs, showing no significant impact of broadband internet access on adult health behaviors. One possible explanation is that the children's parents are middle-aged, and their relatively low level of education limits their ability to discern health information. False information on the internet hindered the growth of parents' health knowledge (Cline & Haynes, 2001), preventing the effectiveness of the channel for increasing parents' health knowledge from being evident.

8.4 Household income channel

Broadband internet access may lead to an increase in household income, which could affect children's health. Chen and Liu (2022) found that broadband internet has a potential positive impact on income. Given this, we are interested in examining whether household income serves as a potential transmission channel in our study. To investigate this, we conducted a mechanism test on the household income channel, as shown in Table 15. However, we did not find a significant effect of broadband internet on household income.

Notably, our sample consists of households with children, where household income primarily comes from parents. Parents with children are typically middle-aged; for example, in our sample, the median age of mothers is 36, and the median age of fathers is 37. A substantial body of research suggests that the positive effects of the internet on employment and income are more pronounced among younger individuals, likely due to their higher levels of digital literacy (Jin et al., 2023; Nguyen et al., 2023). Therefore, our study suggests that the positive impact of broadband internet on the income of older, child-rearing households may be limited.

8.5 Heterogeneity analysis within the mechanism

Building on the above analysis, the primary mechanisms through which broadband internet access affects children's weight are the increase in sedentary time and the greater consumption of snacks. A key question is whether the heterogeneity in these mechanisms aligns with the heterogeneous effects observed in the baseline analysis. In the baseline heterogeneity analysis, we found that both boys' and girls' weight was significantly influenced by broadband internet access. Therefore, we further examine the heterogeneity in mechanisms by gender to assess whether boys and girls experience similar effects through changes in physical activities and dietary intake.

As shown in Appendix Figure A1, several key findings emerge. First, broadband internet access leads to significant changes in both boys' and girls' physical activities and food consumption patterns—specifically, increased sedentary gaming time and higher snack intake—consistent with the mechanisms discussed earlier. Second, compared to boys, the reductions in physical activities and the increase in beverage consumption among girls are less pronounced. A potential explanation is that girls generally engage in lower levels of routine physical activity than boys (Mello et al., 2023) and consume fewer sugary beverages (Bere et al., 2008). As a result, the decline in physical activity and the rise in beverage consumption due to broadband internet access are both less significant for girls, which may explain why the estimated weight effects are slightly larger for boys in the baseline heterogeneity analysis. Third, while some coefficients lose statistical significance due to the smaller sample size, the overall direction and magnitude of the estimated effects remain consistent across boys, girls, and the full sample. This suggests that the heterogeneity in mechanisms is broadly aligned with the baseline heterogeneity findings, confirming that broadband internet access has a significant and positive impact on both boys' and girls' weight.

Table 13. The effect of broadband internet on mothers' health behaviors.

	(1) Smoking of Mother	(2) Cigarette numbers of Mother	(3) Drinking of Mother	(4) Drinking frequency of Mother	(5) Sports of Mother	(6) Sports diversity of Mother	(7) Health insurance of Mother	(8) Checkup of Mother
$Landline_{c,1999} \times After_t$	0.002	0.020	0.003	0.014	-0.001	-0.003	-0.001	-0.002
	(0.002)	(0.024)	(0.006)	(0.013)	(0.006)	(0.007)	(0.010)	(0.003)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12823	12819	12787	12719	7987	7987	13128	13109
R^2	0.706	0.683	0.524	0.583	0.550	0.531	0.773	0.419

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

Table 14. The effect of broadband internet on fathers' health behaviors.

	(1) Smoking of Father	(2) Cigarette numbers of Father	(3) Drinking of Father	(4) Drinking frequency of Father	(5) Sports of Father	(6) Sports diversity of Father	(7) Health insurance of Father	(8) Checkup of Father
$Landline_{c,1999} \times After_t$	0.009	0.412**	-0.004	0.018	0.004	-0.002	-0.008	-0.001
	(0.006)	(0.161)	(0.008)	(0.036)	(0.008)	(0.008)	(0.011)	(0.002)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11557	11491	11650	11478	7312	7312	12573	12560
R^2	0.733	0.745	0.627	0.692	0.608	0.597	0.774	0.414

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

Table 15. The effect of internet access on household income.

	(1) Log of Household income	(2) Log of Household income	(3) Log of Household income
$\text{Landline}_{c,1999} \times \text{After}_t$	-0.006	-0.006	0.009
	(0.009)	(0.009)	(0.020)
Control Variables	No	Yes	Yes
$W_{c,1999} \times \text{After}_t$	No	No	Yes
Wave FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	15413	15413	15413
R^2	0.647	0.651	0.651

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $\text{Landline}_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. After_t is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

9 Economic burden

Our main results indicate that the internet speed upgrading project in China had a significant positive impact on the incidence of overweight among Chinese children. In this section, we discuss the economic burden this project has imposed on Chinese children. Specifically, following the approach of Chen and Liu (2022), we assess this burden by estimating the direct increase in medical costs associated with the rise in the number of overweight children.

First, we estimated the number of overweight children due to the China Internet Acceleration Project. We used the estimated impact of internet access on the incidence of childhood overweight, 0.02 (as shown in Column 3 of Table 2), to estimate the program's effect on children. Given that the fixed-line telephone coverage rate increased from 10.65% in 1999 to 19.05% in 2015, with an annual increase of 3.95 percentage points, the estimated program effect suggests that a 3.95% increase in fixed-line coverage leads to an increase in overweight incidence by 0.079 percentage points. Using CHNS data, we calculated the actual overweight rate of Chinese children, as shown in Column 1 of Table 16. We subtracted 0.079 percentage points from these figures to obtain the counterfactual overweight rate, as shown in Column 2. We then multiplied the total children population by 0.079 percentage points to estimate the number of additional overweight children due to the project, as shown in Column 4. Adding all years together, a cumulative total of approximately 3.52 million children were overweight because of the program between 2000 and 2015.

