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Exposure to High-Speed Internet and Early Childhood Development

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Is High-Speed Internet Detrimental for Early Childhood Development? Evidence from a Countrywide Program

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We estimate the effects of high-speed internet in early childhood on cognitive and non-cognitive outcomes exploiting cross-cohort and geographic differences in the introduction of fiber-optic-to-the-home (FTTH). Using the variation in lifetime cumulative exposure to fiber optic and combining survey and administrative data, we estimate intention-to-treat effects on early childhood development measured by validated screening tests for developmental delays. Our results show that an increase in 10 percentage points in lifetime exposure to fiber optic decreases development scores between 8% and 18% of a standard deviation in the areas of communication, problem solving and social skills. Effect sizes are larger for girls, children with more educated parents and living in smaller cities. Regarding the mechanisms, our results suggest that the effects are driven by an increase in children's screen time and by changes in parental practices.

Keywords: developmental test, internet, screen exposure.
JEL Codes: D60, I30, J13.

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1 Introduction

In recent years, exposure to devices connected to high-speed internet has increased significantly, with new information and communication technologies (ICT) becoming a ubiquitous element of everyday life (Kardefelt Winther et al. 2019). In this context, children have become more engaged with digital screens, particularly in early childhood. Children are starting to use internet connected devices at increasingly younger ages, with a rise in overall screen time during the last decades, especially for toddlers and preschoolers (Holloway et al. 2013, Chen & Adler 2019, Goode et al. 2019). Given that early childhood constitutes a crucial life period for cognitive and socio-emotional development, understanding the possible effects of new technologies on child development is a fundamental aspect of public policy, since it may affect the human capital of generations to come (Heckman 2008, WHO 2020). However, the study of the impact of new technologies on child development is still in its early stages (Anderson & Kirkorian 2015, Kostyrka-Allchorne et al. 2017, Gottschalk 2019). This study fills a gap in the literature by providing an analysis of the causal effects of high-speed internet accessibility on cognitive and non-cognitive outcomes in early childhood.

We analyze the causal effects of exposure to new technologies on early childhood development by exploiting geographic and cross-cohort variation in high-quality internet access, due to a significant expansion in the fiber-optic-to-the-home (FTTH) network in Uruguay. Access to FTTH installation gives households the possibility to purchase a fiber optic internet plan that raises connection speed and quality, affecting internet consumption decisions. This improvement in internet conditions is likely to increase screen exposure in the household, potentially affecting the achievement of children's developmental milestones. Three main channels linking screen exposure to development outcomes have been identified in the literature: a direct effect due to the increase in screen time of the child, an indirect effect produced by a reduction in time spent in other activities (substitution effect), and an indirect effect related to the behavior of caregivers. The setting of our study allows us to estimate the overall effects of high-speed internet on child development between 0 to 5 years of age, and shed light on the potential channels. To the best of our knowledge, this is the first study that analyzes the effects of exposure to modern media during early childhood on cognitive and non-cognitive skills using an exogenous source of variation.

To conduct our analysis, we use the FTTH rollout implemented in Uruguay since 2010, which delivered fiber optic infrastructure to all dwellings with a fixed telephone line throughout its territory, free of charge. Our treatment assignment is defined as the share of months a child is exposed to FTTH accessibility throughout her life, which depends on her neighborhood of residence and date of birth. This allows us to identify the intention-to-treat effects of FTTH connectivity through the effects of fiber optic accessibility at home throughout the lifetime of the child. We combine administrative data on FTTH rollout with a nationally representative study on early childhood, the "Nutrition, Child Development and Health Survey" (NCDHS), performed during the same period in which the fiber optic expansion took place. This survey collected data on a wide array of outcomes for children born between 2010 and 2018, including: child development psychometric tests, demographic and socioeconomic characteristics of the child and household, screen time of the child, and parental practices and beliefs. By exploiting the fact that developmental outcomes are available for children from different geographic regions and cohorts, we are able to study the causal effects of a universal policy that provided a significant improvement in internet quality.

Results show a deterioration in children's outcomes caused by an increase in the quality of internet connectivity. A 10 percentage points (pp) increase in the probability of FTTH during early childhood decreases development scores in communication, problem solving, and social skills, with effect sizes between 8% and 18% of a standard deviation (SD). For communication and social skills, this translates into a decrease of 4 pp and 3 pp in the proportion of children developing within normal ranges, indicating that the worsening in child development scores occurs at key parts of the distribution of outcomes. An analysis of heterogeneous effects shows that the negative impact is slightly larger for girls, children with more educated parents and children living in smaller cities. This goes in line with the idea that these populations experience a higher opportunity cost in the worsening of adult-child interactions, also found in previous literature (Fort et al. 2020). Moreover, differences in treatment take-up across educational levels may also explain these higher effects.

Our study of mechanisms shows that results are driven by changes in children's screen exposure, in the number of hours and in the quality of exposure, and by changes in caregivers' behavior. We observe an increase in the proportion of children that use screens as a primary activity for more than the recommended one-hour threshold, together with a worsening of parental practices concerning screen exposure. This is given by an increase in the agreement that leaving children in front of a screen for a long period constitutes a valid solution when caregivers are busy, going against the co-viewing recommendations made by health institutions. Moreover, we find an increase in internet use by adults and an increase in risky parental practices, indicating an indirect channel through caregivers' behavior. We do not find a substitution effect concerning the extensive margin of alternative activities performed with parents (reading books and singing songs), but we do find a decrease in the number of children's books available in the household. The information available on this channel is insufficient to disregard it. Overall, our analysis of mechanisms indicates that an increased exposure to high-speed internet affects the child's home environment lowering parent-child high-quality interactions, which are crucial for cognitive and non-cognitive development during early childhood.

This paper contributes in several ways. First, it provides evidence for the causal effects of high-speed internet for a crucial period of life, early childhood. Second, it conducts the analysis by taking advantage of high-quality data, using child psychometric tests for developmental achievements measured in a large probability sample of the urban population aged 0 to 5. Third, it provides evidence on the overall effect when offering high-speed internet connectivity through a universal policy, which has relevant policy implications for the future generations of children. Fourth, it illustrates the effects of new technologies beyond the United States and Europe, allowing to study the challenges of internet accessibility in more vulnerable contexts. The availability of high-quality cognitive and non-cognitive outcomes at the same period in which the introduction to fiber optic took place, makes our setting unique for the study of the causal effects of high-speed internet on early childhood development. Our results inform the design of evidence-based recommendations on children's and caregivers' screen exposure that enhance learning from new technologies without generating risks for the future development of children.

This study relates to two strands of the literature. On the one hand, it is associated with the abundant medical literature that analyzes the relation between screen media exposure and children's outcomes (see for example reviews by DeLoache & Chiong 2009, Anderson & Kirkorian 2015, Calvert 2015, Chassiakos et al. 2016, Moreno et al. 2016, Radesky et al. 2016, Anderson et al. 2017, Kostyrka-Allchorne et al. 2017, Gottschalk 2019). Results provided in this literature have shown an ambiguous association between screen exposure and child development, reporting negative, null and positive effects on early childhood development. Although there is still no clear evidence on a safe level of screen time or whether it actually causes harm as a general fact, this literature has stood out for its notoriety in supporting recommendations against excessive use of screens made by various institutions, such as the American Academy of Pediatrics and the World Health Organization. However, this literature has several limitations. First, it mostly focuses on correlational studies and experiments involving small sample sizes, making it difficult to infer causal effects and extrapolate conclusions to the general population. Second, most evidence is related to traditional television, when in fact children are increasingly exposed to non-traditional platforms due to the spread of the internet, which modifies the patterns of use and type of content consumed (Anderson & Kirkorian 2015, Kostyrka-Allchorne et al. 2017, Gottschalk 2019). Conversely, this literature does show robust findings regarding the presence of heterogeneous effects of screen exposure according to: the age of the child, the type of programming (such as educational or entertainment, produced for children or adults), the context of viewing (the child alone or in interaction with an adult), the type of exposure (foreground or background) and whether the media is interactive (Anderson et al. 2017, Kostyrka-Allchorne et al. 2017). Children are more likely to learn from screens when they are exposed to educational content in interaction with a caregiver, and when they are old enough to understand it (at least 18 months of age).

On the other hand, this study relates to the growing economic literature on the effects of media on socioeconomic outcomes. Several authors have studied the effects of internet availability on subjective well-being, mental health, and educational achievements in middle childhood and adolescence (Faber et al. 2015, Dettling et al. 2018, Grenestam & Nordin 2019, McDool et al. 2020, Sanchis-Guarner et al. 2021, Arenas-Arroyo et al. 2022, Donati et al. 2022). Focusing on those that evaluate educational outcomes, Faber et al. (2015) use administrative test scores of primary and secondary school students in England to analyze the effects of internet speed over the period 2002-2008. They exploit the exogenous variation due to distance to telephone exchange stations, and find that internet connection speed does not affect overall educational attainments. They justify this finding by a null effect on time spent studying online or offline, and on the productivity of time spent studying. Grenestam & Nordin (2019) study the effects of fiber optic broadband on the GPA of Swedish students graduating upper secondary school between 2010 and 2012, by exploiting the geographic and temporal variation in fiber optic rollout. They find that reaching full coverage in the student's area of residence leads to a reduction of 3% to 6% of a standard deviation in GPA. They provide evidence for an increase in the number of hours spent online during weekdays as a potential mechanism. Sanchis-Guarner et al. (2021) estimate the effects of high-speed internet on standardized test scores of English students at age 14 over the period 2005-2008, using the variation in the distance to telephone local exchange station. They find that increasing broadband speed by 1 Mbit/s increases test scores by 5% of a standard deviation in the national score distribution. Finally, Dettling et al. (2018) examine the effects of high-speed internet on SAT scores and college applications in the U.S. by exploiting geographic variation in broadband availability during junior year. Using data on students graduating between 2001 and 2008, they find that broadband availability increases SAT scores by 0.7 scale points, and that their application portfolio increases in both size and quality. These results seem to be explained by a reduction in the direct effort and informational costs. As can be observed, the literature is still not conclusive on the results of internet accessibility on educational outcomes. Furthermore, it only analyzes the effects of internet access during teenage years, leaving the questions regarding internet exposure during the first years of life still unanswered.

Considering older technologies that also affected screen exposure, a few studies can be found on the effects of television exposure during early childhood on educational outcomes. However, the analysis is performed using the 1950's and 70's television, which is fundamentally different from modern screen media (Gentzkow & Shapiro 2008, Kearney & Levine 2019). More recently, some studies have been conducted on the effects of cable television and the digital television transition on children's cognitive abilities, academic performance, and health outcomes (Nieto & Suhrcke 2021, Nieto 2019, Hernæs et al. 2023). Nonetheless, these studies are only available for school-age children and adolescents.

The gap regarding the estimation of the causal effects of high-speed internet on cognitive and non-cognitive skills in the first years of life has not yet been filled due to several empirical challenges. On the one hand, there are ethical limitations in trying to estimate the causal effects of internet and screen exposure on child development though a controlled experiment. Given the preliminary evidence on the potential risks of excessive exposure, any incentives to increase it could harm children. Moreover, trying to measure these effects by considering only the direct use of screens of the child would imply incurring in a large measurement error, given the rise of screen time as a secondary activity in the background and the indirect effects that go trough the screen time of caregivers. When moving beyond controlled experiments to quasi-experimental strategies, survey data on child development using screening tests are not common to find at the population level given its large costs. Our setting takes advantage of a unique opportunity in which we exploit a natural experiment that changed the incentives for media consumption, allowing to consider channels running through the child and the caregiver, while overlapping with a probability survey of the whole population of children aged 0 to 5 that measured child development using well-know and high-quality instruments.

The remainder of the paper is structured as follows. Section 2 introduces our conceptual framework. Section 3 presents the background and data. Section 4 describes our empirical strategy. Section 5 shows the results, and Section 6 presents our final remarks.

2 Fiber Optic Accessibility and Early Childhood Development

In this study we analyze the effects of fiber optic accessibility on early childhood development. Our treatment assignment depends on the possibility of connecting to fiber optic inside the dwelling, which is determined by the FTTH installation performed by the internet service provider. When this is the case, households can choose to purchase a fiber optic internet plan, increasing connection speed and quality, and thereby exposing the child and her household environment to the fiber optic treatment. This treatment makes the use of internet connected devices more appealing, since data transmission is faster and more reliable, consequently affecting internet consumption decisions and increasing exposure to digital screens in the household. Studies show that access to digital technologies has resulted in an overall increase in screen time, given that there is not a one to one substitution from old to new devices in media consumption (e.g. from traditional television to tablets or cellphones) (Anderson & Kirkorian 2015, Rideout et al. 2013, Goode et al. 2019). Hence, FTTH accessibility is likely to increase screen consumption of the child and the caregiver, ultimately altering overall time use patterns. Since we are assessing the effects of high-speed internet on child development, which reflects the skill accumulation process since birth, our treatment assignment variable is defined as the average exposure to fiber optic throughout the lifetime of the child.

Two aspects regarding our treatment assignment variable are worth noting. First, our estimates provide the marginal effects of increasing internet quality derived from a change in internet infrastructure, from a copper network to a fiber optic network. Second, our results reflect the general equilibrium effects of FTTH accessibility, given that our treatment assignment took place within a country-wide program in a period of significant increases in internet speed worldwide. The availability of high-speed internet plans at the household level brought along changes on the firm's side, with companies developing innovative services that became feasible with this new technology.[1] Therefore, our estimates will also reflect these changes on the supply side.

