Universitat Autònoma de Barcelona

Three essays on how new technologies are changing our lives

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A contribution from Applied Economics

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Contents

Introduction

New technologies are a ubiquitous element in our everyday life. We use them for entertainment, to work, to learn, and in many other contexts. Having an internet connection and smart devices that take advantage of this connectivity has become the norm. For example, the number of mobile cellular subscriptions per 100 people worldwide has been increasing yearly, reaching 106 in 2020.[1] In addition, internet use accelerated during the COVID-19 pandemic going from 54% in 2019 to 63% in 2021. The extended use of new technologies is present across all ages, showing that these changes have affected our society as a whole and not only the new generations (ITU, 2021).

The incorporation of new technologies has offered multiple and substantial benefits in many dimensions. Still, preliminary data has shown that there are also potential risks associated with certain types of use. For example, new technologies increased access to information and connectivity among people. However, more access to the internet and social media use could have a negative effect on mental health (Braghieri et al., 2022; Donati et al., 2022). Other example comes from the literature in economics of education that shows that the impact of Information and Communication technologies and computer-aided instruction on educational outcomes are mixed (Bulman and Fairlie, 2016) and also differ between developing and developed economies.

Nonetheless, the recent technological advances and their use in our daily lives will not stop anytime soon. This stresses the importance of understanding the effects of new technologies in our society, their benefits, and potential risks. With this thesis, I aim to contribute to this objective. The dissertation consists of three empirical studies that analyze the role of new technologies and innovation, focusing on three particular dimensions: early childhood, tertiary education, and inequalities in the functional distribution of income.

The first chapter, coauthored with Karina Colombo, provides empirical evidence on the causal effect of high-speed internet on early childhood development. To do this, we exploit the geographic differences in the introduction of fiber-optic-to-the-home (FTTH) in Uruguay and survey data on development tests for early childhood. Access to FTTH increases connection speed and quality, making the use of internet connected devices more appealing. Since data transmission is faster and more reliable, this is likely to increase internet and, therefore, screen consumption in the household, potentially affecting the achievement of chil-

[1] Figure obtained from the World Bank Dataset (https://data.worldbank.org/indicator/IT.CEL.SETS.P2) based on the World Telecommunication/ICT Indicators Database from the International Telecommunication Union (ITU).

dren's developmental milestones. The literature identifies three main channels linking screen exposure and development outcomes: 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. Our setting allows us to identify intention-to-treat effects on cognitive and non-cognitive outcomes of children under five years of age and provide suggestive evidence on the mechanisms. Results show that an increase in 10 percentage points in the lifetime exposure to fiber optic during early childhood decreases development scores between 8% and 18% of a standard deviation in the areas of communication, problem solving, and social skills. Our heterogeneous effects analysis shows that the effect sizes are larger for girls, children with more educated parents and living in the capital city. In addition, the analysis of potential mechanisms behind the effect suggests that effects are driven by an increase in children's screen time and by changes in parental practices.

The second chapter focuses on youth and how new technologies can affect the educational system. More specifically, I analyze the impact of COVID-19 and the shift to online learning on students living far away from a university campus. Distance to university has been shown to be a relevant factor in students' decisions to continue studying and their academic outcomes. Therefore, the generalized shift to online learning could have opened a window of opportunity for those students living far away from the major urban centers. To do the analysis, I take advantage of three facts about the institutional setting in Uruguay. First, the main public university is free of tuition and without entrance exams but with campuses only in half of the territory. Second, the pandemic broke out after the 2020 enrollment and course registration period. Third, in contrast to 2020, when enrollment was not affected by online teaching, in 2021, new students could enroll and register for courses knowing that classes were going to be online. I follow a difference-in-differences strategy where I define the treated group as those living far away from a university. Treatment is given by the fact that for the treated group, COVID-19 and the subsequent switch to online learning implied the possibility of return to (or avoiding leaving) their hometowns and/or reducing commuting long distances. Overall, I am able to answer two questions: what are the effects of the pandemic and the online shift on (i) academic outcomes for those students already enrolled in 2020, and (ii) enrollment decisions in 2021. The data come from administrative records of first-year students for the period 2017-2021. Regarding the first question, results show a reduction in the dropout rates for the freshmen students in 2020, but no other effects are found on academic outcomes conditional on dropout. Concerning the second question, I find an enrollment increase in places without university campuses for 2021, suggesting that online learning could be a strategy to increase tertiary education enrollment.

Finally, in the third chapter, I shift the attention to the labor market to study the relationship between innovation and inequality. Particularly, I aim to contribute to the understanding of how technology relates to the labor share at the firm level for a Latin-American developing country. This is relevant because inequality is of special concern for these countries, and investing in technological change and innovation is a recommended strategy to achieve growth and development. However, the literature shows that technological change and innovation could be a cause of a decline in the labor share. Therefore, studying empirically if innovation is related to the labor share is relevant for designing public policies aiming to achieve growth and equality by taking advantage of innovation in the Latin-American context. I contribute to this objective by first describing the labor share at a micro-level in Uruguay. To do that, I use administrative records from the tax office at the firm level. Second, I combine two data sources to obtain a panel of firms for which I can measure innovation and labor share. Taking advantage of this data, I estimate the relationship between innovation and labor share using an ordinary least squared and a fixed effect regression. My findings show that the micro-level behavior of the labor share is more stable than the aggregate figure but with large dispersion. I also observe an increase in the value-added share by firms with low labor shares during the period. Regarding the relationship between innovation and labor share, I find a negative association, mainly driven by innovation in intangibles. On the other side, innovation in training activities is positively associated with the labor share.

Overall, with this dissertation, I expect to shed light on how new technologies and innovation affect different dimensions of our lives and society. I do this using different empirical strategies and methodologies. With these results, I aim to contribute to the public policy discussion on the topic, highlighting the benefits and risks of new technologies to make the most of all opportunities that innovation and technology bring.

Chapter 1

Exposure to High-Speed Internet and Early Childhood Development

1.1 Introduction[1]

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 (UNICEF, 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 pre-schoolers (Holloway et al., 2013; Chen and 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 (WHO, 2020; Heckman, 2008). However, the study of the impact of new technologies on child development is still in its early stages (Anderson and Kirkorian, 2015; Gottschalk, 2019; Kostyrka-Allchorne et al., 2017). 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.

[1]This study is coauthored with Karina Colombo. We are thankful for the advice and suggestions of Sule Alan, Thomas Crossley, and Xavier Ramos. We are also thankful to Sara Ayllón, Andrea Ichino, Alessandro Tarozzi and Alicia Adsera for their comments. We presented a similar version of this paper in the SEHO Conference, the WIPE PhD student Workshop, the Applied Economics Conference, the 46º Simposio de la Asociación Española de Economía, the Annual Meeting Impact Evaluation of RIDGE, the NIP – LACEA workshop, and in the departmental seminars at Instituto de Economía at UDELAR, Applied Economics department at UAB, Microeconometric working group at EUI and UNICEF Innocenti Office Seminar. We want to thank all the comments and suggestions in those instances. In addition, we thank the Uruguayan Ministry of Social Development (Uruguay Crece Contigo), the public telecommunications operator (ANTEL) and the National Institute of Statistics for the provision of data.

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. 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 and shed light on the potential channels. To the best of our knowledge, this is the first study that analyzes the effect 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. We identify the intention-to-treat effects of FTTH connectivity, that is, the effects of fiber optic becoming accessible in the dwelling. Our treatment assignment is defined as the share of months a child is exposed to FTTH accessibility throughout her life, which depends on the neighborhood of residence and date of birth. 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 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% and 3% 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 the capital city. 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 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 beliefs 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 pediatric and 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-quality internet connection 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 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. However, this literature has several limitations. First, studies have shown an ambiguous association between screen exposure and child development, reporting negative, null and positive effects on early childhood development. Nonetheless, a consistent finding in this literature is that effects are heterogeneous 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). Second, this literature mostly focuses on correlational studies and experiments involving small sample sizes, making it difficult to extrapolate conclusions to the general population. Third, 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 and Kirkorian, 2015; Gottschalk, 2019; Kostyrka-Allchorne et al., 2017). Although there is still no clear evidence on a safe level of screen time or whether it actually causes harm, 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.