However, we did not find data on per capita medical expenses for children and the proportion of medical cost savings for non-overweight children. Therefore, we used per capita medical expenses for all age groups and the proportion of cost savings for non-overweight adults to make an approximate estimate. Specifically, we first approximated the additional medical expenses due to overweight by multiplying per capita medical expenses by the proportion of medical cost savings if not overweight.

Next, we estimated the total additional medical expenses by multiplying the increase in the overweight children population due to the project by the additional per capita medical expenses. That is, multiplying per capita medical expenses by the proportion of medical cost savings if not overweight, and then further multiplying by the increase in the overweight children population. This yielded the additional medical expenses incurred each year due to childhood overweight, as shown in Column 7. We calculated the increase in medical expenses from 2000 to 2015, as shown in Column 7. In 2000 currency terms, the total amounted to 321 million RMB.

Table 16. The potential economic burden of childhood overweight.

Year	(1) Actual Overweight Rate (%)	(2) Counterfactual Overweight Rate (%)	(3) Total Child Population (million)	(4) Increase in Overweight Child Population (million)	(5) Per Capita Medical Expenses (RMB)	(6) Proportion of Medical Cost Savings if Not Overweight (%)	(7) Increased Medical Expenses (Million RMB)
2000	0.139	0.13821	320.04	0.253	361.9	1.18	1.08
2001	0.15	0.14921	320.73	0.253	393.8	1.69	1.69
2002	0.161	0.16021	315.61	0.249	450.7	2.42	2.72
2003	0.172	0.17121	310.40	0.245	509.5	3.46	4.32
2004	0.183	0.18221	302.35	0.239	583.9	4.96	6.92
2005	0.186	0.18521	300.35	0.237	662.3	5.39	8.47
2006	0.189	0.18821	289.58	0.229	748.8	5.86	10.04
2007	0.191	0.19021	276.55	0.218	876	6.31	12.08
2008	0.192	0.19121	262.28	0.207	1094.5	6.8	15.42
2009	0.194	0.19321	252.89	0.200	1314.3	7.32	19.22
2010	0.221	0.22021	269.39	0.213	1490.1	7.74	24.54
2011	0.247	0.24621	248.65	0.196	1807	8.18	29.04
2012	0.253	0.25221	249.42	0.197	2076.7	8.65	35.40
2013	0.259	0.25821	246.52	0.195	2327.4	9.15	41.47

2014	0.265	0.26421	244.46	0.193	2581.7	9.67	48.21
2015	0.271	0.27021	249.54	0.197	2980.8	10.23	60.11

Notes: This table reports the calculation of increased medical expenses due to the China Internet Acceleration Project. Data sources: China Health and Nutrition Survey data, China Health Statistical Yearbook, Chen and Liu (2022).

10 Conclusion

This paper discusses the impact of broadband internet on children's weight using the exogenous shock brought by the internet speed upgrading project in China. We find that broadband internet increases children's weight, which contrasts with previous research regarding its effect on adult weight (Chen & Liu, 2022).

Compared to other literature examining the impact of electronic computer and internet use on children's overweight status, we not only used a more stringent identification strategy to verify the positive causal impact of broadband internet on children's weight (Suziedelyte, 2015), but we also found that internet infrastructure has a relatively greater impact on children's overweight status than internet usage time (Ning et al., 2024). Compared to Ning et al. (2024), which focuses on internet usage time that mixes the effects of both mobile and fixed networks, one possible explanation for the larger effect identified in this study is our focus on fixed broadband internet. Unlike early-stage mobile internet, fixed broadband offers higher-quality and more continuous content delivery, which may more easily induce internet addiction and sedentary behavior among children, thereby leading to relatively greater weight gain. Specifically, for every one standard deviation increase (7.07) in pre-project internet infrastructure conditions, the probability of children being overweight post-project increases by 14.14 percentage points, equivalent to an increase of 0.37 (=0.1414/0.38) standard deviations.

We conduct robustness checks on the main results of this paper in several ways. We find that our main results are consistent whether we replace the weight measurement standards, the measurement indicators of treatment variable, or add additional control factors. Placebo results indicate that our findings are unlikely to be due to random factors.

In the heterogeneity analysis, we observe that children from urban areas and those who are older have a greater impact from broadband internet. The more pronounced results in urban areas may be attributed to the significant gap in internet infrastructure between urban and rural regions. This suggests that in the early stages of China's internet development, there may have been a negative gradient between income and childhood health. The fact that urban children's obesity rates were consistently higher than those of rural children before 2015 provides additional evidence for this argument (Dong et al., 2019).

In the mechanism tests, we find that broadband internet increases children's sedentary game activity and time, which replaces their physical activities but has no substitution effect on other sedentary activities. This leads to a reduction in children's physical activity intensity and energy expenditure. Additionally, we find that broadband internet significantly increases children's snack intake, mainly Ethnic food and cake, leading to additional energy intake. Meanwhile, we find no evidence of increased consumption of vegetables or fruits by children. We also do not observe an increase in the health knowledge and behaviors of children's parents following broadband internet access. Combining the above analyses, after the introduction of broadband internet, children's energy expenditure decreases while energy intake increases, resulting in a net increase in energy intake. According to the Energy Balance Model, a long-term positive energy balance leads to weight gain as the only way to achieve energy balance (Hill et al., 2012), which directly increases the risk of overweight and obesity in children.

Policies aimed at limiting children's online game time can help block the mechanism through which broadband internet affects children's weight. However, directly prohibiting children's access to online games does not achieve the expected results (Choi et al., 2018) and incurs high enforcement costs. According to our results, in families that limit children's screen time, children's sedentary game activities do not change significantly. We suggest that the government should require game providers to include parental control features in their games and provide relevant information to parents, encouraging them to control children's gaming activities. This can reduce implementation and supervision costs, effectively limit children's online gaming time, and minimize excessive intervention in the gaming industry and personal freedom.