Internet and screen media exposure can affect children's development through direct and indirect mechanisms. The first ones refer to the effects from direct exposure of the child to screen media, while the second ones are not produced by the child's exposure per se, but are still a consequence of using a certain device in the child's environment. First, there is a direct channel derived from the potential increase in the child's use of screens through different platforms and devices, such as televisions, tablets and smartphones. This includes time engaged with screen media either as a primary or secondary activity. We refer to screen use as a primary activity when this is the main focus of attention and energy, and as a secondary activity when this is done as a background activity while undertaking a primary activity at the same time (e.g. watching a TV show while eating or playing with physical toys) (Goode et al. 2019). Theoretically, direct screen exposure could affect: children's knowledge acquisition, their capacity to sustain attention, the benefits of a primary activity when using screens in the background, children's creativity and mental elaboration, and children's spatial and temporal cognition (Anderson & Kirkorian 2015). The medical literature on the topic shows either no association or a negative relation between direct exposure and child development for children up to 30 months of age (Chassiakos et al. 2016, Radesky et al. 2016, Anderson et al. 2017, Kostyrka-Allchorne et al. 2017). This can be partially explained by the phenomenon denominated "video deficit", which refers to the lower ability infants and toddlers have to learn new verbal and nonverbal problem solving skills from videos compared to live sources (Radesky et al. 2016, DeLoache & Chiong 2009). For preschool children older than 30 months, there is evidence suggesting that educational media has a positive impact on child development

[1] Companies providing online entertainment expanded their services during our period of analysis. For example, YouTube introduced high definition videos in 2009 and Netflix started operating outside the U.S. with its video on demand service in 2010 (Brennan 2018, Pacella 2019). Also, social media evolved to image-based platforms such as Instagram and TikTok, which launched in 2010 and 2017 respectively (Lenhart et al. 2007, Vogels et al. 2022).

and subsequent academic performance (Anderson & Kirkorian 2015, Radesky et al. 2016, Anderson et al. 2017, Kostyrka-Allchorne et al. 2017). However, there is also evidence that children can learn non-beneficial attitudes from advertising or inadequate content (Calvert 2015, Chassiakos et al. 2016). Moreover, research shows that the potential effects of screen time are mediated by the quality of exposure, especially by the type of content consumed and by the presence of adults co-viewing with the child. Hence, the quality of exposure functions as a mediator between hours of exposure and development outcomes (Anderson & Kirkorian 2015, Kostyrka-Allchorne et al. 2017, Gottschalk 2019).

A second mechanism is given by the fact that the increase in screen time could imply a reduction in the allocation of children's time devoted to other activities that are more or less effective for the production of skills. This can be seen as a substitution effect derived from the opportunity cost of screens. For example, an increase in the use of digital screens could displace time spent reading books or performing physical activities. The different productivity rates in the skill production function of the displaced activities compared to screen time would account for the opportunity cost of screen media (Anderson & Kirkorian 2015).

Third, internet availability could affect the behavior of caregivers when taking care of the child, indirectly affecting child development. For example, evidence has shown that caregivers' screen exposure could lead to a reduction in the quantity and quality of interactions with the child. Being that parental involvement is critical for cognitive and emotional development, the use of screens by caregivers could have negative effects on child development (Moreno et al. 2016, Radesky et al. 2016, Kostyrka-Allchorne et al. 2017). In addition, internet use by caregivers could also affect parental beliefs and practices, changing the home environment of the child and affecting her development.

Fourth, high-speed internet accessibility could also affect caregivers' behavior and beliefs in other areas, modifying household conditions and ultimately affecting child development. For instance, research has shown that high-speed internet can alter the labor supply of married women with children, as well as fertility decisions for highly educated women (Dettling 2017, Billari et al. 2019).

In this study we provide evidence for the impact of FTTH accessibility on cognitive and non-cognitive outcomes in early childhood. Overall, considering the reviewed literature, we expect to find negative effects on child development from the improvement in internet connectivity. These effects reflect the overall impact derived from changes in screen exposure in the household, considering both direct and indirect mechanisms. We present suggestive evidence to understand which mechanisms are explaining the effects, considering: children's screen time and its quality (mechanism one), time spent in other activities (mechanism two), and changes in caregivers' parental practices and beliefs from internet exposure (mechanism three). The analysis of indirect mechanisms that go through the caregiver beyond changes in their parental beliefs and behavior while taking care of the child will not be considered in this paper. A summary of our theory of change from treatment assignment to final outcomes is presented in Figure 1 in the Online Appendix.

3 Background and Data

3.1 The Deployment of the FTTH Network in Uruguay

Over the last decades the Uruguayan government has implemented a wide array of policies to foster the ICT sector, provide high-quality internet connection and guarantee digital inclusion. This was part of a strategic plan seeking to place Uruguay in the top positions worldwide. Examples of these policies are: a basic broadband plan that offered entry-level connectivity at no extra cost for households with landlines, the one-laptop-per-child program and the FTTH project. In this study we focus on the effects of the FTTH project, which aimed to provide fiber optic accessibility to all households in the country.

The project started in 2010 and was conducted by the government-owned telecommunication operator named ANTEL, which was the only authorized provider for fixed broadband connections in Uruguay (FTTH Council Americas 2015). It implied the installation of fiber optic infrastructure to deliver internet connection inside the dwellings, adding this option to the existing connection through the copper wire telephone network (ADSL). The main characteristic of the FTTH network architecture is that fiber optic is laid from the provider's central up to the user's dwelling, what is referred to as "the last mile". ANTEL provided this connection to all households with a fixed telephone line free of charge. The installation was done gradually by geographical areas reaching all households within a certain area by default, without the need of preregistering or requesting the installation in advance. The ultimate goal was to provide fiber optic connectivity to all Uruguayan households, reaching geographical areas that would not have been profitable for private companies. Yearly deployment objectives were set out in terms of the number of "Homes Passed", a term used in the literature to indicate the number of households with fiber optic accessibility. In 2010, 6,537 km of fiber optic were installed, growing at a yearly rate of approximately 8% in the 2011-2018 period and reaching 11,730 km in 2018 (URSEC 2018). In 2011 the first fiber optic connection was done in the country's capital, quickly expanding to the rest of the country. By the end of 2012, 14% of households with fixed telephone lines had fiber optic accessibility, a figure that increased to 64% by the end of 2014 and to 83% in 2018. Figure A.1 in the Appendix shows the geographic and yearly variation in the FTTH rollout since the beginning of the deployment by administrative units, named departments (Uruguay is divided into 19 units for local administration).

Once the fiber optic was connected, clients could choose between staying with their current plan or opting for a fiber optic one. The main advantage of fiber optic is related to its larger bandwidth and speed, together with its higher reliability (lower data loss and interference), which increased transmission quality. This allowed users to access more technologically advanced services that demanded high-quality internet connection, such as High Definition (HD) video streaming, gaming, media sharing, etc. On the other hand, migrating to a fiber optic plan implied an increase in the monthly rate paid by the consumer. Given the significant differences in speed and amount of megabytes between FTTH and ADSL internet plans, the comparison of prices is not straightforward. To provide a reference point, in 2012 the flat rate FTTH plan was only 5% more expensive than the ADSL flat rate, with notorious gains in speed. Conversely, the cheapest FTTH plan was four times more expensive than the ADSL one. Consequently, treatment take-up is expected to be almost total among higher-income households given that the price difference was almost negligible for consumers with high-end plans. On the other hand, for those with less expensive ADSL contracts, the price difference could refrain them from changing to an FTTH internet plan. Information on treatment take-up is presented in Section 4.

3.2 Internet Data

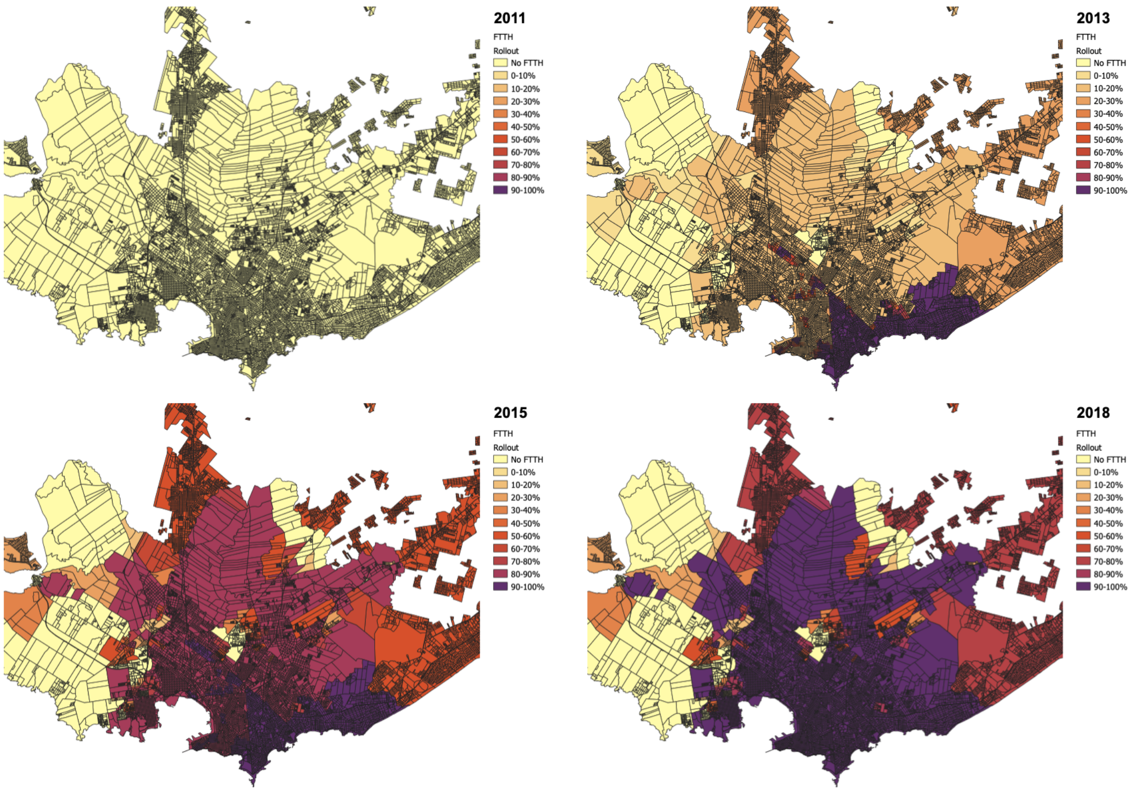
For our analysis we use original data on the FTTH rollout in Uruguay. Ideally, we would have preferred using block level information for the period 2012-2018 provided by the telecommunication operator. Given that this information was not stored over time, we construct a novel database by combining two types of administrative data from the telecommunication operator and Census data. On the one hand, we use information on the proportion of fixed telephone lines with FTTH connection by year and departments for the period 2012-2018. On the other hand, we construct granular data on FTTH installation for the year 2012 by using an Internet Archive on ANTEL's web page.[2] This data provides very precise information on the geographic deployment of FTTH reaching up to the block level. Information at the block level for the year 2020 is obtained directly from the telecommunication operator. Moreover, we use information on the number of landlines by small geographical areas from the 2011 Census conducted by the National Institute of Statistics (NIS).

In order to best capture and exploit the variability in fiber optic accessibility, we create artificial "neighborhoods" within departments that refer to smaller geographical areas. Taking advantage of the staggered design of the policy, we combine the department level information with the granular data for 2012 and 2020 to estimate corrected probabilities of FTTH accessibility for the years 2012-2018 at a lower level of disaggre-

[2]Information was posted online through static maps in PDF format. We recover it by using the Internet Archive Wayback Machine (a service that stores archived versions of Web sites), and then convert it into shape files through a manual data entry process. We use as base the geographic information provided by the Ministry of Social Development at https://mapas.mides.gub.uy/.

gation. The procedure for the neighborhood level imputation is detailed in Section B of the Appendix. The final database consists of 444 neighborhoods in the capital city and 40 neighborhoods in the rest of the country that cover the total extension of urban areas in Uruguay (localities with 5,000 inhabitants or more). For these neighborhoods we have the yearly probability of having FTTH accessibility, which by construction is the same within neighborhood. As an example, Figure 1 shows the FTTH deployment for the capital city, Montevideo, at the neighborhood level.

Figure 1: FTTH Rollout in Montevideo by Neighborhood



Notes: Own computations based on ANTEL and Census 2011 data.

3.3 Children Data

The information on children outcomes comes from the "Nutrition, Child Development and Health Survey" (NCDHS), a probability sample of children living in the urban country conducted by the National Institute of Statistics and the Ministry of Social Development.[3] Its objective is to study the overall situation of early childhood in Uruguay collecting a wide array of information, including: socioeconomic conditions of the child's household, parental attitudes and opinions, and child development through psychometric tests. Interviews were conducted face-to-face by students and professionals from the

[3]The survey has the approval of the Ethics Committee from the Faculty of Medicine of Universidad de la República (Uruguay).

health area, or by enumerators specially selected and trained to conduct this survey. The main survey respondent was the mother of the child (over 95%) followed by the father and grandparents.

Data was collected for a 1st cohort in 2013 and 2015, and for a 2nd cohort in 2018. While in 2013 information on development tests was collected only for the sample of children living in the capital city, in 2015 and 2018 this information was collected for the whole sample, being representative of children living in the urban country. For this reason we mainly conduct our estimations using the 2015 and 2018 waves, and use the 2013 wave only as a robustness check. This implies that our data is pool of repeated cross-sections, where each child is observed only once. For the first cohort, the effective sample size was 3,077 children in the 2013 wave, while 2,611 children were part of the 2015 wave. For the second cohort, information on 2,598 children was collected. The first cohort covers children born between 2010 and 2013, while the second one covers children born between 2013 and 2018. The final composition of the sample per age and wave is presented in Table 1. We use sampling weights calibrated against population totals provided by the NIS. The sampling design and basic descriptive statistics are presented in Sections 2.1 and 2.2 of the Online Appendix.

Table 1: Observations per Age Bracket and Survey Wave.

	2015		**2018**	
Age in months (years)	**Freq.**	**%**	**Freq.**	**%**
0-11 months (0 years)	0	0.0	646	24.9
12-23 months (1 years)	0	0.0	531	20.4
24-35 months (2 years)	245	9.4	462	17.8
36-47 months (3 years)	731	28.0	484	18.6
48-59 months (4 years)	941	36.0	475	18.3
60-83 months (5 and 6 years)	694	26.6	0	0.0
Total	2,611	100.0	2,598	100.0

Notes: Columns 2 and 4 report the number of observations in each age bracket per NCDHS wave. Column 3 and 5 report the proportion of observations in each age bracket per NCDHS wave.