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 health outcomes, subjective well-being, and educational achievements in middle childhood and adolescence, leaving the questions regarding internet exposure during the first years of life still unanswered (McDool et al., 2020; Faber et al., 2015; Grenestam and Nordin, 2019;

Sanchis-Guarner et al., 2021). Additionally, 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 and Shapiro, 2008; Kearney and 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 and Suhrcke, 2021; Nieto, 2019; Hernæs et al., 2019). Nonetheless, these studies are only available for school-age children and adolescents.

This paper contributes to the literature 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 representative of the urban population aged 0 to 5. Third, it provides evidence beyond the United States (US) and Europe, allowing to study the challenges of new technologies in more vulnerable contexts. The availability of high-quality cognitive and non-cognitive outcomes at the same period in which the introduction to FTTH 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 screen exposure that enhance learning from new technologies without generating risks for the future development of children.

The remainder of the paper is structured as follows. Section 1.2 introduces our conceptual framework. Section 1.3 presents the background and data. Section 1.4 describes our empirical strategy. Section 1.5 shows the results, and Section 1.6 presents some final remarks.

1.2 Conceptual Framework

In this study we analyze the effects of fiber optic accessibility on early childhood development. A summary of our theory of change from treatment assignment to final outcomes is presented in Figure 1.1. Our treatment assignment consists of 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 household 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.[2] Hence, FTTH accessibility is likely to increase screen consumption of the child and the caregiver, ultimately altering overall time use patterns.

Internet and screen media exposure can affect children's development through

[2]Studies show that access to digital technologies has not resulted in a one to one substitution of media consumption from old to new devices (e.g., from television to tablets or cellphones), implying an overall increase in screen time (Anderson and Kirkorian, 2015; Goode et al., 2019; Rideout et al., 2013).

direct and indirect mechanisms. The first one refers to the effects from the 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 by the child or caregivers. First, there is a direct channel derived from the potential increase in the child 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.[3] 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 and 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 (Anderson et al., 2017; Chassiakos et al., 2016; Kostyrka-Allchorne et al., 2017; Radesky et al., 2016). 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.(DeLoache and Chiong, 2009; Radesky et al., 2016) For preschool children older than 30 months, there is evidence suggesting that educational media has a positive impact on child development and subsequent academic performance. (Anderson and Kirkorian, 2015; Anderson et al., 2017; Kostyrka-Allchorne et al., 2017; Radesky et al., 2016) 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 and Kirkorian, 2015; Gottschalk, 2019; Kostyrka-Allchorne et al., 2017).

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. 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 and Kirkorian, 2015).

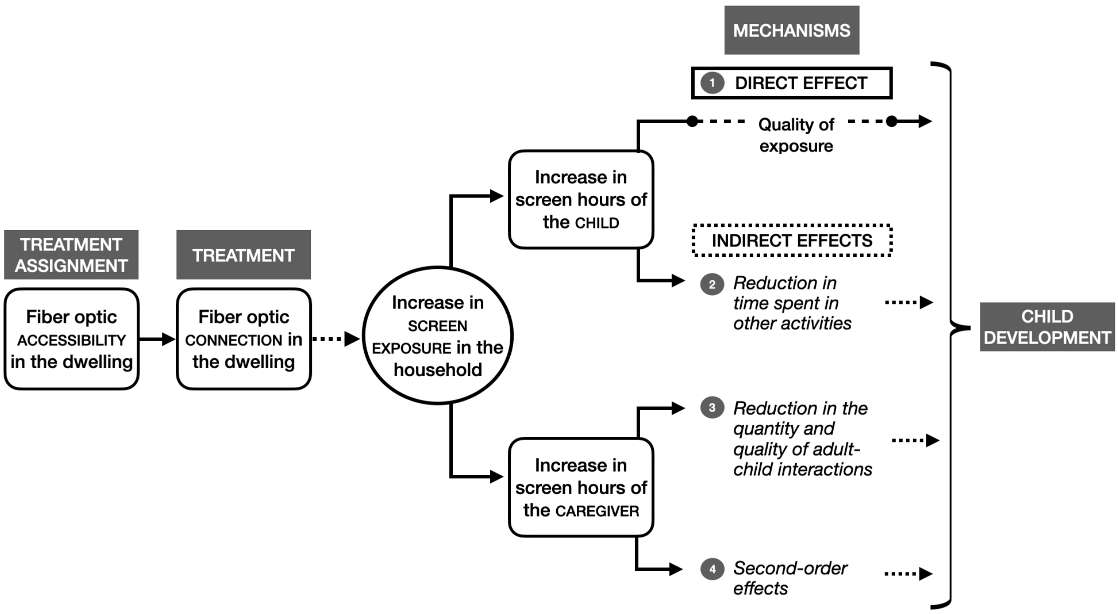
Third, internet availability could affect the behavior of caregivers in several ways, indirectly affecting child development. Two main channels can be distinguished. First, evidence has shown that caregivers' screen exposure could lead to a reduction in the quantity and quality of interactions with the child. Being that parental involvement is critical for cognitive and emotional development, the use of media by caregivers could have negative effects on child development.(Kostyrka-Allchorne et al., 2017; Moreno et al., 2016; Radesky et al.,

[3]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).

2016) Second, high-speed internet accessibility could affect adult outcomes in other areas, modifying household conditions and ultimately affecting child development as a second-order effect. For instance, research has shown positive effects on labor market participation for married women with children, as well as positive effects on fertility 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 effect, considering: children's screen time and its quality (mechanism one), time spent in other activities (mechanism two), and screen exposure of the caregiver (mechanism three). The analysis of second-order effects (mechanism four) will be incorporated in future work.

Figure 1.1: Conceptual Framework



1.3 Background and data

1.3.1 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 for the government, 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 fixed phones, the one-laptop-per-child program and the FTTH project.[4] 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 is the only authorized provider for fixed broadband connections in Uruguay (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 usually 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 pre-registering 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 shows the geographic and yearly variation in the FTTH rollout since the beginning of the deployment by administrative units (from now on, departments).[5]

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 was 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

[4]The one-laptop-per-child program was launched in 2007. In addition to the provision of laptops to students attending public education institutions, it supplied internet connection to schools and certain public areas. By the end of 2009 all public primary schools were covered, hence, this policy was fully implemented by the time period in which the FTTH project took place (Ceibal, 2017). Therefore, considering that the one-laptop-per-child program did not change during the period 2011-2018, our results are not affected and are conditional on the existence of the program in the country.

[5]Uruguay is divided into 19 administrative divisions called departments.

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 1.4.