Furthermore, besides regulating parental behavior, the influence of broadband internet on children's weight can be mitigated in the following ways. First, in the digital environment, the government should implement age-appropriate restrictions on entertainment content to ensure that the design of gaming platforms promotes children's health. This can include time limits, mandatory breaks, and content ratings for different age groups. Second, school education should be strengthened: educational programs promoting balanced lifestyles should be implemented to teach children the importance of physical activity and healthy habits. Schools can also incorporate digital literacy courses to help students understand the negative impacts of excessive screen time on their health. Third, promote outdoor activities: schools and community organizations should be encouraged to organize outdoor activities and recreational events, providing alternatives to online entertainment for children. Local governments can support this by funding parks, playgrounds, and sports facilities. Fourth, address the broader social context: advocate for public events and social interventions that reduce the prevalence of sedentary behavior associated with digital entertainment and encourage a cultural shift toward more active lifestyles. Fifth, we recommend coordinated efforts among families, schools, and communities to enhance children's digital literacy. Such efforts can help foster healthy internet habits and sound time management skills, thereby reducing the risk of overweight associated with excessive internet use.

The limitations of this paper are: (1) It lacks direct variables for children's online gaming time, and using overall playtime as a proxy variable may lead to overestimation of coefficients. (2) The dietary data used in this paper was obtained through the 24-hour recall method, which may have issues with incomplete recall and high randomness. Future work needs to address these aspects further.

Regarding the external validity of our findings, although our conclusions are drawn from the context of China’s early-stage broadband development, the implications may extend to other developing countries that are currently undergoing rapid digital infrastructure expansion. In settings where broadband access is growing without parallel investments in children’s health education or physical activity promotion, similar patterns of increased sedentary behavior and heightened risk of childhood overweight may emerge. However, caution is warranted when generalizing our results, as differences in children’s online content consumption, the availability of alternative leisure activities, and the development of mobile platforms may lead to varying degrees of impact. Future research should particularly examine the potential effects of mobile internet development and the rising popularity of mobile gaming on children’s weight outcomes.

Finally, we emphasize the marginal contributions of this paper to the existing literature: (1) It is the first to identify the impact of broadband internet on children's weight using causal inference methods. In this process, we address the endogeneity of broadband internet using a reliable identification strategy, making the estimation results more authentic and reliable. (2) Broadband internet does not bring positive health impacts to all groups. Children affected by broadband internet are more likely to play online games, increase sedentary activity and time, and increase snack intake, leading to overweight and obesity risks, while parents' health information does not necessarily increase significantly.

Appendix for online publication

Table A1. The effect of internet access on children's overweight excluding the age variable.

	(1)	(2)	(3)
	Overweight	Overweight	Overweight
$Landline_{c,1999} \times After_t$	0.007^{**}	0.007^{**}	0.020^{***}
	(0.003)	(0.003)	(0.006)
Control Variables	No	Yes	Yes
$W_{c,1999} \times After_t$	No	No	Yes
Wave FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	15413	15413	15413
R^2	0.554	0.554	0.555

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variable contains the household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

Table A2. Robustness checks considering the regional healthcare service level.

	(1)	(2)	(3)	(4)	(5)
			Overweight		
$\text{Landline}_{c,1999}\times\text{After}_t$	0.029***	0.019***	0.022***	0.018***	0.024***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)
Control Variables	Yes	Yes	Yes	Yes	Yes
$\text{W}_{c,1999}\times\text{After}_t$	Yes	Yes	Yes	Yes	Yes
Hospital beds per capita$\times\text{After}_t$	Yes	No	No	No	Yes
Hospitals per capita$\times\text{After}_t$	No	Yes	No	No	Yes
Doctors per capita$\times\text{After}_t$	No	No	Yes	No	Yes
Proportion of health service expenditures to total$\times\text{After}_t$	No	No	No	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Observations	15413	15413	15413	15413	15413
R^2	0.556	0.556	0.556	0.556	0.556

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $\text{Landline}_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. After_t is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $\text{W}_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

Given the large population of left-behind children in China, we are concerned about whether the impact of broadband internet on children's weight differs significantly between left-behind and non-left-behind children. Unfortunately, we do not find a significant additional effect among left-behind children.

Specifically, we define left-behind children as those with at least one parent living away from home, while non-left-behind children are those with both parents living at home. We do not classify children whose both parents are absent as left-behind children because the sample size for this group is too small to produce reliable estimates. In fact, children without both parents present account for only about 5% of the total child population (Li et al., 2015).

As shown in Table A3, we find that the coefficient of broadband internet's impact on the weight of left-behind children is larger than that for non-left-behind children. However, a test for intergroup differences indicates that this difference is not statistically significant. One possible explanation is that in our sample of left-behind children, more than two-thirds have only one parent absent, meaning that many left-behind children remain under the supervision of the parent who stays at home. This parental supervision may function similarly to having both parents present, leading to no significant difference in the impact of broadband internet on children's weight between the two groups.

Table A3. Left-behind heterogeneity.

	Left-behind children	Non-left-behind children
	(1)	(2)
	Overweight	Overweight
$Landline_{c,1999} \times After_t$	0.021^{**}	0.019^{***}
	(0.011)	(0.007)
Control Variables	Yes	Yes
$W_{c,1999} \times After_t$	Yes	Yes
Wave FE	Yes	Yes
Individual FE	Yes	Yes
Observations	3014	12399
R^2	0.560	0.554
p-value for the difference in treatment effect between groups	0.482	

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999. The Fisher permutation test is used to assess the statistical significance of the difference in estimated coefficients between the two groups.

Table A4. The effect of internet access on children's overweight using the samples from the mechanism analysis.