Regarding the children psychometric tests, we use two instruments that have been validated and are of extensive use to screen for developmental delays in young children: the Ages and Stages Questionnaires Third Edition (ASQ-3) and the Ages and Stages Questionnaires Socio-Emotional (ASQ-SE). The ASQ-3 is an instrument that assesses child development in five areas: communication, gross motor, fine motor, problem solving, and personal-social. It provides 21 questionnaires to evaluate age-specific outcomes in different age brackets between 1 and 66 months of age. Each questionnaire contains six questions per area which can be answered as "yes", "sometimes" or "not yet", scoring 10, 5 or 0 points respectively. Scores are then summed within each area, summarizing the developmental progress of the child. Obtaining the maximum, 60 points, implies that the child can perform all the developmental milestones expected for her age. In addition to this continuous measure, the test suggests comparing the scores to age-specific cutoffs based on empirical research considering a reference population in the U.S. Three categories are defined: the child is developing normally, the child should be monitored, and the child may be at risk for developmental delays. A child is defined in the monitor category if she scores 1 to 2 SD below the mean of the reference population, and in the risk category if she scores 2 SD or more below the mean (Squires et al. 2009). The ASQ-SE was developed as a complement to the ASQ-3 and focuses on the social and emotional development of children in seven behavioral areas: self-regulation, compliance, social-communication, adaptive functioning, autonomy, affect, and interaction with people. It provides 8 questionnaires that are age-specific for children between 3 and 65 months. Each questionnaire has 22 to 36 questions for the parents to answer as "often or always", "sometimes" or "rarely or never", with scores of 0, 5 and 10 for each category. A higher overall score means a worse developmental situation. A continuous global score considering all behavioral areas is obtained. In addition, empirically-derived and age-specific cutoffs are provided to identify children at risk that should be referred for further assessment (Squires et al. 2002). In this study, we consider a continuous score for each of the development areas in the ASQ-3 and an overall score for the ASQ-SE. We construct these by standardizing the ASQ-3 and ASQ-SE raw scores by age groups according to the distribution in our sample. Age groups are defined by aggregating the original age test brackets, that is, the age brackets for which each questionnaire is designed. For the ASQ-3 the aggregated age brackets are: 1-12 months, 13-22 months, 23-38 months, 39-50 months, and 51-66 months. For the ASQ-SE the aggregated age brackets are: 3-14 months, 15-26 moths, 27-41 months, 42-53 months, and 54-65 months. Since the ASQ-3 scores measure achievements and the ASQ-SE score measures socio-emotional problems, we present the results for for the continuous ASQ-SE score with the opposite sign to facilitate the interpretation of results. Moreover, we analyze categorical variables indicating children developing within the normal range. For each area of the ASQ-3 we construct a binary variable considering children developing within normal ranges vs. those that should be monitored or are at risk of developmental delays. For the overall ASQ-SE we construct a binary variable considering children that are not at risk of developmental delays vs those that are at risk.

In addition to the main development outcomes, secondary outcomes are used to analyze the mechanisms driving our results. We combine different questions to study the direct and indirect effects of FTTH on the child, analyzing not only changes in children's time use but also alterations in the beliefs and behavior of caregivers (as stated in Section 2). First, we estimate the direct effect of fiber optic availability on children's screen exposure by using information on screen time. We construct an indicator variable for spending at least one hour a day on screen media, recovered from global time estimates of screen time reported by the caregiver in the NCDHS. This cutoff is in line with the recommendations made by the American Academy of Pediatrics and the World Health Organization, who suggest either no exposure or, at most, one hour a day in the 0-5 age range.[4] Even though global time estimates are the most common way of measurement of screen time because of its low costs and ease of implementation, it has limitations compared to time use diaries. Particularly, it may underestimate the screen exposure of the child if the parent does not include the hours of screens as a secondary activity and the hours of background exposure, and answers may be more sensitive to social norms and stereotypes (Vandewater & Lee 2009). Complementary to this measure, we proxy the quality of exposure by analyzing caregivers' agreement or disagreement with the following statement: "Leaving kids in front of the TV for a long period of time is a solution when mothers are busy". We use this question as an approximation for the quality of children's direct exposure, given that it informs on using screens to entertain children without parental presence as a general practice. Although agreeing with the statement does not necessarily mean that the caregiver is engaging in this practice, we believe it denotes a higher prevalence and acceptance of this behavior in her environment. Given the recommendations on adult co-viewing practices made by health institutions, we use this variable as an indicator of low quality of exposure.

Second, we study the displacement of alternative activities that are beneficial for child development as another potential mechanism using information available on the NCDHS. This survey asks questions on whether adults perform activities together with the child, including telling stories and singing songs with the child. We construct a variable that counts the number of activities, taking the value of 2 if adults tell stories and sing songs with the child, 1 if adults engage in only one of these activities, and 0 if they do not engage in any of the two. Although the NCDHS inquires on additional activities besides the ones considered for this indicator, these are the only two compatible across waves 2015 and 2018. Additionally, we construct a variable on the number of children's books available in the household to use as a proxy for the activities of reading or looking at books with the child, or the child using books by herself. We construct a categorical variable that takes the value 0 if there are no children's books at home, 1 if there are 1-9 books, and 2 if there are more than 10 books.[5]

Third, we analyze the indirect effects of FTTH exposure that go through the caregivers. We approximate caregivers' internet use by using information available in an additional survey, the Continuous Household Survey (CHS), which is a yearly survey

[4] Ideally we would have set the cutoff at more than one hour a day (instead of 1 hour or more), but informational limitations in the 2015 wave did not allow for this.

[5] In the original variables the middle category is defined in a slightly different way in each wave. In the 2015 wave the middle category corresponds to 1-10 books and in the 2018 wave it corresponds to 1-9 books.

conducted by the NIS using a random sample representative of the whole population in Uruguay. Since information from the CHS and the NCHDS cannot be merged directly, we merge the CHS data with information on fiber optic deployment, and consider adults living in households with children of the same age and neighborhood as in our NCDHS sample. We use two mutually exclusive variables for the frequency of internet use that indicate if an adult uses internet at least once per day or at least once per week (but less than once per day).

Fourth, we analyze the effects on caregivers' beliefs regarding parental practices using information available in the NCDHS. We consider an instrument that evaluates child-rearing practices following an adaptation of a sub-module of the 'Nurturing Practices Assessment Instrument" (IPC-GIEP), developed by the Interdisciplinary Group of Psychosocial Studies (GIEP - Universidad de la República) that was included in the NCDHS (Cerutti et al. 2014). This instrument considers caregivers' opinions on how children learn, the use of punitive parenting practices, and sexist practices. We consider the agreement or disagreement with 22 statements, and construct an index of risky parental practices by counting the number of answers that indicate a risk factor.[6]

In addition to our primary and secondary outcome variables, control variables for our regressions are obtained from the NCDHS. These are: neighborhood of residence of the child, age of the child in months, gender of the child, ethnicity of the child, maternal age at birth, caregiver's educational level and cohabitation with both parents. We complement this information with neighborhood-level variables obtained from the CHS, which are: sanitation by neighborhood and income per capita by neighborhood. The construction of these variables is presented in Table 2 in the Online Appendix and more details on how are they included in our estimation is presented in Section 4.

3.4 FTTH Exposure of the Child

Our objective is to estimate the intention-to-treat effects of fiber optic throughout the lifetime of a child, that is, the effect of having the possibility to purchase a fiber optic internet plan in her dwelling, regardless of whether the household actually purchases it. As stated, this is given by the yearly probability of having FTTH accessibility at the neighborhood level. Since our outcome variables reflect the development of a child from birth to the time of the outcome assessment, we construct a measure that reflects the average exposure to fiber optic throughout the lifetime of the child. We define this as an age-weighted cumulative measure of FTTH exposure, computed as the mean value of FTTH accessibility over the exposure period (from birth to the outcome assessment), as follows:

[6] We consider 22 out of the 23 questions present in the NCDHS since we exclude the one that inquires directly about using TV as a solution when caregivers' are busy, given that we already use it to approximate the quality of screen exposure of the child.

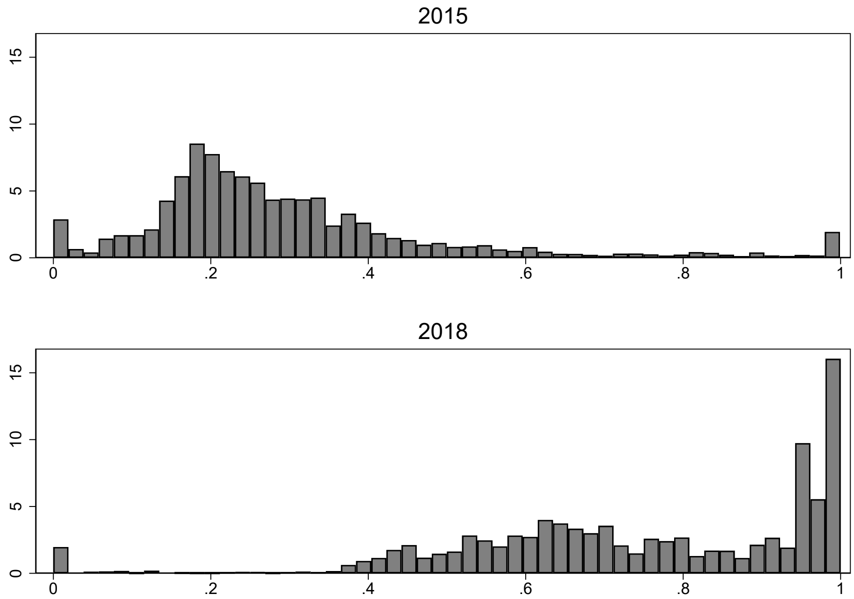
$$\text{FTTH\_E{\scriptsize XPOSURE}}_i = \frac{\sum_{month/year=b_i}^{month/year=s_i} FTTH_{month/year,n_i}}{a_i} \tag{1}$$

where i refers to the child, b_i is the month and year of birth of the child, s_i is the survey month and year, n_i is the neighborhood of residence of the child, $FTTH_{month/year,n_i}$ is the probability of FTTH in each $month/year$ at neighborhood n_i, and a_i is the age in months of the child at the time of the survey. Since we only have the probability of FTTH accessibility at the end of each calendar year, for each month in year t we use the FTTH accessibility in year $t-1$. Moreover, given that we only have information on the place of residence of the child at the time of the survey (and not the history of neighborhoods of residence), we assume that the child has lived in the in the same neighborhood since birth. Data from the CHS for the same years and age brackets as in the NCDHS informs that between 90% and 93% of children have lived in the same locality since birth.

Our treatment assignment variable can be interpreted as the lifetime exposure to fiber optic at the time of the outcome measurement. As an example, if a 20-months-old child lives in a neighborhood with a probability 1 of having had fiber optic accessibility since birth, FTTH exposure takes a value of 1. However, if the probability was 0.5 for the first 10 months and 1 for the last 10 months, FTTH exposure is 0.75. The definition of our treatment assignment variable implies that this is a relative measure according to the child's age. This allows us to maintain consistency with the way in which the ASQ-3 and ASQ-SE measure skill acquisition. In these tests, scores do not increase in absolute terms as children grow, since questions change with age to reflect that children should develop different skills at different stages. This is because their objective is to detect developmental delays in the acquisition of skills expected in each age range, and this is relative to the number of months in a child's lifetime. Accordingly, our FTTH exposure measure is computed relative to the number of months a child has had to develop her cognitive and non-cognitive skills.

Below we present the histograms for our variable of internet exposure for the survey waves 2015 and 2018. As Figure 2 shows, the distribution of FTTH exposure is skewed to the right in 2015, with a mean exposure of 30% during a child's lifetime. In 2018 this distribution shifts towards the right, with a mean exposure of 75%. This reflects the fact that more recent cohorts have, on average, higher exposure to fiber optic accessibility. Our empirical strategy takes advantage of the variation across cohorts within and between waves.

Figure 2: FTTH Exposure by Survey Wave



Notes: Own computations based on ANTEL data, 2011 Census and NCDHS data. Histograms of FTTH exposure by survey wave using sample weights. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility.

4 Estimation Strategy

To analyze the effects of fiber optic accessibility on child development outcomes we exploit the geographic and cross-cohort differences in the timing of fiber optic penetration. The main specification is the following:

$$y_i = \beta \text{FTTH\_E}\textsc{xposure}_i + \gamma_{na} + \lambda_t + (Z_n \lambda_t)'\psi + X_i'\alpha + \epsilon_i$$

where i refers to the child, t to the survey year, n to the neighborhood of residence of the child and a to her age in months. The treatment assignment variable is FTTH_Exposure$_i$, which varies according to the age of the child, neighborhood of residence, and survey date. Each of the outcome variables, y_i, corresponds to the score in the five dimensions of the ASQ-3 test and the overall ASQ-SE score. Our coefficient of interest is β.

We include γ_{na} as the neighborhood and age fixed effects, where ages are categorized according to an aggregation of the original tests age brackets. This allows to control for unobservable permanent characteristics specific to the region of residence and age bracket of the child. λ_t indicates the survey year fixed effects, which control for year-specific shocks common to all individuals. Z_n is a vector of pre-treatment neighborhood level covariates interacted with λ_t, included to control for survey year trends in baseline characteristics. The pre-treatment covariates are the average income per capita and the percentage of households with sanitation by neighborhood in 2010. X_i is a vector of child level covariates correlated with the outcome of interest and most likely unaffected by the treatment, included to reduce the standard errors of the estimated coefficients. These are: gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE. Table 2 in the Online Appendix presents a detailed definition of the variables included as controls in the regressions. Since these controls do not affect identification and to avoid losing observations, we impute missing values of continuous variables with the mean by wave and missing values in categorical variables with the median by wave. The proportion of observations with imputed missing values in waves 2015 and 2018 is 1.1%.

By controlling for neighborhood-age and survey year fixed effects, we are exploiting the variation derived from having children of the same age and neighborhood born in different years. This allows us to compare children with the development tests measured at the same age and living within the same neighborhood, that were exposed to different intensities of FTTH accessibility throughout their lives because the were born in different years. This assumes that there are no cohort effects that could potentially bias our results. As we are considering children born between 2010 and 2018, we believe that this assumption is plausible. Moreover, we assume that there were no other policies affecting child development with the same rollout across neighborhoods and cohorts as the FTTH project. One possible confounding policy could have been the one-laptop-per-child program. Considering the details of its implementation, the estimation of our effects is not likely to be biased by the effects of this program. They are however conditional on the existence of the program in the country. More details are presented in Section C of the Appendix.