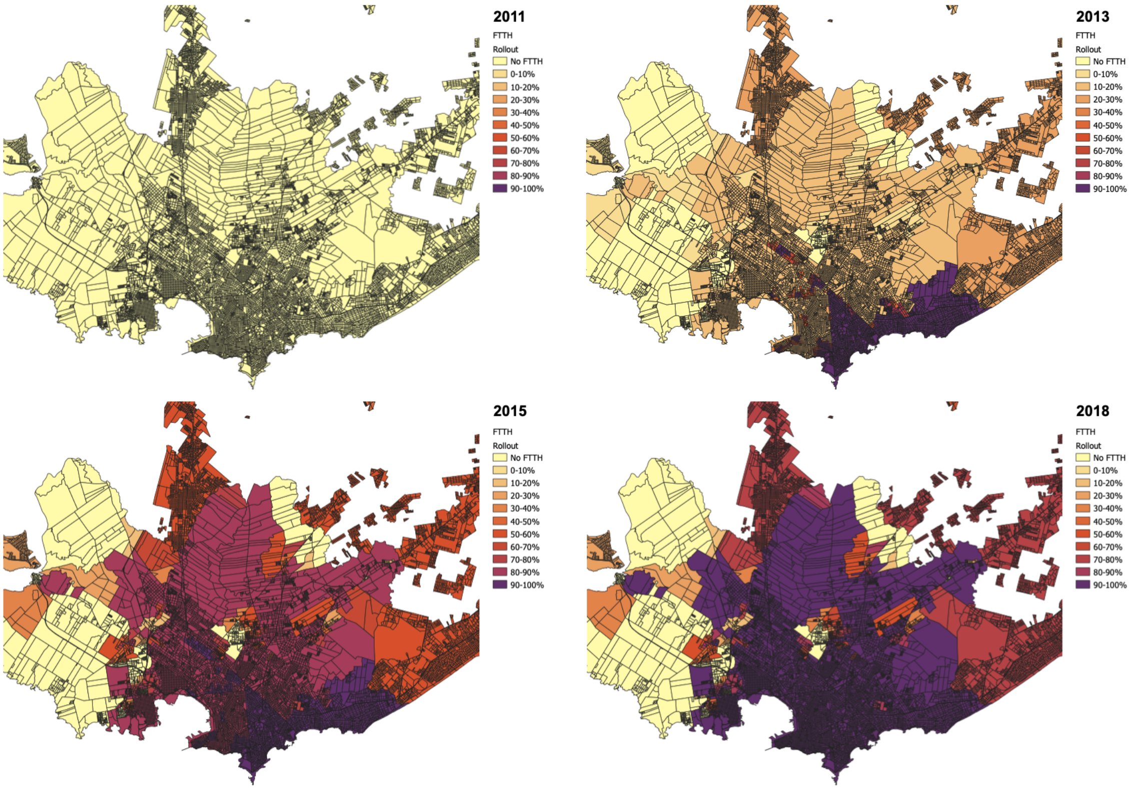
1.3.2 Internet Data

For our analysis, we use original data on the FTTH rollout in Uruguay constructed by combining two types of administrative data from the telecommunication operator together with Census data. On the one hand, we used 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 constructed granular data on FTTH installation for the year 2012 by using an Internet Archive on ANTEL's web page. This data provides very precise information on the geographic deployment of FTTH, up to the block level. Information at the block level for the year 2020 was obtained directly from the telecommunication operator.[6] Moreover, we used information on the number of landlines by small geographical areas from the 2011 Census (NIS).

In order to best capture and exploit the variability in fiber optic accessibility, we created 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 disaggregation. The procedure for the neighborhood level imputation is detailed in Section A.3 of the Appendix. The final database consists of 444 neighborhoods in the capital city and 40 neighborhoods in the rest of the country, for which we have the yearly probability of having FTTH accessibility. As an example, Figure 1.2 shows the FTTH deployment for the capital city, Montevideo, at the neighborhood level.

[6] Ideally, we would have used block level information for the period 2012-2018 constructed by the telecommunication operator. However, this information was not stored over time, and hence, at the time our research started only the information on the year 2020 was available. Given that for the years 2011 and 2012 this information was posted online through static maps in PDF format, we managed to recover it by using the Internet Archive Wayback Machine (a service that stores archived versions of Web sites), and then converted it into shapefiles through a manual data entry process.

Figure 1.2: FTTH Rollout in Montevideo by Neighborhood



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

1.3.3 Children data

The information on children outcomes comes from the "Nutrition, Child Development and Health Survey" (NCDHS), conducted by the National Institute of Statistics (NIS) and the Ministry of Social Development, with the objective of studying the situation of early childhood in Uruguay.[7] This survey collected 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 health area, or by enumerators specially selected 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 for 2013 information on development tests was collected only for children living in the capital city, in 2015 and 2018 information is representative for children living in the urban country (localities with 5,000 inhabitants or more). For this reason, we focus our estimations on the 2015 and 2018 waves, and we use the 2013 wave as a robustness check. 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 2,599 children was collected. The first cohort covers children born between 2010 and 2013,

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

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 1.1. We use sampling weights calibrated against population totals provided by the NIS.[8] Basic descriptive statistics are presented in Section A.4.2 of the Appendix.

Table 1.1: 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 1 and 3 report the number of observations in each age bracket per NCDHS wave. Column 2 and 4 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 Ages and Stages Questionnaires Socio-Emotional (ASQ-SE). The ASQ-3 (Squires and Bricker, 2009) 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 assess age-specific outcomes in different age brackets between 1 and 66 months of age. One numerical score per area summarizing the developmental progress of each child is obtained.[9] This score is compared to age-specific cutoffs based on empirical research for a reference population, leading to three categories: the child is developing normally, the child should be monitored, or the child may be at risk for developmental delays.[10] The ASQ-SE (Squires et al., 2002) was developed as a complement to the ASQ-3 and focuses on the social and emotional development of children older than three months in seven behavioral areas: self-regulation, compliance, social-communication, adaptive functioning, autonomy, affect, and interaction with people. The questionnaires are age-specific, and a global score considering all behavioral areas is obtained.[11] In addition, empirically-derived and age-specific cutoffs are provided to identify children at risk that should be referred for further assessment. In this study, we consider the raw scores provided by the ASQ-3 and ASQ-SE tests, standardized by age groups according to the distri-

[8] The sampling design is described in Section A.4.1 of the Appendix.

[9] Each questionnaire contains six questions per area which be answered as "yes", "sometimes" or "not yet", scoring 10, 5 and 0 points respectively. Scores are summed within each area with a maximum of 60, meaning in that case that the child is perfectly on track and can perform all the developmental milestones expected for her age.

[10] A child is defined in the monitor category if he scores 1-2 SD below the mean of the reference population. A child is defined in the risk category if he shows a score of 2 SD or more below the mean.

[11] Each questionnaire has 22 to 36 questions for the parents to answer as "often or always", "sometimes" or "rarely or never", with a score of 0 or 10 for the first and last category, and 5 for the middle category. A higher overall score means a worse developmental situation.

bution in our sample. These groups are constructed by aggregating the test age brackets for each specific questionnaire. Moreover, we analyze the categorical variables defined in the ASQ-3 test that indicates whether a child is developing within normal ranges vs. those that should be monitored or are at risk of developmental delays, and the variable defined in the ASQ-SE test that indicates whether a child is not at risk of developmental delays.[12] Sample questions for the ASQ-3 and ASQ-SE for the developmental tests are presented in Section A.4.3 of the Appendix.

In addition to the main development outcomes, secondary outcomes are used to analyze the mechanisms driving our results. First, we estimate the direct effect of fiber optic availability on children's screen exposure by using information on screen time. For this purpose, we construct an indicator variable for spending more than one hour a day on screen media. 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. It is worth mentioning that our measure of hours of screen of the child is a global time estimate reported by the parent, without the use of time diaries. Even though this is the most common way of measurement because of its costs and ease of implementation, it has limitations. 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. Also, answers are more sensitive to social norms and stereotypes ((Vandewater and Lee, 2009)). Complementary to this measure, we proxy the quality of exposure by analyzing the caregivers' opinion on 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 a positive answer to this question does not necessarily mean that the caregiver is engaging in this practice, it denotes a higher prevalence and acceptance of this behavior in her environment. Therefore, given the recommendations on co-viewing practices, we use this variable as an indicator of low quality exposure.

Second, we study the displacement of alternative activities that are beneficial for child development. We construct a categorical variable considering information on activities that parents perform together with the child. This variable takes the value of two if parents tell stories and sing songs with the child, one if parents engage in only one of these activities, and zero if they do not engage in any of the two. 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 of two if there are more than ten books, one if there are one to nine books, and zero if there are no children's books at home.[13]

[12] Since the ASQ-3 scores measure achievements and the ASQ-SE score measures socio-emotional problems, we present the results for ASQ-SE with the opposite sign to facilitate the interpretation of results.