	(1)	(2)	(3)
	Overweight	Overweight	Overweight
$Landline_{c,1999} \times After_t$	0.009^{**}	0.009^{**}	0.016^{**}
	(0.004)	(0.004)	(0.008)
Control Variables	No	Yes	Yes
$W_{c,1999} \times After_t$	No	No	Yes
Wave FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	7260	7260	7260
R^2	0.697	0.697	0.698

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is shown on the top of each column. $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000. Control Variables contain the child's age and household size. $W_{c,1999}$ is a vector that contains the logarithm of population density, the logarithm of per capita GDP, and the ratio of tertiary industry output to secondary industry output at the city level in 1999.

There is some degree of sample attrition in our child sample. Our primary concern is the potential correlation between sample attrition and the broadband internet policy shock. If such a correlation exists, it could lead to biased estimation results.

To further examine this issue, we follow the approach of Huang and Liu (2023) to test whether child sample attrition is random. Specifically, for each surveyed child, we observe whether they drop out of the survey in any wave after entering the sample. Based on this, we construct a dummy variable, Attrition, to indicate whether the child has dropped out. We then replace the dependent variable in the baseline model with this dummy variable and perform a regression. The results, shown in Column 1 of Table A5, indicate that the broadband internet policy shock is not significantly associated with child sample attrition in the baseline model.

Additionally, following the methodology of Zhao et al. (2021), we examine the correlation between child sample attrition and all difference-in-differences (DID) terms, which are constructed as interactions between wave dummies and the treatment variable. As shown in Column 2 of Table A5, we find that natural sample attrition among children is not correlated with any of the DID terms.

Table A5. Correlation between child sample attrition and broadband internet.

	(1)	(2)
	Attrition	Attrition
Aftert×Landlinec,1999	-0.007	
	(0.005)	
1{year=1989}×Landlinec,1999		-0.001
		(0.006)
1{year=1991}×Landlinec,1999		-0.003
		(0.005)
1{year=1993}×Landlinec,1999		-0.001
		(0.004)
1{year=1997}×Landlinec,1999		-0.003
		(0.006)
1{year=2004}×Landlinec,1999		-0.009
		(0.007)
1{year=2006}×Landlinec,1999		-0.006
		(0.008)
1{year=2009}×Landlinec,1999		-0.011
		(0.008)
1{year=2011}×Landlinec,1999		-0.002
		(0.007)
1{year=2015}×Landlinec,1999		-0.004
		(0.007)
Constant		0.157***

		(0.031)
Wave FE	Yes	Yes
Individual FE	Yes	Yes
Observations	17,635	17,635
R2	0.582	0.583

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The standard errors clustered at city-wave level are presented in parentheses. The dependent variable is a dummy variable indicating a missing value for the child sample (1=missing, 0=not missing). $Landline_{c,1999}$ indicates the city-level landline telephone penetration rates in 1999. $After_t$ is a dummy variable, which equals one if wave>2000.

TableA6. The comparison of the effects of broadband internet on health behaviors with Chen and Liu (2022).

	(1) Smoking	(2) Cigarette numbers	(3) Drinking	(4) Drinking frequency	(5) Sports	(6) Sports diversity	(7) Health insurance	(8) Checkup
Chen and Liu (2022)	−0.022	−0.369	−0.005	−0.211	0.085	0.108	0.301**	−0.009
	(0.040)	(0.786)	(0.063)	(0.263)	(0.086)	(0.107)	(0.125)	(0.024)
Mother	0.002	0.020	0.003	0.014	-0.001	-0.003	-0.001	-0.002
	(0.002)	(0.024)	(0.006)	(0.013)	(0.006)	(0.007)	(0.010)	(0.003)
Father	0.009	0.412**	-0.004	0.018	0.004	-0.002	-0.008	-0.001
	(0.006)	(0.161)	(0.008)	(0.036)	(0.008)	(0.008)	(0.011)	(0.002)

Notes: * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. The dependent variable is shown on the top of each column. The standard errors are reported in parentheses.

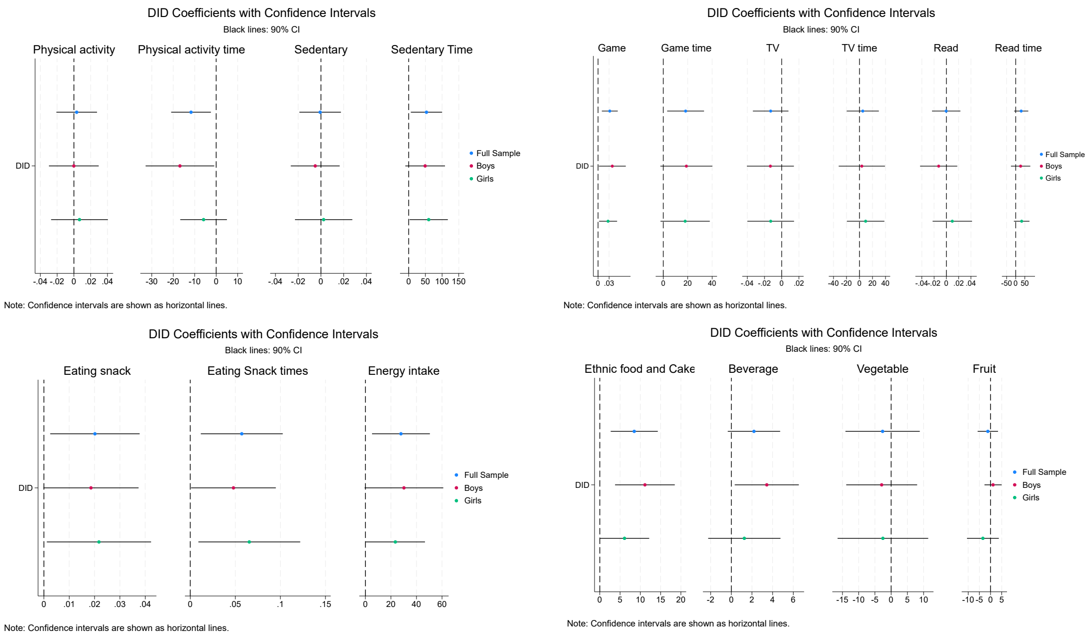

Figure A1. The heterogeneous effects on boys and girls through activities and dietary intake channels.