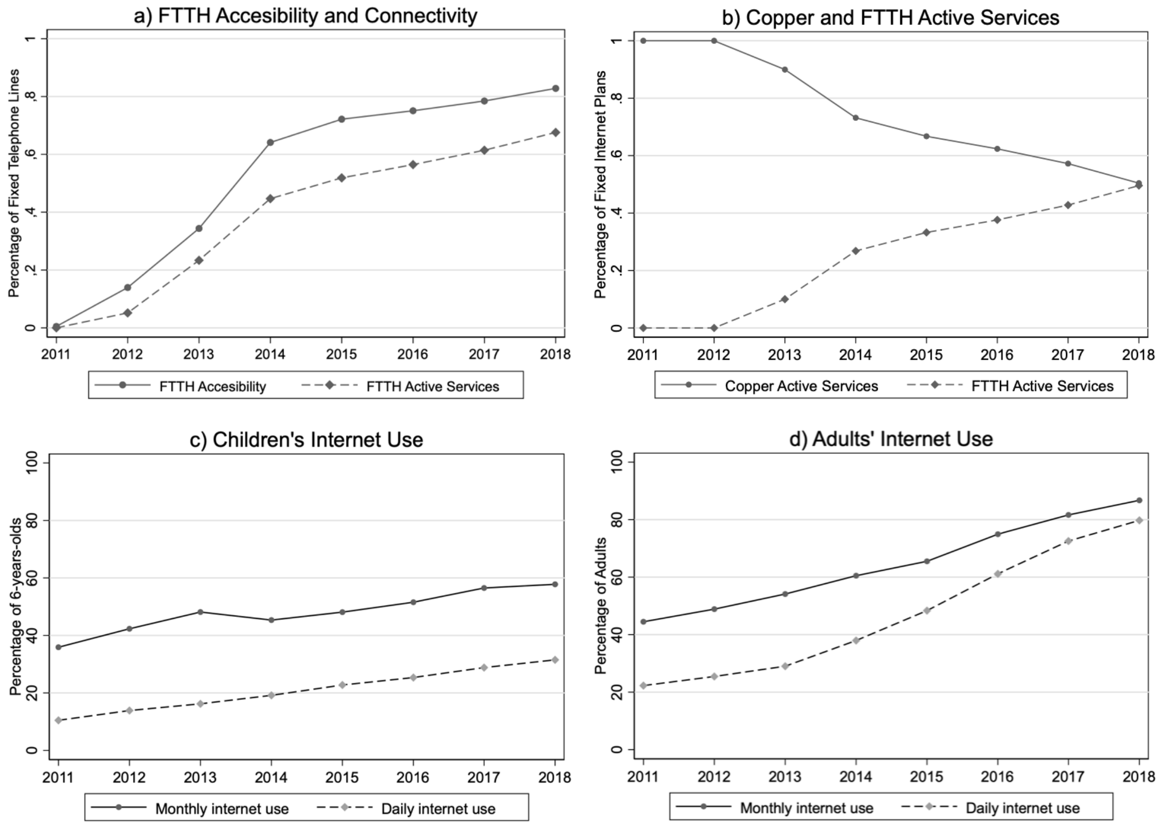
This strategy identifies the intention-to-treat effect of fiber optic, that is, the effect of being assigned to treatment, which depends on the probability of fiber optic accessibility in the dwelling. Treatment assignment is defined by the FTTH rollout strategy of the internet service provider, which is outside the control of the households and most likely uncorrelated with children's test outcomes after we control for neighborhood fixed characteristics. The specified regression can be interpreted within an IV approach, where identification is based on the conditional exogeneity of assignment to treatment and on the relevance condition implied by an increased probability of treatment when assigned to treatment. Hence, the validity of our estimation depends on the fulfillment of both, the exogeneity and the relevance condition.

The conditional exogeneity assumption implies that there are no omitted variables affecting both FTTH rollout and children's outcomes. Since we control for static differences correlated with outcomes and FTTH deployment, our main assumption is that there are no time-varying characteristics potentially explaining both variables. Although we cannot test this assumption per se, we provide suggestive evidence in favor of this premise. First, we perform a Principal Component Analysis to identify the main variables guiding the deployment of the FTTH network in the period 2012-2018. We find that pre-treatment levels of income per capita and sanitation (percentage of households with flush to piped sewer system) were the main relevant variables in explaining deployment at the neighborhood level. This is consistent with the fact that the logistical challenges implied by the type of public work involved in sanitation infrastructure are closely related to that of fiber optic connectivity. Our analysis shows that approximately 60% of the total variation in FTTH rollout across years is explained by static variables at the 2010 level, which is controlled for by the inclusion of neighborhood fixed effects. Moreover, we regressed treatment assignment on time-varying characteristics of the child, finding no significant or very small relations. In Section D of the Appendix we present the details on these two exercises. In addition, for robustness, we include the pre-treatment levels of income per capita and sanitation by neighborhood interacted with time. This controls for any variation in trends without incurring in the bad controls problem, since the yearly evolution of these variables could be affected by the treatment (Angrist & Pischke 2009). Moreover, to account for the potential effects of year-specific shocks that affect children's tests scores, such as economic growth, we include year fixed effects to control for common time trends.

Regarding the relevance condition, the assumption in this case is that fiber optic accessibility effectively increases the probability of purchasing a fiber optic plan. If this is not the case, FTTH rollout would not affect internet speed connection and internet consumption decisions. Administrative data from the telecommunications operator presented in Panel a of Figure 3 shows that the number of fiber optic active plans increased with fiber optic installation. The take-up of the policy was high, with the evolution of FTTH active services closely following the timing of the rollout. By the end of the period, 82% of the clients with fiber optic accessibility had actually purchased a fiber optic plan. This tendency is also observed in survey data, with the percentage of households with a fiber optic plan increasing from 17.8% in 2013 to 43.4% in 2016 (Information and Communication Technologies Usage Survey, NIS). In addition, when considering the distribution of copper and FTTH plans among clients with fixed internet contracts, Panel b in Figure 3 shows a clear increasing pattern for fiber optic and a decreasing one for copper plans. Copper internet plans went from representing 100% of the contracts in 2011 to an equal division between fiber and copper in 2018. Regarding internet consumption in children, survey data on 6-year-old children indicates that internet use surged in our period of analysis, with daily users going from almost 11% to more than 30% (Panel c Figure 3). Moreover, the use of internet by adults in households with children in early childhood also shows sharp improvements in the period (Panel d Figure 3).

To analyze the channels behind the effects, we follow the same estimation strategy presented above using each mechanism variable as the outcome variable y_i. We estimate the effects of FTTH on: (i) children screen time (screen time $\geq$ 1 hour), (ii) caregivers' opinion on using TV as a solution to entertain children when they are busy (TV as a solution), (iii) children's activities with caregivers (activities with caregivers), (iv) number of children's books in the household (number of books), (v) adult internet use (internet daily and weekly use by adults) (vi) risky parental practices (risky practices). The definition of these variables was presented in Section 3.3. With this exercise, we estimate the causal effect of FTTH exposure on mediators proposed by our conceptual framework for the impact of high-speed internet on child development.

Figure 3: Internet Access and Use



Notes: Own computations based on ANTEL data, 2011 Census and the CHS 2006-2018. Figure a is constructed by using ANTEL data on FTTH rollout and active services as a proportion of fixed telephone lines given by the 2011 Census. Figure b is constructed by using ANTEL data on copper and FTTH active services as a proportion of fixed internet contracts over time. Figures c-d are constructed using CHS data with survey weights representative for the whole country. Figure c considers 6-year-old children as a proxy for children aged 0-5 due to lack of information. Figure d considers 18 year-old individuals and older living in households with children between 0 and 5 years of age. In Figures c and d we present those who use internet at least once a month and at least once a day (the monthly category includes daily internet users). errors.

We estimate our models by using Ordinary Least Squares (OLS) regressions with clustered standard errors. Since the treatment assignment variable is defined at the neighborhood level, clustering is recommended to allow for cross-sectional and temporal correlation within clusters (Abadie et al. 2017). Given that clustered errors assume zero correlation across clusters, we define a more aggregated geographical unit as the clustering unit: we use the district level for observations in the capital city and the department level for the rest of the country. With this we are taking a more conservative approach in the estimation of our standard errors, compared to using neighborhood as the clustering unit. We estimate standard errors using two approaches: we compute Liang-Zeger cluster robust standard errors and also estimate standard errors using Wild Cluster Bootstrap (WCB) in the restricted version with Rademacher weights (Cameron & Miller 2015, Angrist & Pischke 2009, Roodman et al. 2019). Since the Liang-Zeger errors may exhibit issues when the number of observations across clusters is substantially different, we base our analysis on WCB standard errors.

We only conduct the reduced form estimation with OLS and not a Two-Stage Least Squares (2SLS) estimation for two reasons. First, since we do not have information on FTTH connectivity in the NCDHS we cannot identify children living in households with fiber optic plans, ruling-out the possibility to identify treated children with this criteria. Second, although we could conduct a 2SLS estimation considering the hours of screen of the child as our treatment variable, this would imply underestimating the potential effects of fiber accessibility. As stated in Section 2, the increase in screen exposure in the household can potentially affect the child through indirect channels that refer to the caregiver. With this strategy we would not be able to consider these mechanisms, missing potential changes in the environment of the child. Moreover, the measurement of screen time in the NCDHS does not explicitly consider hours of screen as a secondary activity or as background exposure, identifying a lower bound of screen time considering the recent increase in screen watching as a secondary activity (Goode et al. 2019).

5 Results

5.1 Main Results

In this section we present the intention-to-treat effects of high-speed internet exposure on child development. Table 2 presents the results for the continuous development outcomes at the neighborhood level without (Panel a) and with (Panel b) child controls. Our estimations show that an increase in lifetime exposure to fiber optic during early childhood has a negative and statistically significant effect on the development of communication, problem solving, personal-social and socio-emotional skills.[7] The size of the effects is considerable, with point estimates between -0.79 and -1.76 SD (Panel b). These results should be interpreted as the causal effect of going from no possible access to fiber optic in the home throughout early childhood, to a 100% probability of having the possibility to connect to fiber optic since birth. Given that our estimation of effect sizes suffers from low precision, we prefer to adopt a conservative approach and consider the lower

[7]We refer to statistically significant effects when the estimated p-value is 0.10 or less.

bounds of the effects in absolute terms given by the confidence intervals provided in the WCB procedure.[8] Using this statistic, we can confidently say that fiber optic accessibility throughout a young child's life has effects of at least -0.79 SD in communication skills, -0.51 SD in problem-solving, -0.16 SD in socio-emotional skills, and -0.04 SD in personal-social outcomes. Another way of interpreting the results is in absolute terms considering the number of developmental milestones measured in each skill. Considering WCB upper bounds, effects imply a reduction of approximately 88% of a milestone out of 6 for communication, 64% of a milestone out of 6 for problem solving, 4% of a milestone out of 6 for personal-social outcomes, and 48% of a milestone out of 26 for socio-emotional skills.[9] Regarding gross and fine motor skills, we are not able to detect significant effects. Point estimates are negative for gross motor and positive for fine motor, but they are not precisely estimated. The comparison between the results with and without child control shows that all coefficients are stable across estimations. Moreover, they are robust to multiple hypothesis testing using the Romano-Wolf step-down procedure, as shown in Table A.2 in the Appendix (Romano & Wolf 2016, Clarke et al. 2020).

[8] Since our significant effects are negative, the lower bound in absolute terms refers to the upper bound of the WCB confidence interval.

[9] As mentioned in Section 3.3, the ASQ-3 considers the achievement of 6 developmental milestones for the assessment of each skill. For the ASQ-SE the number of questions differs according to the age-bracket, but on average, there are 26 developmental milestones measured.

Table 2: Effects of FTTH Exposure on Continuous Outcomes

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
Panel a: without child controls						
FTTH Exposure	-1.76***	-0.48	0.33	-1.44***	-0.90**	-0.84**
	(0.50)	(0.39)	(0.45)	(0.47)	(0.45)	(0.36)
P-value	0.00	0.21	0.46	0.00	0.05	0.02
P-value WCB	0.00	0.22	0.46	0.01	0.04	0.01
Lower bound WCB	-2.79	-1.24	-0.60	-2.37	-1.76	-1.53
Upper bound WCB	-0.78	0.28	1.24	-0.49	-0.03	-0.17
N	5,035	5,035	4,027	5,034	5,033	4,909
Panel b: with child controls						
FTTH Exposure	-1.76***	-0.48	0.36	-1.44***	-0.90**	-0.79**
	(0.49)	(0.39)	(0.44)	(0.46)	(0.44)	(0.34)
P-value	0.00	0.21	0.41	0.00	0.04	0.02
P-value WCB	0.00	0.22	0.42	0.00	0.04	0.02
Lower bound WCB	-2.76	-1.23	-0.56	-2.34	-1.73	-1.43
Upper bound WCB	-0.79	0.25	1.22	-0.51	-0.04	-0.16
N	5,035	5,035	4,027	5,034	5,033	4,909

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects and linear trends in sanitation and income per capita by neighborhood, using sample weights. Panel b also includes child controls: gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-value WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving and personal-social) and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility.

To complement the analysis, in Table 3 we present the effects on the probability that a child is developing normally in each dimension, vs. being in the monitor or risk categories. Results show that FTTH accessibility decreases the probability of developing within normal ranges for communication and socio-emotional skills, with point estimates of 39 pp and 28 pp, respectively (Panel b). This indicates that the worsening in the continuous scores for these skills is evidenced at key parts of the distribution of outcomes, yielding an increase in the percentage of children being monitored or at risk for developmental delays. The upper bounds of the WCB confidence intervals show that a 10 pp increase in fiber optic exposure decreases the probability of being in normal ranges in at least 1.4 pp for communication skills, and in at least 0.1 pp for socio-emotional abilities. These effect sizes are large compared to a mean of 0.90 and 0.87 in the normal categories of communication and socio-emotional skills in 2013. Again, the comparison between the results with and without child controls shows that all coefficients are stable.

Table 3: Effects of FTTH Exposure on Categorical Outcomes

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
Panel a: without child controls						
FTTH Exposure	-0.39***	-0.13	-0.07	-0.18	0.01	-0.30**
	(0.13)	(0.10)	(0.19)	(0.15)	(0.12)	(0.14)
P-value	0.00	0.20	0.72	0.25	0.91	0.04
P-value WCB	0.01	0.22	0.72	0.24	0.92	0.03
Lower bound WCB	-0.66	-0.34	-0.45	-0.49	-0.20	-0.57
Upper bound WCB	-0.13	0.05	0.30	0.14	0.25	-0.03
N	5,035	5,035	4,027	5,034	5,033	4,904
Panel b: with child controls						
FTTH Exposure	-0.39***	-0.13	-0.06	-0.18	0.01	-0.28**
	(0.13)	(0.10)	(0.19)	(0.15)	(0.11)	(0.14)
P-value	0.00	0.20	0.76	0.24	0.90	0.05
P-value WCB	0.01	0.21	0.75	0.24	0.91	0.05
Lower bound WCB	-0.64	-0.33	-0.46	-0.48	-0.20	-0.56
Upper bound WCB	-0.14	0.05	0.32	0.13	0.24	-0.01
N	5,035	5,035	4,027	5,034	5,033	4,904

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects and linear trends in sanitation and income per capita by neighborhood, using sample weights. Panel b also includes child controls: gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-value WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving and personal-social) and the last column to the ASQ-SE. ASQ-3 outcomes refer to the categorical variables that indicate whether a child is developing within normal ranges (should not be monitored and is not at risk of developmental delays). The ASQ-SE outcome refers to the categorical variable that indicates whether a child is not at risk of developmental delays. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility.