[13] Compatibility between the two waves is not perfect due to differences in the answer

Third, we analyze the effects on parental practices and beliefs regarding other aspects beyond screen exposure. We consider an instrument that assesses values related to how children learn, the use of punitive parenting practices, and beliefs on sexist practices. We construct an index of risky parental practices considering "Yes/No" answers to 22 statements.[14]

Fourth, we approximate caregivers' screen time by the use of the internet. Given that this information is not available in the NCDHS we use an additional survey, the Continuous Household Survey (CHS).[15] We merge the CHS with the information on fiber optic deployment and consider the frequency of internet use in adults living in households with children between 0 and 5 years of age by neighborhood.[16] We use two mutually exclusive variables that indicate if the adult used internet at least once per day or once per week in the last month.

By combining these questions, we are able 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 behavior of caregivers. All questions used in the construction of variables that evaluate potential mechanisms are detailed in Section A.4.4 of the Appendix. In addition, Table A.1 presents all the data sources used for the analysis.

1.3.4 FTTH Exposure of the Child

Our objective is to estimate the intention-to-treat effects of fiber optic, that is, the effect of having the possibility to purchase a fiber optic internet plan in the 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:

$$\text{FTTH\_Exposure}_i = \frac{\sum_{month/year=b_i}^{month/year=s_i} FTTH_{year,n}}{a} \tag{1.1}$$

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 is the neighborhood of residence of the child, $FTTH_{year,n}$ is the probability of FTTH at the neighborhood n in each year,

options to this question. Particularly, the middle category corresponds to 1 to 10 books in the 2015 wave and to 1 to 9 books in the 2018 wave.

[14] We follow the Index for Parental Practices (IPCG) index developed by the Interdisciplinary Group of Psychosocial Studies (GIEP) from the Universidad de la República ((Cerutti et al., 2014). The original version includes 23 statements instead of 22. We exclude the one that inquires directly about using TV as a solution when caregivers' are busy, since we use it to approximate the quality of screen exposure of the child.

[15] The CHS is conducted by the National Institute of Statistics using a random sample representative of the whole country.

[16] Since the information from the CHS and the NCHDS 2015 and 2018 cannot be merged directly, we consider in the CHS children of the same age and neighborhood as in the NCDHS.

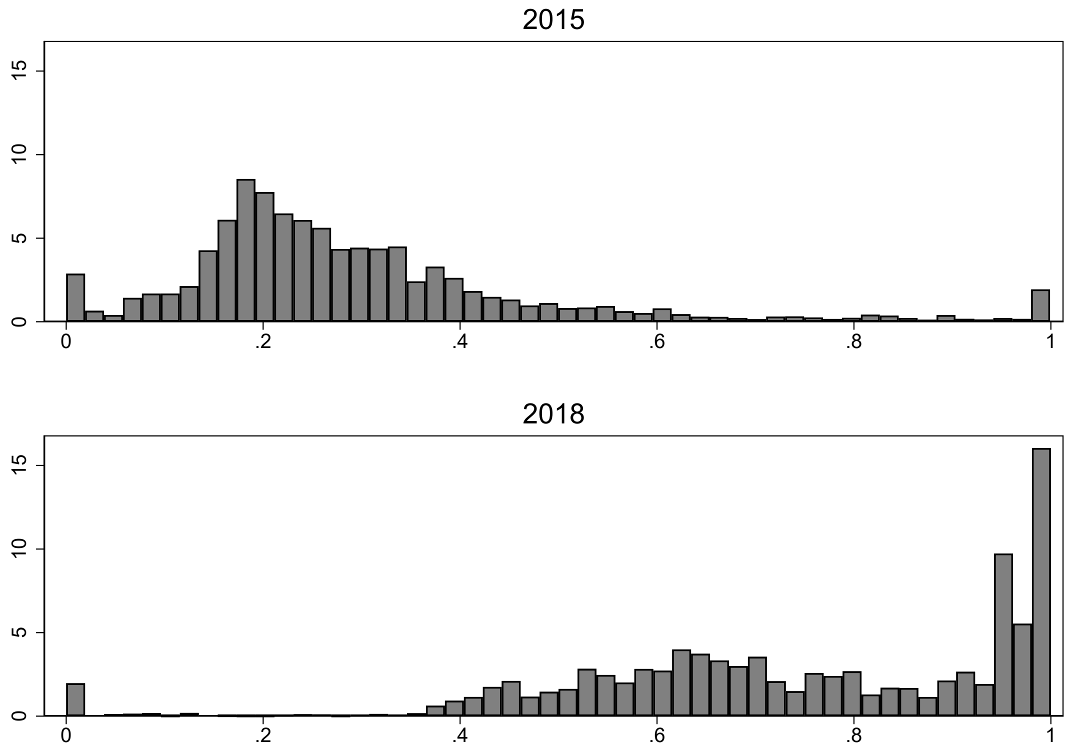
and a is the age in months of the child at the time of the survey.[17] Therefore, the treatment assignment variable can be interpreted as the lifetime exposure to fiber optic at the time of the outcome measurement. As an example, if a 20-months-old child lives in a neighborhood with a probability 1 of 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 variable as a relative measure according to the child's age 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. That 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 1.3 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.

[17] Since the FTTH variable refers to the probability of fiber optic at the end of each calendar year, we consider the lagged variable.

Figure 1.3: FTTH Exposure by Survey Wave



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

1.4 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[18]. 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 scores in the five dimensions of the ASQ-3 tests 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 mainly control for year-specific shocks common to all individuals, such as changes due to economic growth in the period. Z_n is a vector of pre-treatment

[18] Our data is a pool of repeated cross-sections for different years. Therefore, we do not include the subindex t in the specification, as each child is observed only once

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.[19] 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 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.

This strategy identifies the intention-to-treat effect of fiber optic, that is, the effect of being assigned to treatment, which occurs when fiber optic becomes accessible 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.[20] Moreover, we regressed treatment assignment on time-varying characteristics of the child, finding no significant or very small relations.[21] In addition, for robustness, we include the pre-treatment

[19] Table A.3 presents a detailed definition of the variables included as controls in the regressions.

[20] In Section A.6 of the Appendix we present a detailed analysis of the Principal Component Analysis.

[21] We regressed FTTH exposure on: NBH interacted with age brackets and survey year fixed effects, survey year trends in pre-treatment assignment variables and varying characteristics of the child. As a result, we find that most time-varying variables are not significant

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 and Pischke, 2009). Moreover, to account for the potential effects of year-specific shocks common to all individuals, such as economic growth, on children's tests scores, we include year fixed effects to account for common time trends.