Reference

Aghasi, M., Matinfar, A., Golzarand, M., Salari-Moghaddam, A., & Ebrahimpour-Koujan, S. (2020). Internet Use in Relation to Overweight and Obesity: A Systematic Review and Meta-Analysis of Cross-Sectional Studies. *Advances in Nutrition*, *11*(2), 349-356. https://doi.org/https://doi.org/10.1093/advances/nmz073

Akerman, A., Gaarder, I., & Mogstad, M. (2015). The Skill Complementarity of Broadband Internet. *The Quarterly Journal of Economics*, *130*(4), 1781-1824. https://doi.org/10.1093/qje/qjv028

Asirvatham, J., Thomsen, M. R., Nayga, R. M., & Goudie, A. (2019). Do fast food restaurants surrounding schools affect childhood obesity? *Economics & Human Biology*, *33*, 124-133. https://doi.org/https://doi.org/10.1016/j.ehb.2019.01.011

Bass, R., & Eneli, I. (2015). Severe childhood obesity: an under-recognised and growing health problem. *Postgraduate Medical Journal*, *91*(1081), 639-645. https://doi.org/10.1136/postgradmedj-2014-133033

Bere, E., Sørli Glomnes, E., te Velde, S. J., & Klepp, K.-I. (2008). Determinants of adolescents' soft drink consumption. *Public Health Nutrition*, *11*(1), 49-56. https://doi.org/10.1017/S1368980007000122

Bound, J., Brown, C., & Mathiowetz, N. (2001). Chapter 59 - Measurement Error in Survey Data. In J. J. Heckman & E. Leamer (Eds.), *Handbook of Econometrics* (Vol. 5, pp. 3705-3843). Elsevier. https://doi.org/https://doi.org/10.1016/S1573-4412(01)05012-7

Boynton-Jarrett, R., Thomas, T. N., Peterson, K. E., Wiecha, J., Sobol, A. M., & Gortmaker, S. L. (2003). Impact of Television Viewing Patterns on Fruit and Vegetable Consumption Among Adolescents. *Pediatrics*, *112*(6), 1321-1326. https://doi.org/10.1542/peds.112.6.1321

Bozkurt, H., Özer, S., Şahin, S., & Sönmezgöz, E. (2018). Internet use patterns and Internet addiction in children and adolescents with obesity. *Pediatric Obesity*, *13*(5), 301-306. https://doi.org/https://doi.org/10.1111/ijpo.12216

Cai, Z., Jiang, K., Wang, T., Li, S., Xian, J., Zhao, Y., & Shi, Z. (2023). Influence of adolescents' and parental dietary knowledge on adolescents' body mass index (BMI), overweight/obesity in 2004–2015: a longitudinal study. *Archives of Public Health*, *81*(1), 188. https://doi.org/10.1186/s13690-023-01197-x

Carneiro, P., Kraftman, L., Mason, G., Moore, L., Rasul, I., & Scott, M. (2021). The Impacts of a Multifaceted Prenatal Intervention on Human Capital Accumulation in Early Life. *American Economic Review*, *111*(8), 2506-2549. https://doi.org/10.1257/aer.20191726

Casey, B. J. (2015). Beyond Simple Models of Self-Control to Circuit-Based Accounts of Adolescent Behavior. *Annual Review of Psychology*, *66*(Volume 66, 2015), 295-319. https://doi.org/https://doi.org/10.1146/annurev-psych-010814-015156

Casey, B. J., & Caudle, K. (2013). The Teenage Brain: Self Control. *Current Directions in Psychological Science*, *22*(2), 82-87. https://doi.org/10.1177/0963721413480170

Cawley, J., & Spiess, C. K. (2008). Obesity and skill attainment in early childhood. *Economics & Human Biology*, *6*(3), 388-397. https://doi.org/https://doi.org/10.1016/j.ehb.2008.06.003

Chaput, J.-P., Drapeau, V., Poirier, P., Teasdale, N., & Tremblay, A. (2008). Glycemic Instability and Spontaneous Energy Intake: Association With Knowledge-Based Work. *Psychosomatic Medicine*, *70*(7). https://journals.lww.com/psychosomaticmedicine/fulltext/2008/09000/glycemic_instability_and_spontaneous_energy.7.aspx

Chaput, J.-P., Visby, T., Nyby, S., Klingenberg, L., Gregersen, N. T., Tremblay, A., Astrup, A., & Sjödin, A. (2011). Video game playing increases food intake in adolescents: a randomized crossover study. *The American Journal of Clinical Nutrition*, *93*(6), 1196-1203.