5.2 Robustness Checks

To analyze the validity of our results, we perform several robustness checks. First, we consider different model specifications. One potential concern in our estimations is given by the fact that children within a test age bracket are assessed with the same questionnaire, although they differ in their monthly age. Therefore, potential flaws in the design of the tests may generate spurious variation in development outcomes since younger children would get lower scores by default, especially when using continuous outcomes. This could be a problem since our treatment assignment variable shows higher values for younger children within each age and neighborhood fixed effect. The fact that the tests are internationally validated and that we obtain similar results using the categorical variable reduces the concern of the problem. However, to further assess the robustness of our findings, we replicate our main estimations by controlling for a dichotomous variable that indicates whether each child's age is below the midpoint of her test age bracket. Results for continuous outcomes are mostly unchanged, with a slight decrease in the precision of the estimation when using WCB (Table A.3 in the Appendix). In addition, we estimate our main results without considering linear trends in income and sanitation and without child controls. Results are mostly unaffected: communication, problem solving, personal-social and socio-emotional skills continue to show a negative effect of similar magnitude (Table A.4 in the Appendix). We also run our regressions without considering sample weights and the results are not affected (Table 3 in the Online Appendix).

Second, we estimate the model using alternative samples. We estimated our preferred specification without considering the 2013 wave in which results are only available for the country's capital. As a robustness check, we perform an estimation considering all the observations in the three waves 2013-2015-2018 (Table 4 in the Online Appendix). Results are qualitatively equivalent to those obtained with the 2015-2018 waves. Communication, problem solving and personal-social skills show negative and significant results (only the effect for socio-emotional becomes non-significant). In addition, we estimate our results by using only the neighborhood/age groups that were available in both 2015 and 2018 waves (Table 5 in the Online Appendix). Results with the balanced panel are similar to those with the complete sample. Moreover, we also estimate regressions excluding always and never treated neighborhoods since they could potentially be different from other neighborhoods, and also excluding always and never treated children (Table 6 and 7 in the Online Appendix). We find again statistically significant, and slightly larger, coefficients for communication, problem solving, personal-social, socio-emotional and, additionally, gross motor skills. Besides, we estimate our results without considering children up to one year old given that developmental tests are less precise for this age range, and the results are again similar to our main estimation (Table 8 in the Online Appendix). Finally, to corroborate that our results are not driven by any particular observation, we perform a dfbeta analysis. This procedure implies measuring the difference between the estimated coefficient and the analogous coefficient when the ith observation is excluded, scaled by the estimated standard error. If an observation has an absolute value of dfbeta higher than one, it should be analyzed with caution. In our case, we find that all observations show a dfbeta lower than one (Table A.5 in the Appendix). Additionally, we graph the beta coefficient obtained for each skill, and results show a mass concentration close to the value of our main estimated coefficient (Figure A.3 in the Appendix).

The third block of robustness checks is related to differences in the treatment assignment variable. On the one hand, we estimate our main regression using the FTTH data provided by ANTEL at the department level, constructing the treatment exposure variable without any imputations (Table A.6 in the Appendix).[10] Compared to the neigh-

[10]In this case, the number of clusters is smaller than recommended for the use of the Liang-Zeger

borhood level, results are slightly higher but qualitatively similar, and as expected, the estimation shows lower precision. In addition, since the FTTH variable is a key aspect for the construction of the treatment assignment variable, we analyze our results using different assumptions for the computation of the FTTH probability at the neighborhood level. Once again, results are robust to these alternatives (Table 9 in the Online Appendix). Finally, we estimate the model using an indicator variable of treatment assignment. To do this, we remove children in the central part of the distribution and consider as untreated those children from percentiles 1 to 35 in the distribution of FTTH exposure, and as treated those children from percentiles 65 to 100. Results are similar, with coefficients of a lower magnitude (Table A.7 in the Appendix). We find significant results for communication and socio-emotional skills, and a p-value of 0.10 for problem-solving.

Finally, we address the issue of potential negative weights in the OLS estimation due to heterogeneous treatment effects posed by the two-way fixed effects literature (e.g de Chaisemartin & D'Haultfœuille 2020, Goodman-Bacon 2021). However, our setting differs from the framework developed by this literature since our continuous treatment variable has variability within each treatment group, defined by the neighborhood/age and year fixed effects. Therefore, we cannot directly apply the techniques developed so far to address this issue. To have a sense of the influence of negative weights in our estimations, we identify the negative weights following de Chaisemartin & D'Haultfœuille (2020) when using the binary treatment assignment variable defined in the previous paragraph. Since the binary treatment assignment variable has considerably less variability compared to our continuous treatment assignment variable, we can reach homogeneity in treatment assignment within each treatment group by removing a small number of observations from our sample. Using this procedure, we find that between 3% and 4% of the treatment groups have negative weights depending on the outcome considered. To get a sense of the importance of these weights in the estimation of our treatment effects, we compute the ratio between the negative weights and the sum of all weights in absolute value. We find a ratio between 0.24 and 0.25, indicating that negative weights account for approximately one fourth of overall weights. Additionally, we re-estimate our results removing the groups with negative weights in an iterative process following Valente et al. (2020). After three iterations negative weights are completely removed in all outcomes, except for fine motor, which requires an additional iteration. Treatment effects in communication, problem solving and socio-emotional skills remain qualitatively similar (Table A.8 in the Appendix). By this, we provide evidence that the negative effects of FTTH on cognitive and non-cognitive skills are not derived by the presence of negative weights when using two-way fixed effects.

cluster robust standard error. However, the WCB technique performs better when the number of clusters is small, overcoming this limitation (Cameron & Miller 2015, Roodman et al. 2019).

5.3 Heterogeneous Effects

The potential effects of internet exposure might be mediated by different attributes of the child and family characteristics. We test for heterogeneous effects across: gender, educational level of the child's caregiver, and region of residence of the child. We estimate our preferred specification with individual controls including interactions between FTTH exposure and the predetermined characteristics mentioned above. In Table 4 we present the effects of our treatment assignment for each group (with stars indicating its significance according to the WCB p-value) and the WCB p-values for the the test of equal effects between each group and the base group.

The psychological literature shows that, at an early age, girls are capable of absorbing more cognitive stimuli than boys (Fort et al. 2020). Therefore, the opportunity cost of reducing adult child-interactions because of the presence of internet connected devices is likely to be more significant for girls, resulting in a larger negative effect. This is precisely what we obtain in our analysis by gender. Considering the continuous outcomes, girls show a greater deterioration in skills compared to boys. The estimated effect is higher in problem solving skills at the 5% significance level, and the effects for communication and socio-emotional skills are also higher, although the difference is not significant (p-values of 0.11 and 0.15 respectively).

Given the critical role of parents in the first years of life, the educational level of the caregiver could mediate the effects of internet availability in different ways. Higher educated parents could have access to more information about the possible adverse effects of screens in early childhood, and try to compensate them by having more co-viewing experiences and choosing higher-quality programs. Moreover, these parents could have extra resources to offer alternative activities to screen exposure that are more beneficial, such as engaging in physical activities in sports centers, attending early education centers, and offering toys specially designed to foster development, among others. On the other hand, the opportunity cost of screen time could be larger for children with higher educated caregivers. In addition, these households are expected to show a higher treatment take-up, since the probability of purchasing a fiber optic plan when having the possibility to do so is higher. The results show that for the continuous outcomes, children with caregivers with higher educational levels are the ones that are most negatively affected in communication, problem solving and socio-emotional skills. The more pronounced effects on girls and children with highly educated parents go in line with previous literature finding larger negative effects on populations with higher opportunity costs when reducing one-to-one interactions with adults (Fort et al. 2020).

Considering the region of residence, different effects could be found, although the direction is not clear a priori. On the one hand, children living in areas that are more populated, as the capital city, could have a lower availability of outdoor spaces. On the other hand, they could have access to a wider offer of educational and recreational activities compared to children living in less urbanized cities. Results show a more pronounced negative effect in personal-social skills for children living in smaller cities, and, in addition, a negative and significant effect in gross motor skills.

Table 4: Heterogeneous Effects of FTTH Exposure on Continuous Outcomes

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
Panel a: Gender						
Girls	-1.82***	-0.51	0.26	-1.54***	-0.90**	-0.88***
Boys	-1.66***	-0.44	0.53	-1.28***	-0.89**	-0.67**
P-value girls-boys	0.11	0.50	0.02	0.02	0.89	0.15
N	5,035	5,035	4,027	5,034	5,033	4,909
Panel b: Caregiver's educational level						
Primary	-1.48***	-0.43	0.64	-1.05**	-0.90**	-0.50
Lower secondary	-1.58***	-0.15	0.55	-1.22***	-0.74*	-0.61*
Upper secondary	-1.83***	-0.48	0.39	-1.39***	-0.97**	-0.86**
Tertiary	-1.85***	-0.60	0.10	-1.66***	-0.96**	-0.84***
P-value primary-lower sec.	0.65	0.28	0.59	0.40	0.40	0.56
P-value primary-upper sec.	0.09	0.82	0.22	0.07	0.72	0.05
P-value primary-tertiary sec.	0.06	0.35	0.01	0.00	0.77	0.09
N	5,005	5,005	3,998	5,004	5,003	4,879
Panel c: Region of residence						
Rest of the country	-2.27***	-1.39**	0.18	-2.38***	-1.48**	-0.98*
Capital	-1.75***	-0.47	0.35	-1.43***	-0.89**	-0.79**
P-value rest-capital	0.34	0.04	0.61	0.09	0.05	0.65
N	5,035	5,035	4,027	5,034	5,033	4,909

Notes: Reported estimates for each panel are obtained from an OLS regression including FTTH exposure, binary indicators for each group of the variable considered for heterogeneous effects, interactions between these groups and FTTH exposure, neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood and child controls. We use sample weights for the estimation. For each variable, we report the effects for each group with stars indicating their significance level, and the WCB p-values for the test of equal effects between each group and the base group. The first effect reported in each panel is that of the reference group, which is obtained from the coefficient on FTTH exposure in the regression. The effects for non-omitted groups are obtained by summing the FTTH exposure coefficient and the coefficient for the respective interaction. The WCB p-value for the difference between each group and the reference group is the WCB p-value for the interaction term in the regression. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving and personal-social) and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility.

5.4 Mechanisms

In this section we provide evidence to uncover the potential channels behind the overall effects estimated in Section 5.1. First, we analyze the direct effect of screen exposure using information on the amount of children's screen time. We consider the one-hour-a-day threshold suggested by health institutions. As the first column in Table 5 shows, we find a positive effect of child exposure to fiber optic on the probability of using screens for more than one hour (WCB p-value of 0.11). It is worth noting that this indicator is likely to provide a lower bound for the direct effect on screen hours of the child, given that it does not specifically consider exposure to screens as a secondary activity. Complementary to this question, we analyze the effect of FTTH exposure on caregivers' opinion on screen use as a potential solution when they are busy (second column of Table 5). We observe an increase in the acceptance of using screens for prolonged periods of time to entertain children without parental presence, indicating a decrease in the quality of exposure given recommendations on co-viewing practices. As mentioned before, this question should be taken with caution since it may reflect that, either the caregiver effectively engages more in this practice, and/or that she finds a higher acceptance of this practice in her environment. Overall, we observe that the direct channel is mediating the effect of FTTH exposure on child development through changes in screen time and in the quality of exposure.

Considering the indirect effects through the displacement of alternative activities that are beneficial for development, the evidence is less clear. On the one hand, we do not find evidence for FTTH affecting beneficial activities performed with parents, as reading books and singing songs (Table 5 third column). However, we find that children more exposed to FTTH have less children's books at home (Table 5 column 4). This could suggest a reduction in time reading or looking at books, and a decrease in time devoted to activities that are advantageous for child development.

Regarding the mechanism that affects adult-child interactions through adult's internet use, we find that FTTH exposure leads to an overall increase in the use of internet connected devices by adults in households with small children. This is indicated by a reduction in internet weekly use and an increment in internet daily use of the same magnitude (columns 5 and 6 of Table 5). Finally, we analyze the mechanism that goes through the caregiver's behavior in other parental areas, finding that FTTH exposure increases risky parental practices (column 7 of Table 5). We interpret these two results together as going in line with previous evidence that shows that when the adult is engaged with technology, the interaction with the child is of lower quality.

Overall, the analyzed mechanisms suggest that the effects of internet on child development are not only driven by an increase in children's screen time, but also by changes in parental practices, such as an increase in internet use by the caregiver and a reduction in co-viewing sessions, together with an increase in risky parental practices. These results, together with the analysis of heterogeneous effects, emphasize the fact that understanding the opportunity costs of new technologies for children and the role of adults concerning internet exposure are key aspects to understand potential risks in terms of child development.

Table 5: Mechanisms

	Screen Time ≥ 1 Hr (1)	TV as a Solution (2)	Activities with Caregivers (3)	Number of Books (4)	Int. Daily Adults (5)	Int. Weekly Adults (6)	Risky Practices (7)
FTTH Exposure	0.36	0.41*	-0.14	-0.56*	0.17	-0.18**	2.24**
	(0.23)	(0.22)	(0.27)	(0.28)	(0.10)	(0.07)	(1.09)
P-value	0.12	0.07	0.60	0.05	0.11	0.01	0.04
P-value WCB	0.11	0.09	0.60	0.06	0.15	0.02	0.04
N	5,037	4,941	5,036	5,036	11,111	11,111	4,941

Notes: Reported estimates are obtained from OLS regressions using sample weights. Columns 1-4 include neighborhood/age and survey year fixed effects, controls for linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level). Columns 5-6 include neighborhood and survey year fixed effects, and controls for linear trends in sanitation and income per capita by neighborhood. The first column shows results on a dichotomous variable indicating one hour or more of daily screen time of the child. The second column shows results on a dichotomous variable indicating a caregiver agrees with following statement "Leaving children in front of the TV for a long period is a solution when mothers are busy". The third column shows results on an index variable that considers whether parents and children usually read books and/or sing songs together. The fourth column shows results on a categorical variable that takes the value 0 when there are no children's books at home, 1 if there are 1-9 books, and 2 if there are more than 10 books. The fifth and sixth columns show results on the frequency of internet use in adults living in households with children between 0 and 5 years of age by neighborhood from the CHS. The seventh column shows results on an index variable of risky parental practices. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility.