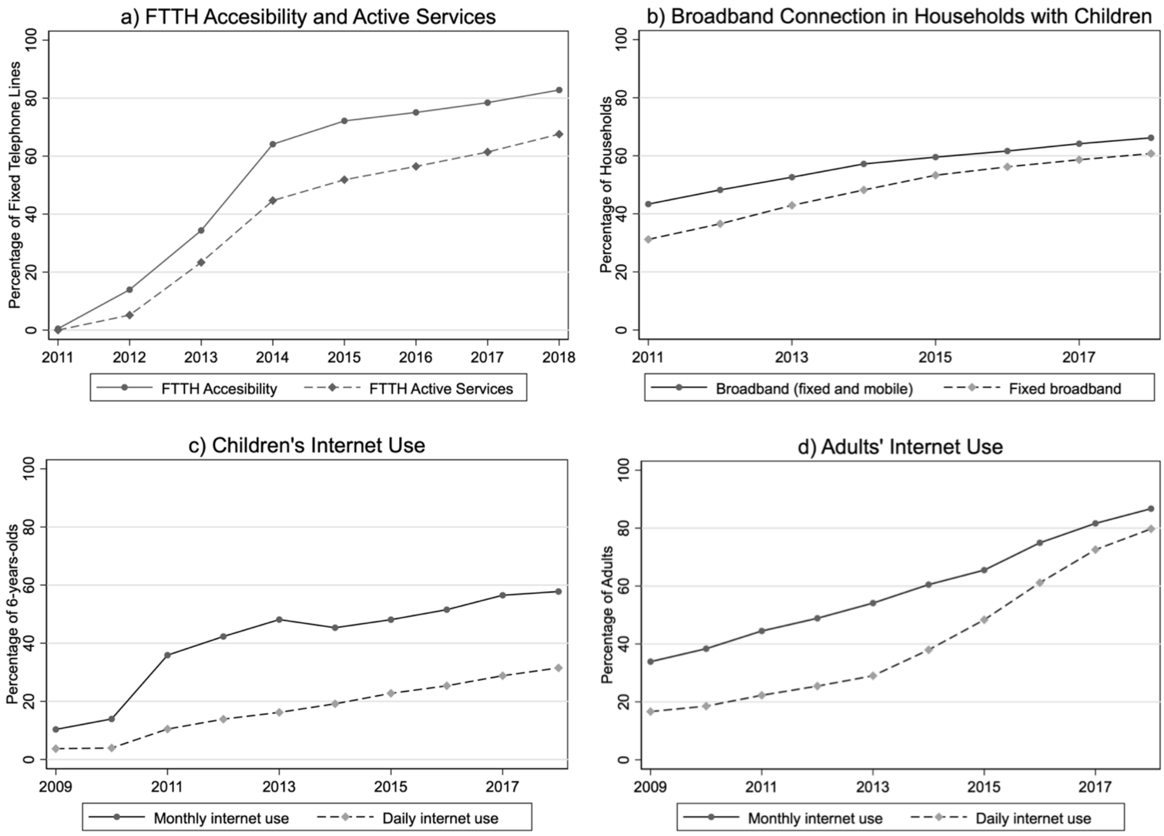
Regarding the relevance condition, the assumption in this case is that fiber optic accessibility effectively increases the probability of purchasing a fiber optic plan. If this is not the case, FTTH rollout would not affect internet speed connection and internet consumption decisions. Administrative data from the telecommunications operator presented in Panel a of Figure 1.4 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.[22] In addition, when considering the distribution of copper and FTTH plans among clients with fixed internet contracts, Panel b in Figure 1.4 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 the past years, with daily users going from almost zero to more than 30% (Panel c Figure 1.4). Moreover, the use of internet by adults in households with children in early childhood also shows sharp improvements in the period (Panel d Figure 1.4).

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 parents (Activities with parents), (iv) the number of children's books (Number of books), (v) adult internet use (Internet daily and weekly use by adults) (vi) risky parental practices (Risk in p.p). The definition of these variables was presented in Section 1.3.3. 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.

at the 5% level, and the significant variables have very low marginal effects (1pp or 2pp at most).

[22] 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).

Figure 1.4: Internet Access and Use



Source: Own computations based on ANTEL data, 2011 Census and the CHS 2006-2018. Notes: 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). Nonetheless, given that clustered errors assume zero correlation across clusters, we define a more aggregate 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. 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) (Angrist and Pischke, 2009; Cameron and Miller, 2015; Roodman et al., 2019).[23] 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.

[23]The wild cluster bootstrap is estimated in the restricted version with Rademacher weights.

1.5 Results

1.5.1 Main results

In this section, we present the intention-to-treat effects of high-speed internet exposure on child development. Table 1.2 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 significant effect on the development of communication, problem solving, personal-social and socio-emotional skills. The size of the effects is considerable, with point estimates between -0.8 and -1.8 SD. 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 of low precision, we prefer to adopt a conservative approach and consider the upper bounds of the confidence intervals provided by the WCB procedure. 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, -0.52 SD in problem-solving, -0.17 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 3/4 of a milestone out of 6 for communication, 3/5 of a milestone out of 6 for problem solving, 1/3 of a milestone out of 6 for personal-social outcomes, and 3/5 of a milestone out of 26 for socio-emotional skills.[24] 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

[24] As it was mentioned before, 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.

child control shows that all coefficients are stable across estimations.

Table 1.2: 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***	-0.49	0.35	-1.45***	-0.90**	-0.80**
	(0.49)	(0.39)	(0.44)	(0.46)	(0.44)	(0.34)
P-value	0.00	0.21	0.42	0.00	0.04	0.02
P-value WCB	0.00	0.22	0.43	0.00	0.04	0.02
Lower bound WCB	-2.76	-1.24	-0.58	-2.35	-1.73	-1.43
Upper bound WCB	-0.79	0.25	1.22	-0.52	-0.04	-0.17
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 1.3 we present the effects on the probability that a child is developing normally in each dimension (vs. being in the monitor and risk categories). Results indicate that FTTH accessibility decreases the probability of developing within normal ranges for communication and socio-emotional skills, with point estimates of 39 pp and 29 pp, respectively. 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 14 pp for communication skills, and in at least 1 pp for socio-emotional abilities. Again, the comparison between the results with and without child control shows that all coefficients are stable.

Table 1.3: 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	-0.29**
	(0.13)	(0.10)	(0.19)	(0.15)	(0.11)	(0.14)
P-value	0.00	0.19	0.75	0.23	0.91	0.05
P-value WCB	0.01	0.21	0.74	0.23	0.92	0.04
Lower bound WCB	-0.65	-0.33	-0.47	-0.49	-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.

1.5.2 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.4). 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.5). We also run our regressions without considering sample weights and the results are not affected (Table A.6).

Second, we estimate the model using alternative samples. We estimate our preferred specifications 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 A.7). Results are qualitatively equivalent to those obtained with the 2015-2018 waves. Communication, problem solving and personal-social show negative and significant results (only 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 A.8). 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 (Table A.9). We find again statistically significant, and slightly larger, coefficients for communication, problem solving, personal-social, socio-emotional and, additionally, gross motor.[25] 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 A.11). 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, the dfbeta analysis indicates that all observations show a dfbeta lower than one (Table A.12). 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.5).

The third block of robustness checks is related to differences in the treatment variable. On the one hand, we estimate the regressions using the FTTH data provided by ANTEL at the department level, constructing the treatment exposure variable without any imputations (Table A.13).[26] Compared to the neighborhood level, results are slightly higher but qualitatively similar, and as expected, the estimation using WCB 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.[27] Once again,

[25]We also estimate regressions without children with FTTH exposure higher than 0.95 and lower than 0.05, finding similar results (Table A.10).

[26]In this case, the number of clusters is smaller than recommended for the use of the Liang-Zeger cluster robust standard error. However, the WCB technique performs better when the number of clusters is small, overcoming this limitation (Cameron and Miller, 2015; Roodman et al., 2019).

[27]Given that the number of fixed telephone lines could be affected by the FTTH rollout (i.e., households that connect to a fixed telephone line only to access fiber optic), the probability of FTTH by neighborhood should be estimated using a fixed denominator over time. For the main estimation, we use the number of fixed telephone lines just before the

results are robust to these alternatives (Table A.14). 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 (Table A.15), with coefficients of a lower magnitude and significant results for communication and socio-emotional skills (problem-solving has a WCB p-value of 0.10).

Finally, we address the issue of negative weights in the estimation due to heterogeneous treatment effects posed by the two-way fixed effects literature (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020). It is worth mentioning that our setting differs from the framework developed by this literature because our continuous treatment variable is not constant inside each treatment group. Therefore, to analyze the potential problems of negative weights, we do the analysis using the binary treatment variable defined before. In this way, we can compute the weights derived in de Chaisemartin and D'Haultfœuille (2020) and we find between 3 % and 4 % of the treatment groups having 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 removed, and the treatment effects in communication, problem solving and socio-emotional skills remain qualitatively similar (Table A.16). 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.

1.5.3 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 the region of residence of the child (Table 1.4 and A.17).

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 larger for girls than for boys, 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

implementation of the FTTH, but as a robustness, we also use the number of planned fixed telephone lines set out by the telecommunications authority for the FTTH rollout (Option 1). In addition, the imputation of FTTH at the neighborhood level is done considering the number of fixed telephones per small geographical areas from the 2011 Census, but we could have also considered the distribution of fixed telephones from the Census 2011 and applied it to the total number of landlines provided by the administrative data (Option 2). We also estimate the results combining the alternative assumptions together (Option 3).