https://doi.org/https://doi.org/10.3945/ajcn.110.008680
Chen, L., & Liu, W. (2022). The effect of Internet access on body weight: Evidence from China. *Journal of health economics*, *85*, 102670. https://doi.org/https://doi.org/10.1016/j.jhealeco.2022.102670
Chen, S., Liu, W., & Song, H. (2020). BROADBAND INTERNET, FIRM PERFORMANCE, AND WORKER WELFARE: EVIDENCE AND MECHANISM. *Economic Inquiry*, *58*(3), 1146-1166. https://doi.org/https://doi.org/10.1111/ecin.12854
Choi, J., Cho, H., Lee, S., Kim, J., & Park, E.-C. (2018). Effect of the Online Game Shutdown Policy on Internet Use, Internet Addiction, and Sleeping Hours in Korean Adolescents. *Journal of Adolescent Health*, *62*(5), 548-555. https://doi.org/https://doi.org/10.1016/j.jadohealth.2017.11.291
Cline, R. J. W., & Haynes, K. M. (2001). Consumer health information seeking on the Internet: the state of the art. *Health Education Research*, *16*(6), 671-692. https://doi.org/10.1093/her/16.6.671
Collaborators, G. O. (2017). Health Effects of Overweight and Obesity in 195 Countries over 25 Years. *New England Journal of Medicine*, *377*(1), 13-27. https://doi.org/10.1056/NEJMoa1614362
Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband Infrastructure and Economic Growth. *The economic journal*, *121*(552), 505-532. https://doi.org/10.1111/j.1468-0297.2011.02420.x
Dasgupta, K., & Solomon, K. T. (2018). Family size effects on childhood obesity: Evidence on the quantity-quality trade-off using the NLSY. *Economics & Human Biology*, *29*, 42-55. https://doi.org/https://doi.org/10.1016/j.ehb.2018.01.004
DiNardi, M., Guldi, M., & Simon, D. (2019). Body weight and Internet access: evidence from the rollout of broadband providers. *Journal of Population Economics*, *32*(3), 877-913. https://doi.org/10.1007/s00148-018-0709-9
Dolton, P. J., & Tafesse, W. (2022). Childhood obesity, is fast food exposure a factor? *Economics & Human Biology*, *46*, 101153. https://doi.org/https://doi.org/10.1016/j.ehb.2022.101153
Dong, Y., Ma, Y., Dong, B., Zou, Z., Hu, P., Wang, Z., Yang, Y., Song, Y., & Ma, J. (2019). Geographical variation and urban-rural disparity of overweight and obesity in Chinese school-aged children between 2010 and 2014: two successive national cross-sectional surveys. *BMJ Open*, *9*(4), e025559. https://doi.org/10.1136/bmjopen-2018-025559
Falck, O., Gold, R., & Heblich, S. (2014). E-lections: Voting Behavior and the Internet. *American Economic Review*, *104*(7), 2238-2265. https://doi.org/10.1257/aer.104.7.2238
Fan, M., Jin, Y., & Zhang, M. (2023). Genetic risk, childhood obesity, and educational achievements. *Economics of Education Review*, *94*, 102408. https://doi.org/https://doi.org/10.1016/j.econedurev.2023.102408
Förster, L.-J., Vogel, M., Stein, R., Hilbert, A., Breinker, J. L., Böttcher, M., Kiess, W., & Poulain, T. (2023). Mental health in children and adolescents with overweight or obesity. *BMC Public Health*, *23*(1), 135. https://doi.org/10.1186/s12889-023-15032-z
Guo, Y., Li, S., Chen, S., Tang, Y., & Liu, C. (2022). Health benefits of having more female classmates: Quasi-experimental evidence from China. *Economics of Education Review*, *91*, 102330. https://doi.org/https://doi.org/10.1016/j.econedurev.2022.102330
Gwozdz, W., Sousa-Poza, A., Reisch, L. A., Ahrens, W., Eiben, G., M. Fernandéz-Alvira, J., Hadjigeorgiou, C., De Henauw, S., Kovács, E., Lauria, F., Veidebaum, T., Williams, G., & Bammann, K. (2013). Maternal employment and childhood obesity – A European perspective. *Journal of health economics*, *32*(4), 728-742. https://doi.org/https://doi.org/10.1016/j.jhealeco.2013.04.003
Hall, K. D., Farooqi, I. S., Friedman, J. M., Klein, S., Loos, R. J. F., Mangelsdorf, D. J., O'Rahilly, S., Ravussin, E., Redman, L. M., Ryan, D. H., Speakman, J. R., & Tobias, D. K. (2022). The energy balance model of obesity: beyond calories in, calories out. *The American Journal of Clinical Nutrition*, *115*(5), 1243-1254. https://doi.org/https://doi.org/10.1093/ajcn/nqac031

Hamilton, D., Dee, A., & Perry, I. J. (2018). The lifetime costs of overweight and obesity in childhood and adolescence: a systematic review. *Obesity Reviews*, *19*(4), 452-463. https://doi.org/https://doi.org/10.1111/obr.12649

Hill, J. O., Wyatt, H. R., & Peters, J. C. (2012). Energy Balance and Obesity. *Circulation*, *126*(1), 126-132. https://doi.org/10.1161/CIRCULATIONAHA.111.087213

Hjort, J., & Poulsen, J. (2019). The Arrival of Fast Internet and Employment in Africa. *American Economic Review*, *109*(3), 1032-1079. https://doi.org/10.1257/aer.20161385

Huang, W., & Liu, H. (2023). Early childhood exposure to health insurance and adolescent outcomes: Evidence from rural China. *Journal of Development Economics*, *160*, 102925. https://doi.org/https://doi.org/10.1016/j.jdeveco.2022.102925

Jackson, L. A., von Eye, A., Biocca, F. A., Barbatsis, G., Zhao, Y., & Fitzgerald, H. E. (2006). Does home internet use influence the academic performance of low-income children? *Developmental Psychology*, *42*(3), 429-435. https://doi.org/10.1037/0012-1649.42.3.429

Jin, X., Ma, B., & Zhang, H. (2023). Impact of fast internet access on employment: Evidence from a broadband expansion in China. *China Economic Review*, *81*, 102038. https://doi.org/https://doi.org/10.1016/j.chieco.2023.102038

Kim, J. Y., & Kang, S. H. (2021). Windows of Opportunity, Capability and Catch-Up: The Chinese Game Industry. *Journal of Contemporary Asia*, *51*(1), 132-156. https://doi.org/10.1080/00472336.2019.1656761

Kotani, K., Nishida, M., Yamashita, S., Funahashi, T., Fujioka, S., Tokunaga, K., Ishikawa, K., Tarui, S., & Matsuzawa, Y. (1997). Two decades of annual medical examinations in Japanese obese children: Do obese children grow into obese adults? *International Journal of Obesity*, *21*(10), 912-921. https://doi.org/10.1038/sj.ijo.0800492

Kshetri, N. (2009). The evolution of the Chinese online gaming industry. *Journal of Technology Management in China*, *4*(2), 158-179. https://doi.org/10.1108/17468770910965019