6 Final Remarks

Understanding the potential effects of new technologies on early childhood development is essential, not only for the relevance of that period in the lives of individuals but also for the consequences of human capital accumulation on economic and social development. Digital technologies have become an element of everyday life, improving opportunities for education and work everywhere. Children are increasingly engaged with them, and digital inclusion is promoted by many institutions such as the UNDP and UNICEF. In this context, the COVID-19 pandemic reinforced the importance of equal access to new technologies to be able to participate in the current economy and society (ECLAC 2020). With this study, we provide evidence that contributes to a better understanding of the effects of new technologies in order to take advantage of its benefits and reduce potential risks.

We aim to contribute to the public discussion on this topic by exploring the consequences of a universal policy that recently expanded internet connectivity. We analyzing the effects of a substantial increase in fiber optic accessibility during early childhood that dramatically changed high-speed internet accessibility in less than a decade. The adoption of FTTH technology substantially increased the demand and supply of new digital platforms and devices, with a surge in the availability of media content, apps and devices able to support digital media, transforming the way in which adults and children interact with screens on a daily basis. Our setting allows measuring the overall intention-to-treat effects of fiber optic in the home environment, which plays a key role in determining children's opportunities for development. This gives the possibility to measure the effects of increased screen exposure on child development considering changes in the time use of children and adults, as well as other alterations in parental practices. Therefore, our study measures the aggregate effects that come with faster and better internet technology at the household level, considering the changes in new digital technologies in recent years.

To conduct this research we use data for Uruguay, taking advantage of a unique setting in which high-quality measures of cognitive and non-cognitive outcomes in early childhood are available for the same period in which the FTTH infrastructure was deployed. Our results show a deterioration in children's outcomes caused by an increase in high-speed internet accessibility. An increase in 10 percentage points in the lifetime exposure to fiber optic during early childhood leads to a decrease in test scores in communication, problem solving personal-social and socio-emotional skills, ranging between 8% and 18% of a standard deviation. This translates into a decrease in the probability of developing within normal ranges for communication and socio-emotional skills. An analysis of heterogeneous effects shows that the negative impact is larger for girls, children with more educated parents, and living in smaller cities, highlighting the importance of considering the opportunity costs of screen exposure when assessing its potential impacts on child development. The study of mechanisms shows that results are explained by a direct channel given by an increase in screen time of the child and a worsening in the quality of exposure, together with an indirect effect given by lower-quality adult-child interactions as a consequence of increased adult internet use and a higher prevalence of risky parental practices. These results show that analyzing the caregivers' behavior is as important as accounting for changes in the time use of the child.

A few caveats are in order to interpret our results. First, although we are using high-quality data to detect developmental delays in cognitive and non-cognitive outcomes, these tests may not capture new abilities that children are acquiring due to exposure to new technologies. Digital technologies may provide new abilities that prove useful and valuable in the educational systems and labor markets for future generations. Given that exposure to digital technologies during early childhood is a brand new phenomenon, we may only be able to fully comprehend it in the years to come. Moreover, these tests allow us to detect developmental delays during early childhood, and in this sense, delays could disappear over time. Therefore, it is crucial to follow the development of these new generations of children to analyze whether abilities are acquired at a later point in time, or if adverse effects persist or even increase in the long run. Given the relevance of the first years of life, our results call for preventive measures that avoid potentially risky situations in the development of cognitive and non-cognitive skills.

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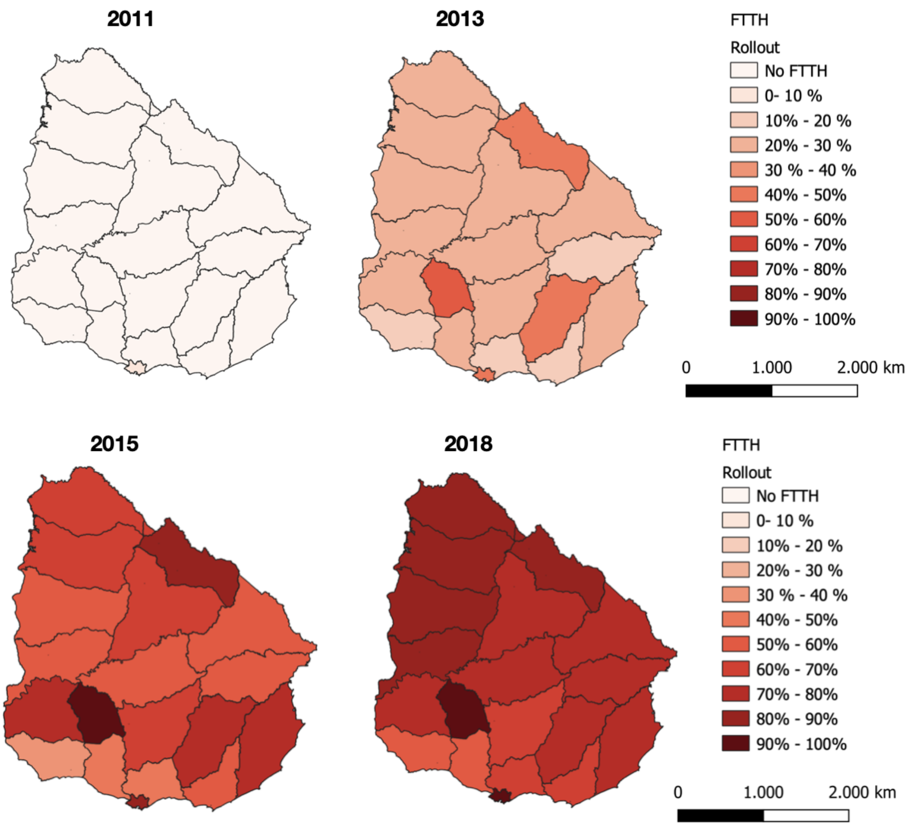
7 Appendix

A FTTH Deployment

Figure A.1: FTTH Rollout by Department



Notes: Own computations based on ANTEL data.

B Neighborhood Imputation of FTTH Accessibility

To construct the adjusted FTTH probabilities by neighborhood, first we use the fiber optic rollout per department and year for the period 2012-2018 provided by ANTEL, which indicates the cumulative percentage of landlines with FTTH connection. We estimate the absolute number of landlines with FTTH accessibility per year and department, by considering the number of landlines just before the implementation of the FTTH rollout. This number is kept fixed over time since the number of landlines could be affected by the FTTH rollout, since households may connect to a fixed telephone line online to access fiber optic.

Then, to define the neighborhood units, we classified small geographical areas into three types: those for which we had accurate information about having FTTH in 2012 (and therefore, for the whole period 2012-2018), those for which we had accurate information about not having FTTH in 2020 (and therefore, not having FTTH for the period

2013-2018), and those for which we knew they transitioned to having fiber optic accessibility between 2012 and 2020. The three sets of areas A_1, A_2 and A_3, can be defined as follows, where d identifies each geographical area a_d, y refers to the year, and $FTTH_t$ is an indicator variable for fiber optic accessibility:

- $a_{d,y} \in A_1 : FTTH_{2012} = 1 \quad \rightarrow \quad FTTH_t = 1, t \in [2012, 2018]$
- $a_{d,y} \in A_2 : FTTH_{2020} = 0 \quad \rightarrow \quad FTTH_t = 0, t \in [2012, 2018]$
- $a_{d,y} \in A_3 : max(FTTH_t = 1), t \in [2012, 2018]$

We impute an adjusted probability of FTTH for the areas without accurate information, those belonging to A_3, in the following way:

$$ftth_{a_{d,y} \in A_3} = \frac{(ftth_{d,y} \times q\_tel_{d,2011}) - \sum_{a \in (A_1 \cap d)} q\_tel_{a,2011}}{q\_tel_{d,2011} - \sum_{a \in (A_1 \cap d)} q\_tel_{a,2011} - \sum_{a \in (A_2 \cap d)} q\_tel_{a,2011}}$$

Where $q\_tel_{d,2011}$ is the number of landlines by small geographical areas from the 2011 Census.

An example of this procedure is presented in Figure 2 in the Online Appendix

C The One-Laptop-Per-Child Program

The one-laptop-per-child program (OLPC), "Plan Ceibal", was launched in Uruguay in 2007. The main intervention of this program involved the provision of laptops to primary and secondary school students in the public system, and the provision of internet connection to public education centers. The delivery of computers started in primary schools in 2007, and by the end of 2009 all public primary schools were covered. The rollout in secondary schools started in 2010 (Plan Ceibal 2017). We believe that the program could pose a risk of bias in the estimation of our results if the deployment of laptops at the primary school level would have occur in the same period as the FTTH rollout. This is because devices are taken home by each child and contain content suitable for children of 6 years of age, which might also be appealing for the older children in our study. Given that the component concerning primary school children was fully implemented by the time in which the FTTH project took place, we assume that all the cohorts considered in our analysis were similarly affected.

Additionally, in 2014 the program started delivering tablets to public early education centers targeting children with 4 and 5 years of age. The tablets were not delivered to each child, but to the education centers to be used in activities proposed by the teacher within the classroom. The cumulative number of tablets delivered increased from 40 in 2014 to 15,230 in 2018, representing approximately 1 tablet every 5 children enrolled in these levels (see A.1). Given that: this policy was deployed by an institution completely separate to the one providing fiber optic connectivity, that tablets were used as an additional resource by the teacher and not taken home by the children, and the size of the policy, we believe it is unlikely for our results to be biased by the effects of this component of the program.

Table A.1: Tablets Delivered in Early Education Centers by OLPC (levels 4 and 5)

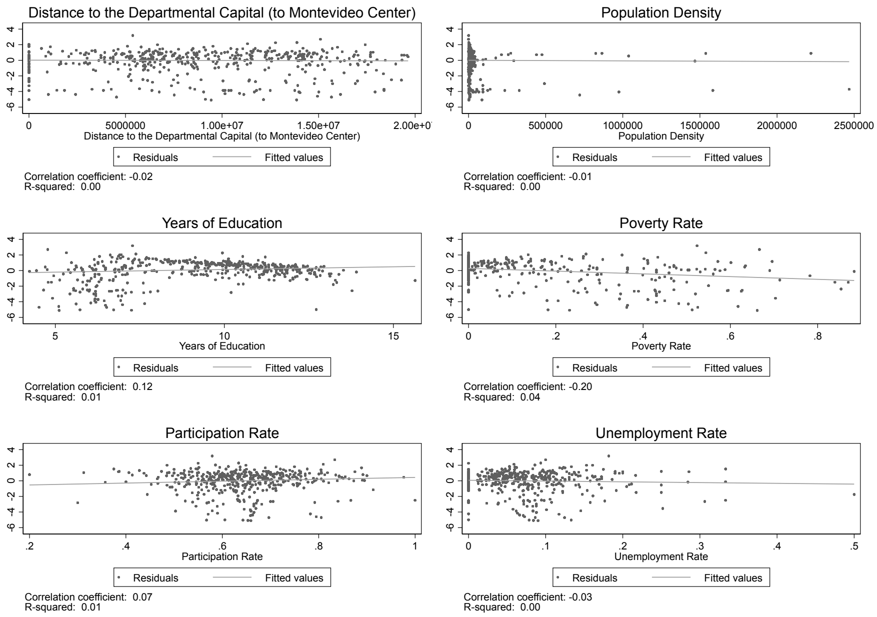
	2010	2011	2012	2013	2014	2015	2016	2017	2018
Enrollment	74,820	72,868	72,886	72,369	71,859	72,318	72,090	73,045	75,166
Tablets	0	0	0	0	40	121	4,530	12,582	15,230
Ratio	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.17	0.20

Notes: The first row shows the student enrollment in public early education centers for levels 4 and 5 obtained from the National Administration of Public Education (accessed on 26th July 2023 at https://www.anep.edu.uy/monitor/servlet/datosnacionales). The second row shows the number of tablets delivered to levels 4 and 5 of public early education centers by the OLPC program, information provided directly by the program to the authors under Law Nº 18.381. The third row shows the ratio between the number of tablets delivered and the number of students enrolled (row 2 and row 1 respectively) as a proxy for the coverage of this component of the program.

D Additional Evidence for Conditional Exogeneity

To assess the conditional exogeneity of FTTH rollout, we apply a Principal Component Analysis (PCA) to summarize FTTH rollout in 2012-2018 by using the 1st component of the PCA. We conduct this analysis twice, using the departments as units and the the neighborhoods as units. The level of inertia explained by the 1st component at the department level is 71% and 89% at the neighborhood level, providing accurate indicators of the FTTH deployment in our period of analysis. We then take advantage of having one unique variable summarizing the deployment to assess the explanatory power of several pre-treatment variables associated with the deployment process and socioeconomic characteristics of the geographic units. These variables are constructed using the NHS 2010, Census 2011 data and geographic information provided by the Ministry of Social Development. We evaluate the correlation coefficients with the 1st component of the PCA, and select the two with highest correlation at the department and at the neighborhood level. We then regress the 1st component of the PCA on the explanatory variables and estimate the R^2. In these regressions we weight each geographic unit (departments or neighborhoods) by the proportion of fixed telephone lines before the treatment assignment. We find that, at the department level, the pre-treatment levels of sanitation (percentage of households with flush to piped sewer system) and population density in urban localities have an explanatory power of 92%. At the neighborhood level, the main explanatory variables are sanitation and income per capita, with a power of 61%. This implies that most of the variation in the FTTH rollout can be explained by pre-treatment variables at the level of our geographical units. In addition, we regress the residuals of the previous regressions against other relevant pre-treatment variables finding low correlation (Figure A.2).

Figure A.2: Residuals Against Relevant Variables - Neighborhood Level



Notes: Own computations based on CHS data and geographic information provided by the Ministry of Social Development. Below each sub-graph we show the correlation coefficient between the variable and the residuals from a regression of the 1st component of the PCA of FTTH rollout at the neighborhood level on sanitation and income per capita. Additionally we show the R-squared from a regression of the residuals on the variable. Distance to the departmental capital is measured, in neighborhoods belonging to Montevideo, as the straight line distance between Montevideo center and the centroid of each neighborhood. For the neighborhoods belonging to the rest of the country, this is measured as the straight line distance between each departmental capital and the centroid of the neighborhood. Population density is the total population by neighborhood over the area of each neighborhood. Years of education is the mean of years of education by neighborhood. Poverty rate is the percentage of poor people by neighborhood according to the monetary national poverty line. Participation rate is the labor force participation rate by neighborhood. Unemployment rate is unemployment rate by neighborhood.