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).[28]

Given the critical role of parents in the first years of life, the analysis by the educational level of the caregiver is relevant. This variable 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.[29] The more pronounced effects on girls and children with highly educated parents go in line with Fort et al. (2020), who find larger negative effects in these populations when reducing one-to-one interactions with adults indicating a higher opportunity cost.

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 in the capital city, could have higher exposition levels due to a lower availability of outdoor spaces. On the other hand, negative effects could be mitigated by the existence of a wider offer of cultural and educational activities. Results show a more pronounced negative effect in personal-social skills for children living in the capital, and, in addition, a negative and significant effect in gross motor skills.[30]

[28]When we consider the categorical outcomes, we find a higher increase in the probability of being outside the normal range for girls in problem solving skills.

[29]These differences are observed for communication and socio-emotional skills when considering the categorical outcomes variables.

[30]For the categorical variables, we observe significant differences between groups in personal-social, with the capital showing a larger negative effect.

Table 1.4: 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***	-0.52	0.26	-1.55***	-0.91**	-0.88***
Boys	-1.67***	-0.44	0.53	-1.29***	-0.89**	-0.68**
P-value girls-boys	0.11	0.49	0.01	0.02	0.88	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**	-0.51
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	0.08
N	5,005	5,005	3,998	5,004	5,003	4,879
Panel c: Region of residenc						
Capital	-2.27***	-1.40**	0.18	-2.39***	-1.48**	-0.98*
Rest of the country	-1.76***	-0.48	0.35	-1.44***	-0.89**	-0.80**
P-value capital-rest	0.34	0.04	0.63	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. 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.

1.5.4 Mechanisms

In this section, we provide evidence to uncover the potential channels behind the overall effects estimated in Section 1.5.1. 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 1.5 shows, we find a positive effect of child exposure to fiber optic on the probability of using screens for more than one hour, though not significant at the 10 percent level (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 1.5). 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 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 1.5 third column). However, we find that children more exposed to FTTH have less children's books at home (Table 1.5 column 4). This could suggest a reduction in time reading or looking at books with an adult or by themselves, therefore decreasing time in activities that are advantageous for 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 1.5). 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 1.5). 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 the 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 1.5: Mechanisms

	Screen Time $\geq$ 1 Hr (1)	TV as a Solution (2)	Activities with Parents (3)	Number of Books (4)	Int. Daily Adults (5)	Int. Weekly Adults (6)	Risk in P.P. (7)
FTTH Exposure	0.36	0.41*	-0.15	-0.57*	0.17	-0.18**	2.30**
	(0.23)	(0.23)	(0.27)	(0.28)	(0.10)	(0.07)	(1.09)
P-value	0.11	0.07	0.58	0.04	0.11	0.01	0.04
P-value WCB	0.11	0.09	0.58	0.05	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 more than one hour of daily screen time in children. The second column shows results on parental opinion regarding the 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 sing songs together. The fourth and fifth 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. 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.

1.6 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. This study aims to contribute to the public discussion on this topic by exploring the consequences of the recent expansion in internet connectivity. We do that by 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 0.4% and 8.0% 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 the capital city, 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 result 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 with 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 mid and 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.

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 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 (CEPAL, 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.

Chapter 2

Taking advantage of COVID-19? Online learning, descentralization and tertiary education

2.1 Introduction

There is a common consensus that higher education is crucial to promote growth and development, not only benefiting the individual but society as a whole.[1]. While for developed economies the tertiary enrollment rate is more than 75%, for developing countries the figure is less favorable, being 38% for middle-income countries.[2] Therefore, analyzing policies to promote tertiary education enrollment, particularly for developing countries, is imperative. In addition, the COVID-19 pandemic and the suspension of face-to-face lessons posed several challenges to the educational system. In most countries, online learning was the response to the impossibility of teaching courses in situ. Tertiary education was not an exception. As many papers have shown, this solution may have widened educational gaps as there could be uneven access to online resources, physical space, or an adequate environment for learning (Rodríguez-Planas, 2022b; Bacher-Hicks et al., 2021). On the other hand, access to virtual learning could reduce the costs associated with studying for students living far away from the university. The distance to the place of residence has been shown as an important factor in students' decisions on attending an educational center and in their academic outcomes (Alm and Winters, 2009; Frenette, 2009; Lapid, 2016). Therefore, the generalized shift to online learning could have opened a window of opportunity for those students living in places where supply of

[1] See for example United Nations Educational, Scientific and Cultural Organization (https://www.unesco.org/en/education/higher-education/need-know) or World Bank Education Overview Caño-Guiral (2018)

[2] The gross enrollment ratio is defined as total enrollment over the population of the age group that officially corresponds to the level of education shown. For Latin American countries, the figure is 54%, while for OECD countries, it is 77%, and 87% for the US. Figures obtained from the World Bank Dataset (https://data.worldbank.org/indicator/SE.TER.ENRR) for the year 2019.

tertiary education is nonexistent. In this chapter, I analyze this hypothesis.

As mentioned, COVID-19 triggered the shift to online learning, implying a reduction of the distance to university virtually to zero. I take advantage of this shift in a particular institutional setting to analyze if the pandemic, and the subsequent shift, affected individuals living far away from a university campus differently in terms of (i) the academic outcomes, for already enrolled students and (ii) the enrollment decision, for potential students. I exploit the particular institutional setting of Uruguay, which is advantageous for four reasons. First, the main public university (Universidad de la República - UDELAR), which covers 85% of tertiary students in the country, has campuses only in half of the territory. Campuses are located in 8 out of 19 departments, and the largest educational offer is concentrated in the capital city, Montevideo. Therefore, after finishing high school, many students who aim to continue studying have no choice but to move to another city.[3] Second, this university is free of tuition and without entrance exams, ruling out other possible causes as discouraging elements of attending university. Third, the pandemic broke out after the 2020 enrollment, implying that enrollment decisions and course registration were already decided for 2020 cohort of students. By comparing students' academic outcomes in 2020 to previous years, I can measure the effect of the pandemic and the online learning shift (i) on academic outcomes. Fourth, in contrast to 2020, in 2021, new students could enroll and register for courses knowing that classes were going to be online. By comparing enrollment rates by geographical localities in 2021 to previous years, I can measure the effect (ii) on enrollment decisions.[4]

I use a rich dataset obtained from different administrative record sources from UDELAR, which contains information on first-year enrolled undergraduate students from 2017 to 2021. In particular, these administrative records have information on students' performance at university and their sociodemographic and socioeconomic characteristics. The empirical strategy follows a difference-in-differences strategy. First, I define the treated group as those students from localities far away from the university campus. For the treated group, COVID-19 and the subsequent switch to online learning implied the possibility of return to (or avoiding leaving) their hometowns and/or reducing commuting long distances. The fact of having this new possibility is what I call treatment. I compare treated and control freshman students' academic outcomes in 2020 versus their peers enrolled in previous years in which face-to-face classes prevailed. Second, I aggregate the number of freshmen students at the locality level and compute the enrollment rate by localities. I compare treated localities (those without a university campus) with control localities (those with a university campus) in 2021 and before.

Results show that due to the pandemic, there was a general increase in university

[3]In 2019, more than 25 % of new students moved to another city

[4]According to the National Institute of Statistics, geographical localities (or census localities) are defined in terms of clearly and precisely delimited territories made up of clusters of buildings, and therefore reflect the representation of landscape changes. A Census Locality corresponds to a set of census tracts characterized by a concentration of population and dwellings. I present a description of these localities in the Appendix B.1

dropout rates.[5] However, dropout was less pronounced for treated students, that is, for students who could move back to their towns or avoid commuting long distances due to the shift to online learning. I do not find differential effects of treatment in other academic outcomes. In addition, the effect was slightly more pronounced for girls. In terms of enrollment rates, I find an increase in the enrollment rate by locality in those localities without a university campus. The size of the effect implied an increase of 13% compared to the levels before 2021 for treated localities, suggesting that online learning could be a strategy to increase tertiary education enrollment. All results are robust to different specifications.