Kubb, C., & Foran, H. M. (2020). Online Health Information Seeking by Parents for Their Children: Systematic Review and Agenda for Further Research. *J Med Internet Res*, *22*(8), e19985. https://doi.org/10.2196/19985

Larsen, J. K., Hermans, R. C. J., Sleddens, E. F. C., Engels, R. C. M. E., Fisher, J. O., & Kremers, S. P. J. (2015). How parental dietary behavior and food parenting practices affect children's dietary behavior. Interacting sources of influence? *Appetite*, *89*, 246-257. https://doi.org/https://doi.org/10.1016/j.appet.2015.02.012

Li, P., Lu, Y., & Wang, J. (2016). Does flattening government improve economic performance? Evidence from China. *Journal of Development Economics*, *123*, 18-37. https://doi.org/https://doi.org/10.1016/j.jdeveco.2016.07.002

Li, Q., Liu, G., & Zang, W. (2015). The health of left-behind children in rural China. *China Economic Review*, *36*, 367-376. https://doi.org/https://doi.org/10.1016/j.chieco.2015.04.004

Loewenstein, G., Price, J., & Volpp, K. (2016). Habit formation in children: Evidence from incentives for healthy eating. *Journal of health economics*, *45*, 47-54. https://doi.org/https://doi.org/10.1016/j.jhealeco.2015.11.004

Lou, J., Wang, M., Xie, X., Wang, F., Zhou, X., Lu, J., & Zhu, H. (2024). The association between family socio-demographic factors, parental mediation and adolescents' digital literacy: a cross-sectional study. *BMC Public Health*, *24*(1), 2932. https://doi.org/10.1186/s12889-024-20284-4

Lundberg, S., Romich, J. L., & Tsang, K. P. (2009). Decision-making by children. *Review of Economics of the Household*, *7*(1), 1-30. https://doi.org/10.1007/s11150-008-9045-2

Luo, S., O'Connor, S. G., Belcher, B. R., & Page, K. A. (2018). Effects of Physical Activity and Sedentary Behavior on Brain Response to High-Calorie Food Cues in Young Adults. *Obesity*, *26*(3), 540-546. https://doi.org/https://doi.org/10.1002/oby.22107

Ma, W., Nie, P., Zhang, P., & Renwick, A. (2020). Impact of Internet use on economic well-being of rural households: Evidence from China. *Review of Development Economics*, *24*(2), 503-523. https://doi.org/https://doi.org/10.1111/rode.12645

MacInnis, B., & Rausser, G. (2005). Does Food Processing Contribute to Childhood Obesity Disparities? *American Journal of Agricultural Economics*, *87*(5), 1154-1158. http://www.jstor.org/stable/3697689

Malamud, O., & Pop-Eleches, C. (2011). Home Computer Use and the Development of Human Capital. *The Quarterly Journal of Economics*, *126*(2), 987-1027. https://doi.org/10.1093/qje/qjr008

Marsh, S., Ni Mhurchu, C., & Maddison, R. (2013). The non-advertising effects of screen-based sedentary activities on acute eating behaviours in children, adolescents, and young adults. A systematic review. *Appetite*, *71*, 259-273. https://doi.org/https://doi.org/10.1016/j.appet.2013.08.017

McDool, E., Powell, P., Roberts, J., & Taylor, K. (2020). The internet and children's psychological wellbeing. *Journal of health economics*, *69*, 102274. https://doi.org/https://doi.org/10.1016/j.jhealeco.2019.102274

McNamee, P., Mendolia, S., & Yerokhin, O. (2021). Social media use and emotional and behavioural outcomes in adolescence: Evidence from British longitudinal data. *Economics & Human Biology*, *41*, 100992. https://doi.org/https://doi.org/10.1016/j.ehb.2021.100992

Mello, G. T. d., Bertuol, C., Minatto, G., Barbosa Filho, V. C., Oldenburg, B., Leech, R. M., & Silva, K. S. (2023). A systematic review of the clustering and correlates of physical activity and sedentary behavior among boys and girls. *BMC Public Health*, *23*(1), 372. https://doi.org/10.1186/s12889-022-14869-0

Meng, Y., Lu, Y., & Liang, X. (2024). Does Internet use alleviate the relative poverty of Chinese rural residents? A case from China. *Environment, Development and Sustainability*, *26*(5), 11817-11846. https://doi.org/10.1007/s10668-023-03531-3

Nguyen, T.-T., Nguyen, T. T., & Grote, U. (2023). Internet use and agricultural productivity in rural Vietnam. *Review of Development Economics*, *27*(3), 1309-1326. https://doi.org/https://doi.org/10.1111/rode.12990

Nie, C., & Wan, J. (2023). How Does Internet Infrastructure Construction Affect the Urban–Rural Income Gap? Evidence from a Quasi-Natural Experiment in China. *Progress in Development Studies*, *23*(3), 317-337. https://doi.org/10.1177/14649934231173819

Nieto, A., & Suhrcke, M. (2021). The effect of TV viewing on children's obesity risk and mental well-being: Evidence from the UK digital switchover. *Journal of health economics*, *80*, 102543. https://doi.org/https://doi.org/10.1016/j.jhealeco.2021.102543

Ning, K., Zhu, Z., Xu, Z., Liu, H., & Lu, M. (2024). Internet use, dietary habits and adolescent obesity: evidence from China. *International Journal of Health Economics and Management*. https://doi.org/10.1007/s10754-024-09386-z

Organization, W. H. (2006). *WHO child growth standards: length/height-for-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: methods and development*. World Health Organization.