To further assess our conditional exogeneity assumption we regress our treatment assignment variable at the child level, FTTH exposure, on: NBH interacted with age brackets fixed effects, survey year fixed effects, survey year trends in pre-treatment assignment variables (sanitation and income per capita), time-varying and time-invarying characteristics of the child, and time-varying characteristics of the neighborhood. We find that most variables are not significant at the 5% level, and that significant variables have very low marginal effects when evaluating the coefficients at extreme values of the distribution of the independent variables (1pp or 2pp at most).

E Robustness Checks

Table A.2: Multiple Hypothesis Testing

	Model p-value	Resample p-value	Romano-Wolf p-value
Comm.	.001	.001	.001
Gross Motor	.215	.086	.163
Fine Motor	.413	.269	.269
Problem Solving	.002	.001	.003
Personal Social	.044	.01	.023
Socio Emotional	.021	.003	.011

Notes: Reported p-values indicate the significance level of the coefficient on FTTH exposure in an OLS regression of development outcomes on neighborhood/age fixed effects, survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). P-Values are obtained using Liang-Zeger cluster robust standard errors. WCB p-value are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights, clustered at the district level (capital) and department level (rest). Romano-Wolf p-values are Romano-Wolf stepdown p-values for multiple hypothesis testing, clustered at the district level (capital) and department level (rest). The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving and personal-social) and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility.

Table A.3: Effects of FTTH Exposure Controlling for Age Differences

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-1.59***	-0.30	0.67	-1.06**	-0.68*	-0.85**
	(0.48)	(0.37)	(0.41)	(0.42)	(0.43)	(0.36)
P-value	0.00	0.42	0.11	0.01	0.11	0.02
P-value WCB	0.00	0.44	0.10	0.02	0.10	0.02
Lower bound WCB	-2.53	-1.03	-0.19	-1.87	-1.49	-1.53
Upper bound WCB	-0.65	0.41	1.48	-0.22	0.19	-0.16
N	5,035	5,035	4,027	5,034	5,033	4,909

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. In addition, we include a dichotomous variable that indicates whether each child's age is below the midpoint of her test age bracket. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility.

Table A.4: Effects of FTTH Exposure without Linear Trends and Child Controls

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-1.30***	-0.38	0.19	-0.98**	-0.54*	-0.73**
	(0.43)	(0.30)	(0.38)	(0.38)	(0.36)	(0.30)
P-value	0.00	0.21	0.62	0.01	0.13	0.02
P-value WCB	0.00	0.22	0.62	0.01	0.10	0.02
Lower bound WCB	-2.18	-0.94	-0.49	-1.66	-1.25	-1.31
Upper bound WCB	-0.49	0.23	0.99	-0.18	0.14	-0.15
N	5,035	5,035	4,027	5,034	5,033	4,909

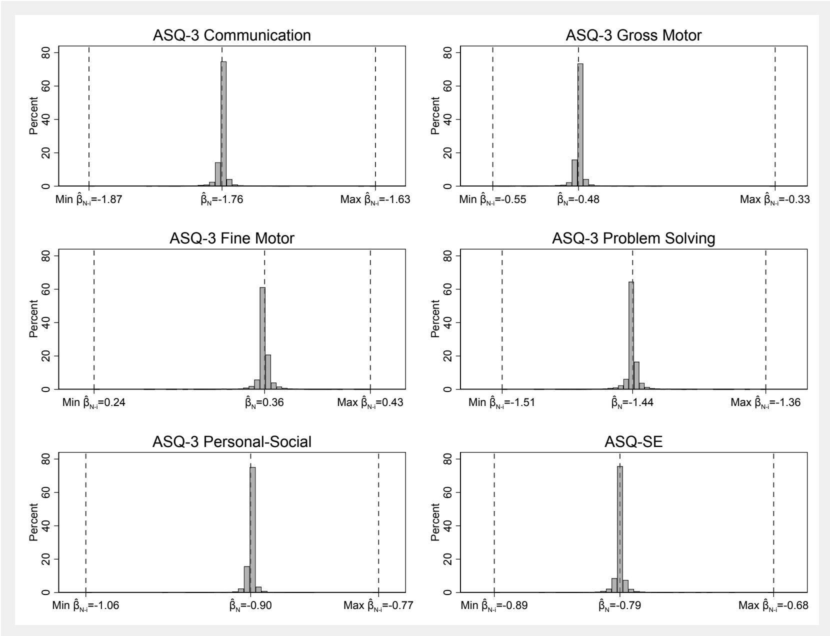
Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, using sample weights. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH.

Table A.5: Dfbeta Analysis

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
$\lvert DFBETA_i \rvert > 1$	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$\lvert DFBETA_i \rvert > 2/\sqrt{N}$	2.64%	3.30%	3.58%	3.04%	3.04%	4.32%

Notes: The table shows the percentage of observations with a dfbeta greater than 1 and with a dfbeta greater than $2/\sqrt{N}$). The dfbeta for each observation is defined as the absolute value of the difference between the estimated coefficient and the analogous coefficient when the ith observation is excluded, scaled by the estimated standard error.

Figure A.3: Beta Distribution Obtained from Dfbeta Analysis



Notes: The graph shows the distribution of betas obtained from the dfbeta analysis, that is, the betas of our main regression excluding each observation one by one.

Table A.6: Effects of FTTH Exposure with FTTH at Department Level

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-2.55*	-1.86***	-0.44	-2.92*	-2.23*	-2.03*
	(0.51)	(0.52)	(0.48)	(0.62)	(0.53)	(0.46)
P-value	0.00	0.00	0.37	0.00	0.00	0.00
P-value WCB	0.09	0.01	0.65	0.08	0.09	0.09
Lower bound WCB	-4.76	-3.85	-1.05	-5.54	-3.11	-4.38
Upper bound WCB	0.39	-1.14	1.90	0.43	0.58	0.42
N	5,051	5,051	4,035	5,050	5,049	4,925

Notes: Reported estimates are obtained from an OLS regression including department/age and survey year fixed effects, linear trends in sanitation and density by department, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the department using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility at the department level.

Table A.7: Effects of Binary FTTH Exposure

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
Binary FTTH Exposure	-0.69***	-0.20	0.20	-0.47	0.02	-0.54*
	(0.25)	(0.28)	(0.26)	(0.28)	(0.25)	(0.26)
P-value	0.01	0.47	0.44	0.10	0.92	0.04
P-value WCB	0.01	0.48	0.49	0.11	0.89	0.07
Lower bound WCB	-1.42	-0.91	-0.23	-1.15	-0.51	-1.09
Upper bound WCB	-0.21	0.46	0.90	0.13	0.59	0.05
N	3,487	3,487	2,697	3,486	3,486	3,378

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility. Binary FTTH exposure is constructed as a dichotomous treatment variable of FTTH exposure, removing the central 30% of the sample. We exclude children from the central part of FTTH exposure distribution (percentiles 36 to 64).

Table A.8: TWFE: Iterations Removing Negative Weights.

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
Iteration 0						
Binary FTTH Exposure	-0.70***	-0.21	0.15	-0.49*	0.02	-0.68**
	(0.24)	(0.28)	(0.30)	(0.27)	(0.24)	(0.28)
P-value	0.00	0.45	0.61	0.07	0.93	0.02
P-value WCB	0.01	0.45	0.64	0.08	0.93	0.03
N	3,487	3,487	2,697	3,486	3,486	3,377
Iteration 1						
Binary FTTH Exposure	-1.37**	-0.70*	-0.38	-0.99	0.13	-1.08*
	(0.43)	(0.45)	(0.31)	(0.53)	(0.41)	(0.30)
P-value	0.00	0.12	0.22	0.07	0.75	0.00
P-value WCB	0.03	0.09	0.88	0.12	0.75	0.08
N	3,364	3,364	2,673	3,363	3,363	3,346
Iteration 2						
Binary FTTH Exposure	-1.26*	-0.49	-0.32	-0.87	0.27	-1.10
	(0.36)	(0.25)	(0.41)	(0.43)	(0.37)	(0.29)
P-value	0.00	0.05	0.44	0.05	0.47	0.00
P-value WCB	0.09	0.33	0.91	0.20	0.48	0.17
N	3,004	3,004	2,330	3,004	3,004	2,881
Iteration 3						
Binary FTTH Exposure	-1.27*	-0.45	-0.33	-0.89	0.31	-1.11
	(0.35)	(0.23)	(0.42)	(0.41)	(0.38)	(0.24)
P-value	0.00	0.05	0.43	0.03	0.41	0.00
P-value WCB	0.09	0.33	0.90	0.20	0.40	0.15
N	2,994	2,994	2,326	2,994	2,994	2,812
Iteration 4						
Binary FTTH Exposure	-	-	-0.33	-	-	-
	-	-	(0.45)	-	-	-
P-value	-	-	0.47	-	-	-
P-value WCB	-	-	0.91	-	-	-
N	-	-	2,258	-	-	-

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. Binary FTTH exposure is constructed as a dichotomous treatment variable of FTTH exposure, removing the central 30% of the sample. For iteration 0, we exclude children from the central part of FTTH exposure distribution (percentiles 36 to 64). For iterations 1, 2, 3 and 4 we also exclude children in groups with negative weights identified using the de Chaisemartin & D'Haultfœuille (2020) procedure.

Is High-Speed Internet Detrimental for Early Childhood Development? Evidence from a Countrywide Program
Online Appendix

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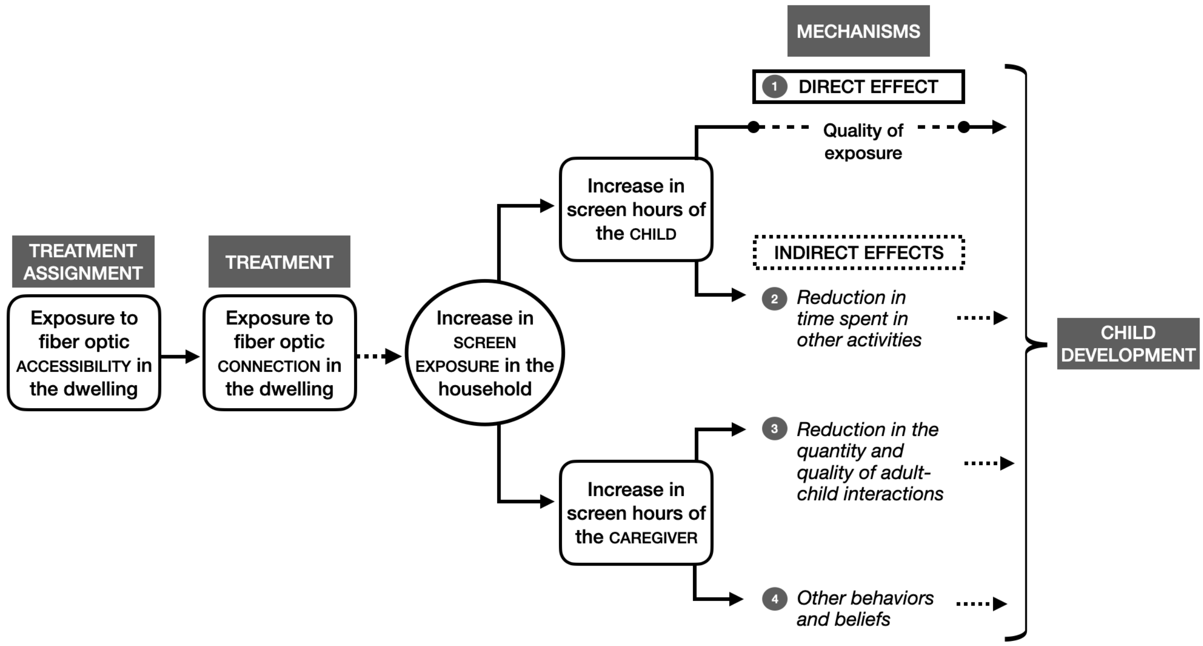
1 Theory of Change

Figure 1 presents a summary of our theory of change from treatment assignment to final outcomes.

Figure 1: Theory of Change



2 Nutrition, Child Development and Health Survey (NCDHS)

2.1 Sampling Design

For the 2013 cohort, the sample for children aged 0-3 was constructed using the households interviewed by the CHS between February 2012 and November 2013 living in urban areas (localities with 5,000 or more inhabitants). The survey design consisted of random sampling implemented in two phases: the first phase corresponds to the CHS, where the design is randomized and stratified in two or three stages of selection; in the second phase, all households with children under four were selected. Under this strategy, the theoretical sample size was 4,029 households, and the effective sample size was 2,665 households, leading to a non-response rate of 34%, mostly due to the inability to re-contact households. The final weights were calibrated with post-calibration techniques to match the population totals by gender and age of the theoretical sample.

With respect to the second survey cohort, the sampling frame was constructed using administrative data from the Live Birth Certificate 2013-2018 provided by the Ministry of Public Health. Children living in urban areas born between October 2013 and August 2018 were selected, so that at the time of the interview, the population covered consisted of children younger than 59 months of age. The sample design was randomized, stratified, and in several stages of selection. To ensure that children under six months were adequately represented, a different strategy was carried out for children under three months: they were directly selected within the strata and localities included in the sample (without selection stages) and priority was given in the field to achieve the necessary sample sizes. Survey weights were constructed considering the sample design and adjusting to non-response rates by stratum and locality of residence. In addition, they were calibrated to match population totals by age and region of residence estimated using the CHS.