This paper relates to two strands of the literature. On the one hand, I contribute to the literature that analyses the role of distance in access to tertiary education. Several papers show the importance of distance in the decision to continue studying, career choices, and academic outcomes (Alm and Winters 2009; Spiess and Wrohlich 2010, among others). However, a challenge in this literature is associated with the cofounders of the student's decision. Frenette (2009) and Lapid (2016) contribute to this problem using the expansion of universities to get the causal effect of distance. In addition, this literature is more scarce in developing countries. An exception is a paper by Katzkowicz et al. (2021) that also exploits the expansion of the university campuses in Uruguay to measure the effects on enrollment. Overall, studies suggest that distance is a relevant factor in understanding students' academic decisions and outcomes. However, the role of online learning and its effect as a way of reducing distance is still an open question. With this study, I contribute to improving this gap.

On the other hand, several papers analyzed the effect of COVID-19 on different outcomes for developed economies finding: positive effects on dropout rates (Aucejo et al. (2020), Rodríguez-Planas (2022b)); delay in graduation ((Aucejo et al., 2020), Rodríguez-Planas (2022b)); improvements in GPA (Rodríguez-Planas (2022a), Bulman and Fairlie (2022)); or no effect on academic outcomes (Bonaccolto-Topfer and Castagnetti (2021)). In addition, some papers focused on understanding the effects of online learning, triggered by COVID-19, on academic outcomes finding negative effects on grades (Kofoed et al. (2021), Bird et al. (2022), De Paola et al. (2022), Altindag et al. (2021)). For developing economies, the results are more scarce, finding an increase in withdrawal from courses (Jaeger et al. (2021), Failache et al. (2022)), difficulties in access to technology (Hossain (2021), Jaeger et al. (2021)), and positive effects in grade Failache et al. (2022). I contribute to this literature first by analyzing the effects for a Latin American country, therefore, adding to the knowledge for countries outside the US, the main country analyzed. Second, I build on the literature by considering a particular group of students that could have benefitted more from the pandemic: students living far away from a university campus.

The rest of the paper is organized as follows. Section 2.2 describes the conceptual framework behind the analysis, and section 2.3 presents the most relevant related literature. The institutional setting is presented in Section 2.4, followed by the data description in Section 2.5. In Section 2.6, I develop the empiri-

[5] I define dropout by the fact of having enrolled in the university but not doing any academic activity after

cal strategy. Finally, Section 2.7 and Section 2.8 present the results and final remarks respectively.

2.2 Conceptual framework

The conceptual framework behind this analysis is based on the idea that distance is relevant in the choices of students. When students finish high school, they face two different decisions. First, they have to define whether to continue studying or not. Second, conditional on continuing studying, they have to choose where to enroll. In both decisions, the distance is likely to matter (Alm and Winters, 2009). When there is no tertiary institution near the student's hometown, attending higher education requires migrating or commuting, and this fact could discourage enrollment. In addition, once the decision to attend university is taken, if the student decides to move or commute long distances, this can have consequences on students' outcomes via a more constrained budget and/or a time-consuming activity. In addition, migration could affect students socioemotionally. There could be a positive side regarding more independence or discovering new things, but also a negative side related to a feeling of loneliness or difficulties in adapting to a new place.

Because distance can affect students' academic decisions and outcomes, online learning could affect differentially those students for whom distance is a potential binding restriction. First, online learning could affect the decision to continue studying due to cost reductions. That is, affecting university enrollment. Second, even if that decision had been to attend university, online learning could save time (from commuting and/or adapting to a new place), thus affecting academic outcomes. Therefore, online education could be an opportunity for improving educational outcomes, particularly for students living far away from a university campus.

It is worth mentioning that, besides the channels mentioned before, online learning could have additional effects on students outcomes for several reasons. As De Paola et al. (2022) point out, online learning has benefits and drawbacks compared to face-to-face lessons. On the benefits, when course recordings are available, students can attend classes when they prefer, avoiding too crowded classrooms. In addition, they can review lessons as many times as they want. Regarding the drawbacks, the lack of in-person peer interactions and interactions with professors could negatively affect students. Moreover, technology-related issues such as unreliable internet or difficulties in technological skills may undermine the learning process. Besides, the lack of routines and timetables might induce students to procrastinate, making study more difficult (De Paola et al., 2022). In my setting, both groups (treated and control) are being exposed to online learning. Therefore, if I assume that online learning affects students living closer or far away from the university similarly, the distance is the salient factor explaining the different results in my analysis.

2.3 Literature review

2.3.1 Student internal migration

As mentioned before, in many cases, the decision to study at the university goes together with the decision to migrate. The literature on student migration to attend tertiary education mainly focused on the US and involved mostly interstate migration, a small part of total migration. In addition, many of these papers focused on the role of financial aid and tuition in the migration process (Alm and Winters, 2009). The papers analyzing the role of distance in enrollment and tertiary educational outcomes are more scarce.

Alm and Winters (2009) study interstate college migration using a gravity model with data from Georgia, finding that the distance from a student's home to the university campus is a relevant variable in the decision. In particular, results show that the probability of attending any tertiary institution decreases with the distance to college elasticity being less pronounced in more prestigious institutions. Spiess and Wrohlich (2010) analyze the role of distance in demand for higher education using data from the German Socio-Economic Panel and university postal codes. They estimate a discrete choice model and find that, after controlling for socio-economic and regional characteristics, the distance to the nearest university affects the enrollment decisions of high-school students. The results suggest that the distance effect is driven mainly by transaction costs rather than by neighborhood effects. However, as Gibbons and Vignoles (2012) point out, one problem of this literature relates to the estimation of causal effects of home-university distances on the decision choice of students due to cofounders driving the results (such as spatial heterogeneity or residential sorting,). The authors try to overcome this issue by using a large administrative dataset for England that can account for many student characteristics and estimate reduced form logit specifications on individual student-level microdata. They find that the geographical distance to the university has little or no impact on the participation decision but is relevant to the institutional choice. Yet, as the authors stated, the distances to the nearest institutions are relatively small in England. In addition, incorporating student fixed effects and a broad set of characteristics could still have endogeneity issues.

To overcome the endogeneity issues, Frenette (2009) exploits the opening of universities in cities in Canada to provide causal evidence of the importance of distance for university and college participation rates. Results show an increase in local youth's university attendance and a reduction in college participation in most cities. Overall, the effect is an increase of 1.3 percentage points in postsecondary participation. These effects are particularly relevant for lower-income family students. Lapid (2016) also exploits the openings of universities to test the importance of distance as a binding constraint for four-year college enrollment. Using data from California, the author uses event study and difference-in-differences models and found a 1.5 percentage points increase in the four-year enrollment rate among recent high school graduates from local high schools. In addition, there is no effect on the share of local graduates who attend farther-away campuses, suggesting minor crowd-out effects compared to impacts on the extensive margin.

This literature is even more scarce for developing countries. Jardim (2020) analyze the impact of university opening on educational outcomes of students using an event study approach with two-way fixed effects. The author finds an average increase of 0.038 SD in test grades in municipalities where the university opened. More related to this work, Katzkowicz et al. (2021) analyze the effect of the expansion of UDELAR outside the county's capital on total enrollment and the share of first-generation university students using a difference-in-differences framework. They find that the decentralization process successfully increased the number of students from localities outside the capital and also increased the share of students with parents that do not hold a university degree.

Overall, the literature that analyses the role of distance in tertiary education suggests that distance is a relevant factor in understanding students' academic decisions and outcomes. However, this literature is still scarce, with most papers providing non-causal evidence. In addition, the role of online learning and its effect as a way of reducing distance is still an open question.

2.3.2 COVID-19 and tertiary education

The literature about the effects of COVID-19 is broad and addresses multiple dimensions such as labor markets, health, economic growth, inequality and education (Bacher-Hicks et al., 2021; Chetty et al., 2020, among others). Regarding education, many papers analyze the effects of the pandemic on elementary school, high school, and tertiary education. In this section, I focus on the work done on the impacts of COVID-19 on tertiary education outcomes.