Paulus, F. W., Ohmann, S., von Gontard, A., & Popow, C. (2018). Internet gaming disorder in children and adolescents: a systematic review. *Developmental Medicine & Child Neurology*, *60*(7), 645-659. https://doi.org/https://doi.org/10.1111/dmcn.13754

Phelps, N. H., Singleton, R. K., Zhou, B., Heap, R. A., Mishra, A., Bennett, J. E., Paciorek, C. J., Lhoste, V. P. F., Carrillo-Larco, R. M., Stevens, G. A., Rodriguez-Martinez, A., Bixby, H., Bentham, J., Di Cesare, M., Danaei, G., Rayner, A. W., Barradas-Pires, A., Cowan, M. J., Savin, S.,…Ezzati, M. (2024). Worldwide trends in underweight and obesity from 1990 to 2022: a pooled analysis of 3663 population-representative studies with 222 million children, adolescents, and adults. *The lancet*, *403*(10431), 1027-1050. https://doi.org/10.1016/S0140-6736(23)02750-2

Russell-Mayhew, S., McVey, G., Bardick, A., & Ireland, A. (2012). Mental Health, Wellness, and Childhood Overweight/Obesity. *Journal of Obesity*, *2012*(1), 281801. https://doi.org/https://doi.org/10.1155/2012/281801

Russell, S. J., Croker, H., & Viner, R. M. (2019). The effect of screen advertising on children's dietary intake: A systematic review and meta-analysis. *Obesity Reviews*, *20*(4), 554-568. https://doi.org/https://doi.org/10.1111/obr.12812

Shen, C.-X., Liu, R.-D., & Wang, D. (2013). Why are children attracted to the Internet? The role of need satisfaction perceived online and perceived in daily real life. *Computers in Human Behavior*, *29*(1), 185-192. https://doi.org/https://doi.org/10.1016/j.chb.2012.08.004

Siervo, M., Gan, J., Fewtrell, M. S., Cortina-Borja, M., & Wells, J. C. K. (2018). Acute effects of video-game playing versus television viewing on stress markers and food intake in overweight and obese young men: A randomised controlled trial. *Appetite*, *120*, 100-108. https://doi.org/https://doi.org/10.1016/j.appet.2017.08.018

Siervo, M., Sabatini, S., Fewtrell, M. S., & Wells, J. C. K. (2013). Acute effects of violent video-game playing on blood pressure and appetite perception in normal-weight young men: a randomized controlled trial. *European Journal of Clinical Nutrition*, *67*(12), 1322-1324. https://doi.org/10.1038/ejcn.2013.180

Sutter, M., Zoller, C., & Glätzle-Rützler, D. (2019). Economic behavior of children and adolescents – A first survey of experimental economics results. *European Economic Review*, *111*, 98-121. https://doi.org/https://doi.org/10.1016/j.euroecorev.2018.09.004

Suziedelyte, A. (2015). The effects of old and new media on children's weight. *Applied Economics*, *47*(10), 1008-1018. https://doi.org/10.1080/00036846.2014.987916

Tim, J. C., Mary, C. B., Katherine, M. F., & William, H. D. (2000). Establishing a standard definition for child overweight and obesity worldwide: international survey. *Bmj*, *320*(7244), 1240. https://doi.org/10.1136/bmj.320.7244.1240

Ullmann, G., Kedia, S. K., Homayouni, R., Akkus, C., Schmidt, M., Klesges, L. M., & Ward, K. D. (2018). Memphis FitKids: implementing a mobile-friendly web-based application to enhance parents' participation in improving child health. *BMC Public Health*, *18*(1), 1068. https://doi.org/10.1186/s12889-018-5968-6

Vandelanotte, C., Sugiyama, T., Gardiner, P., & Owen, N. (2009). Associations of Leisure-Time Internet and Computer Use With Overweight and Obesity, Physical Activity and Sedentary Behaviors: Cross-Sectional Study. *J Med Internet Res*, *11*(3), e28. https://doi.org/10.2196/jmir.1084

Variyam, J. N., Blaylock, J., Lin, B.-H., Ralston, K., & Smallwood, D. (1999). Mother's Nutrition Knowledge and Children's Dietary Intakes. *American Journal of Agricultural Economics*, *81*(2), 373-384. https://doi.org/https://doi.org/10.2307/1244588

Wang, Y., Zhao, L., Gao, L., Pan, A., & Xue, H. (2021). Health policy and public health implications of obesity in China. *The Lancet Diabetes & Endocrinology*, *9*(7), 446-461. https://doi.org/10.1016/S2213-8587(21)00118-2

Willett, R. (2016). Online Gaming Practices of Preteens: Independent Entertainment Time and Transmedia Game Play. *Children & Society*, *30*(6), 467-477. https://doi.org/https://doi.org/10.1111/chso.12155

Yan, Z. (2005). Age differences in children's understanding of the complexity of the Internet. *Journal of Applied Developmental Psychology*, *26*(4), 385-396.

https://doi.org/https://doi.org/10.1016/j.appdev.2005.04.001

Yu, L., Ma, T., Wu, S., & Lyu, Z. (2023). How does broadband internet affect firm-level labor misallocation: The role of information frictions. *China Economic Review*, *82*, 102067. https://doi.org/https://doi.org/10.1016/j.chieco.2023.102067

Zhang, J., Xu, P., & Liu, F. (2020). One-child policy and childhood obesity. *China Economic Review*, *59*, 100938. https://doi.org/https://doi.org/10.1016/j.chieco.2016.05.003

Zhao, J. (2008). ICT4D: Internet Adoption and Usage among Rural Users in China. *Knowledge, Technology & Policy*, *21*(1), 9-18. https://doi.org/10.1007/s12130-008-9041-0

Zhao, L., Wang, F., & Zhao, Z. (2021). Trade liberalization and child labor. *China Economic Review*, *65*, 101575. https://doi.org/https://doi.org/10.1016/j.chieco.2020.101575

Zuo, G. W. (2021). Wired and Hired: Employment Effects of Subsidized Broadband Internet for Low-Income Americans. *American Economic Journal: Economic Policy*, *13*(3), 447-482. https://doi.org/10.1257/pol.20190648