2.2 Descriptive Statistics

Table 1: Child Descriptive Statistics

	2013			2018		
	Mean	SD	Obs.	Mean	SD	Obs.
Monthly Income PC (USD)	528.52	546.97	2,606	486.43	620.60	2,593
Living in Montevideo	0.47	0.50	2,611	0.45	0.50	2,598
Gender (males)	0.52	0.50	2,611	0.51	0.50	2,598
Age in Months	49.51	13.94	2,611	29.61	17.30	2,598
Ethnicity	0.07	0.26	2,611	0.13	0.33	2,598
Maternal Age at Birth	27.17	6.94	2,589	28.30	6.74	2,597
Insufficient Prenatal Care	0.14	0.34	2,303	0.15	0.36	2,597
Premature	0.11	0.31	2,297	0.08	0.27	2,596
Weight at Birth (grs.)	2.78	0.54	2,315	2.76	0.56	2,596
Low Birth Weight	0.06	0.24	2,315	0.06	0.25	2,596
Exclusive Breastfeeding	0.55	0.50	2,611	0.56	0.50	2,549
Cohabitation with Parents	0.72	0.45	2,611	0.77	0.42	2,598
Preschool Attendance	0.78	0.41	2,611	0.56	0.50	2,598
Caregiver's Educational Level	11.07	3.97	2,611	9.90	4.66	2,566

Notes: Own calculations based on NCDHS 2015 and 2018 using survey weights. Monthly income PC is the household income per capita in April 2020 dollars considering all income sources available in the survey, including labor income from the first and second occupations, pensions and other personal and household income transfers. Living in Montevideo is a binary variable indicating that the child lives in the capital city. Gender of the child is a binary variable that indicates if the child is identified as male. Ethnicity is a binary variable for ethnic origin of the child other than white. Maternal age at birth indicates the mother's age when the child was born. Insufficient prenatal care is a binary variable indicating either having the first medical visit after the third month of pregnancy and/or having five or less visits during pregnancy. Premature is a binary variable indicating a child born before week 37. Weight at birth is a variable indicating the weight at birth of the child in grams. Low birth weight is a binary variable identifying a child born with weight below -2 SD when compared to WHO charts. Exclusive breastfeeding is a binary variable indicating exclusive breastfeeding during the first 6 months of the child. Cohabitation with parents is a binary variable indicating a child that lives with both parents in the same dwelling (biological or adoptive). Preschool attendance is a binary variable indicating that the child attends an early childhood education center. Caregiver's educational level indicates the total years of schooling of the child's caregiver (starting in the first year of primary school).

3 Control Variables

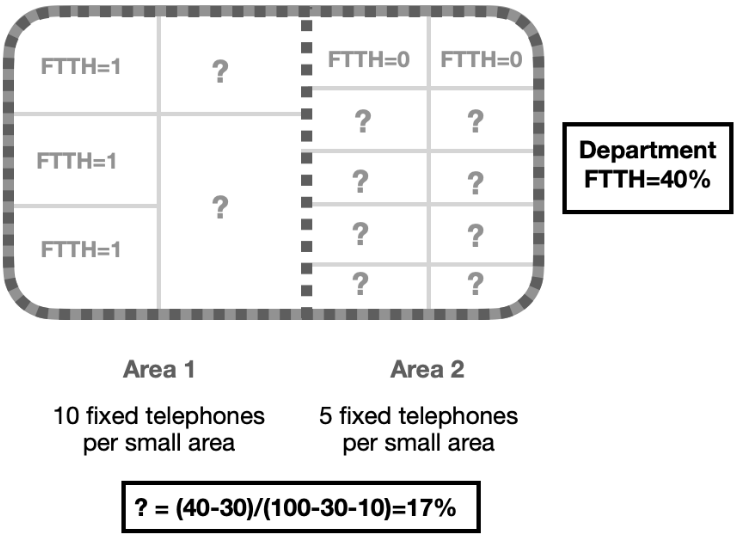
Table 2: Control Variables.

Category	Name	Description	Computation
Conditional Exogeneity	Age	Age of the child according to the outcome test age bracket.	Categorical variable indicating the age bracket of the child when the test outcome was measured. The original categories were collapsed due to the sample size. For the ASQ-3 the categories are: 1-12 months, 13-22 months, 23-38 months, 39-50 months, 51-66 months. For the ASQ-SE the categories are: 3-14 months, 15-26 months, 27-41 months, 42-53 months, 54-65 months. Source: NCDHS.
Conditional Exogeneity	Neighborhood	Neighborhood	Categorical variable indicating the neighborhood of residence of the child when the NCDHS took place. Source: NCDHS.
Conditional Exogeneity	Year	Survey year.	Categorical variable indicating the year when the survey interview took place. Source: NCDHS.
Conditional Exogeneity	Sanitation by neighborhood	Percentage of households with sanitation by neighborhood (department)	Percentage of households with flush to piped sewer system by neighborhood. Source: CHS.
Conditional Exogeneity	Income per capita by neighborhood	Average income per capita by the neighborhood of residence.	Average of household income per capita by neighborhood in 2010. The variable includes income from all available sources (labor, pensions, capital, transfers). It does not include imputed income from owner-occupied housing. Source: CHS.
Child Control	Gender	Gender of the child.	Indicator variable for a child identified as male. Source: NCDHS.
Child Control	Ethnicity	Ethnicity of the child.	Indicator variable for ethnic origin other than white. Source: NCDHS.
Child Control	Maternal age	Mother's age when child was born.	Mother's age in years when the child was born. Source: NCDHS.
Child Control	Caregiver's educational level	Years of schooling of the child's caregiver.	Total years of schooling of the child's caregiver starting in the 1st year of primary. Source: NCDHS.
Child Control	Cohabitation with both parents	Both parents living with the child.	Indicator variable for a child living with both parents (biological or adoptive) in the same dwelling. Source: NCDHS.

4 Neighborhood Imputation of FTTH Accessibility

An example of the neighborhood imputation is presented in figure 2. Suppose that the information provided by ANTEL for a particular department and year is 40%, meaning that 40% of landlines have access to FTTH, and that this department contains 15 small geographical areas. For three of those areas, we know that in 2012-2018 they had FTTH with probability one, and for two of those we know the probability was 0 since they did not have FTTH in 2020. The remaining areas were all collapsed, and the adjusted probability of having FTTH is computed as 17%. In this example, this department has three neighborhoods with a probability 1, two neighborhoods with a probability 0, and one neighborhood with a probability 0.17.

Figure 2: Example - FTTH Neighborhood level



5 Robustness Checks

Table 3: Effects of FTTH Exposure without Sample Weights

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-1.43***	0.01	0.56	-1.14**	-0.79*	-0.62*
	(0.43)	(0.40)	(0.41)	(0.43)	(0.44)	(0.34)
P-value	0.00	0.98	0.17	0.01	0.08	0.07
P-value WCB	0.00	0.97	0.17	0.01	0.07	0.06
Lower bound WCB	-2.28	-0.80	-0.25	-1.95	-1.67	-1.25
Upper bound WCB	-0.57	0.82	1.36	-0.28	0.06	0.03
N	4,454	4,454	3,446	4,453	4,452	4,449

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, controls for linear trends in sanitation and income per capita by neighborhood, and child controls. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH.

Table 4: Effects of FTTH Exposure for 2013-2015-2018

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-0.65*	-0.14	0.31	-0.70*	-0.55*	-0.30
	(0.38)	(0.23)	(0.33)	(0.34)	(0.30)	(0.27)
P-value	0.09	0.53	0.34	0.04	0.07	0.26
P-value WCB	0.10	0.55	0.37	0.08	0.06	0.26
Lower bound WCB	-1.45	-0.61	-0.34	-1.38	-1.10	-0.79
Upper bound WCB	0.10	0.31	1.11	0.10	0.03	0.25
N	6,133	6,150	5,136	6,129	6,146	5,999

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH. The estimation is done using the sample from waves 2013, 2015, and 2018.

Table 5: Effects of FTTH Exposure using the Balanced Panel

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-2.01***	-0.51	0.23	-1.34***	-0.94**	-1.00**
	(0.49)	(0.39)	(0.41)	(0.43)	(0.44)	(0.39)
P-value	0.00	0.20	0.58	0.00	0.04	0.01
P-value WCB	0.00	0.21	0.61	0.00	0.05	0.02
Lower bound WCB	-3.02	-1.31	-0.64	-2.27	-1.79	-1.78
Upper bound WCB	-1.00	0.27	1.06	-0.44	-0.02	-0.24
N	2,425	2,425	1,908	2,424	2,424	2,423

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH. The estimation is done considering only the balanced panel by wave and age bracket in 2015 and 2018.

Table 6: Effects of FTTH Exposure without Always and Never Treated Neighborhoods

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-2.36***	-1.00*	0.27	-2.42***	-1.65***	-1.59***
	(0.61)	(0.57)	(0.62)	(0.69)	(0.51)	(0.45)
P-value	0.00	0.08	0.66	0.00	0.00	0.00
P-value WCB	0.00	0.10	0.70	0.01	0.00	0.00
Lower bound WCB	-3.74	-2.23	-1.06	-3.87	-2.69	-2.60
Upper bound WCB	-1.15	0.22	1.64	-0.80	-0.62	-0.79
N	4,118	4,118	3,153	4,117	4,116	4,046

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH. The estimation is done excluding: children in neighborhoods with FTTH accessibility in 2013 and children in neighborhoods without FTTH accessibility in 2018.

Table 7: Effects of FTTH Exposure without Always and Never Treated Children

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-2.68***	-1.22*	-0.16	-2.48***	-1.87***	-1.59***
	(0.65)	(0.57)	(0.60)	(0.68)	(0.47)	(0.46)
P-value	0.00	0.03	0.79	0.00	0.00	0.00
P-value WCB	0.00	0.06	0.80	0.00	0.00	0.00
Lower bound WCB	-4.33	-2.50	-1.27	-3.86	-2.93	-2.71
Upper bound WCB	-1.36	0.04	1.22	-0.83	-0.84	-0.73
N	4,312	4,312	3,475	4,311	4,310	4,189

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH. The estimation is done excluding children always or never treated, identified as those with FTTH exposure higher than 0.95 and lower than 0.05.

Table 8: Effects of FTTH Exposure without One-Year-Old Children

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	ASQ-SE
FTTH Exposure	-1.76***	-0.46	0.40	-1.46***	-0.91**	-0.82**
	(0.50)	(0.39)	(0.43)	(0.45)	(0.44)	(0.35)
P-value	0.00	0.24	0.36	0.00	0.04	0.02
P-value WCB	0.00	0.25	0.35	0.00	0.04	0.02
Lower bound WCB	-2.77	-1.22	-0.51	-2.34	-1.73	-1.46
Upper bound WCB	-0.79	0.28	1.23	-0.57	-0.05	-0.17
N	4,454	4,454	3,446	4,453	4,452	4,449

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility. The estimation is done excluding one-year-old children.

Table 9: Effects of FTTH exposure considering different assumptions in the computation of FTTH probability

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH exposure Opt. 1						
FTTH Exposure	-1.79***	-0.46	0.42	-1.32**	-0.87*	-0.81**
	(0.54)	(0.44)	(0.46)	(0.49)	(0.44)	(0.36)
P-value	0.00	0.30	0.36	0.01	0.05	0.03
P-value WCB	0.00	0.34	0.37	0.02	0.06	0.02
Lower bound WCB	-2.95	-1.38	-0.53	-2.30	-1.72	-1.48
Upper bound WCB	-0.69	0.40	1.32	-0.29	0.01	-0.14
N	5,035	5,035	4,027	5,034	5,033	4,909
FTTH Exposure Opt. 2						
FTTH Exposure	-1.76***	-0.48	0.36	-1.44***	-0.90**	-0.79**
	(0.49)	(0.39)	(0.44)	(0.46)	(0.44)	(0.34)
P-value	0.00	0.22	0.41	0.00	0.04	0.02
P-value WCB	0.00	0.23	0.42	0.00	0.04	0.02
Lower bound WCB	-2.76	-1.23	-0.56	-2.34	-1.73	-1.42
Upper bound WCB	-0.79	0.26	1.22	-0.51	-0.04	-0.15
N	5,035	5,035	4,027	5,034	5,033	4,909
FTTH Exposure Opt. 3						
FTTH Exposure	-1.79***	-0.46	0.42	-1.32**	-0.87*	-0.81**
	(0.54)	(0.44)	(0.46)	(0.49)	(0.44)	(0.36)
P-value	0.00	0.30	0.36	0.01	0.05	0.03
P-value WCB	0.00	0.34	0.37	0.02	0.06	0.02
Lower bound WCB	-2.95	-1.38	-0.53	-2.30	-1.72	-1.48
Upper bound WCB	-0.69	0.40	1.32	-0.29	0.01	-0.14
N	5,035	5,035	4,027	5,034	5,033	4,909

Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, caregiver's educational level and cohabitation with both parents for the ASQ-SE). We use sample weights for the estimation. Standard errors reported in parentheses, clustered at the district level (capital) and department level (rest) using Liang-Zeger cluster robust standard errors. P-Values are obtained using Liang-Zeger cluster robust standard errors. P-values WCB are derived from a Wild Cluster Bootstrap procedure with 999 repetitions, restricted with Rademacher weights. For hypothesis testing we use WCB P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lower and upper bounds WCB are confidence intervals at the 5% level. The first five columns refer to the ASQ-3 dimensions (communication, gross motor, fine motor, problem solving, and personal-social), and the last column to the ASQ-SE. All outcomes are standardized scores by age groups. FTTH exposure is constructed as the cumulative lifetime exposure of each child to FTTH accessibility at the department level. For FTTH exposure Opt. 1, we use the number of planned fixed telephone lines set out by the telecommunications authority for the FTTH rollout in the imputation, instead of the number of fixed telephone lines just before the rollout as in the main estimation. For FTTH exposure Opt 2, we use the distribution of fixed telephones by small geographical areas from the Census 2011 and applied it to the total number of landlines provided by ANTEL for the imputation, instead of the absolute number of landlines from the Census 2011 as in the main estimation. For FTTH exposure Opt. 3, we use both Opt. 1 and Opt. 2.

6 Mechanisms

Table 10: Mean Reference Values

	Screen Time $\geq$ 1hr	TV as a solution	Activities with parents	Number of books	Daily use Adults	Weekly use Adults	Risky in Practices
2015	0.25	0.39	1.67	1.40	4.44	0.53	0.17
2018	0.43	0.36	1.50	1.29	3.94	0.53	0.17

Notes: Own calculations based on NCDHS and CHS 2015 and 2018 using survey weights. Screen time $\geq$ 1hr is a dichotomous variable indicating one hour or more of daily screen time of the child. TV as a solution is a dichotomous variable indicating a caregiver agrees with following statement "Leaving children in front of the TV for a long period is a solution when mothers are busy". Activities with parents is a count variable that considers whether parents and children usually read books and/or sing songs together. Number of books is a categorical variable that takes the value 0 when there are no children's books at home, 1 if there are 1-9 books, and 2 if there are more than 10 books. Daily use adults is dichotomous variables indicating daily use of internet in adults living in households with children between 0 and 5 years of age by neighborhood. Weekly use adults is dichotomous variables indicating weekly use of internet in adults living in households with children between 0 and 5 years of age by neighborhood. Risky practices is an index of detrimental parental practices.

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