Using a survey sample of 1500 students from a university in the US (Arizona State University), Aucejo et al. (2020) analyze the causal impact of the pandemic by using a questionnaire instrument that collects information about what different outcomes/expectations would have been observed in the absence of COVID-19. Results related to academic performance show that COVID-19 affected the delay in graduation by 13%, increased by 11% the students that withdrew from classes and 12% the students intending to change major. In addition, around 50% of the sample reported a decrease in study hours and academic performance. The authors also find a reduction in preferences for online instruction based on the recent experience of students. The effects are heterogeneous according to different characteristics. As an example, the results by socio-economic backgrounds show that low-income students are more likely to postpone the decision to graduate (55%), more affected in their major choice decision (41%), and COVID-19 implied an increase of nearly 100% of the expected Grade Poing Average (GPA) gap increasing inequalities among groups.

Rodríguez-Planas (2022a) uses administrative records from a college in New York (Queens College - City University of New York) to identify the effects of the COVID-19 pandemic on academic performance using a difference-in-differences and event study approach with individual fixed effects. The author analyses differences in the impact across lower- and higher-income students, finding that lower-income students outperformed their higher-income students. The result is driven mainly by the lower-income students in the bottom quartile of the Fall 2019 cumulative GPA, that obtain a 9% higher GPA than their higher-income peers. Suggestive evidence supports the idea that this result could be due to challenges with online learning faced by lower-income top-performing students. In addition, the differences in GPA are explained by a flexible grading policy adopted by the university. Besides, Rodríguez-Planas (2022b) uses the same dataset and additional information from an online survey collected in 2020 to estimate the causal impact of the pandemic on other academic outcomes. The author finds that the pandemic caused between 14% and 34% of the students to consider dropping a class, a reduction in freshman students' retention rate by 26%, and 30% of students modified their graduation plans, with two-fifths of them postponing graduation. Also using administrative data for the US but for students in the 116-college California Community College system, Bulman and Fairlie (2022) analyze the trend of enrollment, fields of study, and academic outcomes and how these were affected by the pandemic. They found a drop in students enrolled of 11% from 2019 to 2020 and 7% from 2020 to 2021. The reduction was most significant among African-American and Latin students. Regarding academic outcomes, conditional on enrollment, from spring 2019 to spring 2020, course completion fell from 73% to 71%, but course grades of "A" increased from 40% to 50% together with a decrease in grades "B" and "C".

Different results are found by Bonaccolto-Topfer and Castagnetti (2021) using administrative data for an Italian university (University of Pavia). The authors use a difference-in-differences design comparing students' outcomes during the summer term of 2020 to students in the same term but of the previous years and find no substantial effects of COVID-19 on teaching quality and academic performance measured by grades, graduation rates, and exam failure. The results are similar even considering heterogeneous groups according to family wealth, top-performance students or gender.

Because COVID-19 also implied a switch to online learning, some papers focus on understanding the effects of online learning on academic outcomes. Kofoed et al. (2021) analyze the results from a randomized control trial that took place in the fall 2020, where students were assigned either to online or in-person classes for an Introductory Economics course in a US Military Academy. The results show a decrease of 0.215 SD in students' final grades of the ones that took the online course. The authors conducted a survey to disentangle the mechanisms, finding that online students struggled to concentrate in class and felt less connected to their instructors and peers. Bird et al. (2022) use the shift to virtual classes and follow the difference-in-difference framework taking advantage of administrative records of a university in Virginia, US. They estimate a within-instructor-course variation, comparing students that started courses (during Spring) in person or online, and a student fixed effects equation. Both approaches lead to a modest negative effect of online learning, between 3% and 6%, on course completion, driven mainly by an increase in course withdrawals but also by the rise in course failure. Students with lower GPAs suffered more from online teaching. De Paola et al. (2022) also follow the difference-in-differences strategy to investigate the impact produced by the shift on the teaching modality in an Italian university (University of Calabria) using administrative records. The authors compare students' performance in the second semester versus the first semester of 2020 and contrast this with the same difference in previous academic years. Results show adverse effects of online teaching in credits courses per semester (0.11 standard deviations) and for an overall measure of students' performance that considers grades obtained. Results are worst for first-year students. Finally, Altindag et al. (2021) use administrative records from a US public university that already had many online courses before the pandemic and shifted all courses to virtual in the fall of 2020. They estimate a flexible equation that controls for the year and term together with student and instructor fixed effects. Results show that online teaching implied a worse performance in terms of grade, the propensity to withdraw from a course, and approval of the course for students. A relevant finding in their setting is that without the inclusion of instructor-specific factors, the relationship would lead to mistakenly concluding that online classes have better academic outcomes. Once including the fixed effect, face-to-face teaching shows better results for students.

All previous studies focused on developed economies. The literature about the effects of COVID-19 on tertiary education for developing economies is scarce. Hossain (2021) uses survey data from the Young Lives Study, collected in Ethiopia, India, Peru, and Vietnam, to describe differences in the effects of remote schooling according to sociodemographic characteristics. Not surprisingly, using logit regressions, the author finds that students from wealthier households, urban areas, and with internet access are more likely to access remote schooling. In addition, Jaeger et al. (2021) conducted a large worldwide survey to students in many countries, including Mexico, as the only developing economy. Considering respondents from all countries, in terms of educational outcomes, they found that 12% of the students withdrew from at least one course and 41% were not sure about returning to school in the fall of 2020. In addition, 83% of students manifested the lack of contact with faculty or students as a challenge. For Mexico, an additional relevant problem was the lack of a noiseless place to study or lack of access to the internet or computer. Directly related to this study are the results found in Failache et al. (2022) that analyze the effect of COVID-19 on university students in Uruguay using the same administrative records as this paper. The paper estimates the difference in academic outcomes in 2020 compared to previous years. University students in Uruguay dropout more in 2020 and took fewer courses than in previous years. Conversely, the mean grade was higher than in previous years.

My analysis contributes to this literature by understanding the differential effect that the pandemic could have had on a particular group of students: those living far away from the university. For these students, the pandemic and the consequential shift to online learning could be a solution to the distance as a limitation for attending the university.

2.4 Institutional Setting

2.4.1 Universidad de la Republica

University educational system in Uruguay is characterized by the concentration of students in Universidad de la Republica, the main public university in the country. UDELAR offers around 100 undergraduate degrees and more than 200 postgraduate degrees and hosts 86% of Uruguayan university students. One distinctive characteristic of UDELAR is that there are no tuition fees nor admission exams, making university education accesible for everyone.[6] [7] However, because the graduation rate in secondary school is low, the gross enrollment tertiary ratio is 65%.[8] In 2019, 140.000 undergraduate students were enrolled at UDELAR, from which close to 20.000 were new students.

The second distinctive characteristic of the Uruguayan tertiary system is its geographical concentration. Uruguay is organized into 19 geographical administrative units, called departments, of which Montevideo is the capital. Located in the south centre of the country, Montevideo is the smallest department in terms of extension but the most populated, with half of the population living there (close to 1.3 million people).[9] Most of UDELAR's supply degrees are offered only in Montevideo, and this is the case also for the majority of courses provided by private universities, vocational or teacher training programs.

Since 2007 a university territorial decentralization process has taken place by progressively expanding the supply of degree programs over the country. By 2017, when the last expansion occurred, seven out of nineteen departments had a university building in their capital city, with 8 degree programs offered on average per department (Figure 2.1). As an example of the effect of the decentralization policy in terms of distances, the expansion implied that for someone living in Artigas, the department furthest from Montevideo, before the decentralization, the university was 500 km away. After the expansion, Artigas has the closest university campus 130 km away, in Rivera.[10] Despite the decentralization process, the percentage of students enrolled in the campus in Montevideo is still the vast majority, around 85% in 2019, with 56% of students that lived outside the capital the previous year to enter university (Udelar, 2020). This implies that for a substantial number of students, commuting for long periods or migrating to the capital is a factor to take into account when deciding to go to the university.

[6]There are a limited number of bachelor degrees for which the access is defined by lottery given the limited number of slots

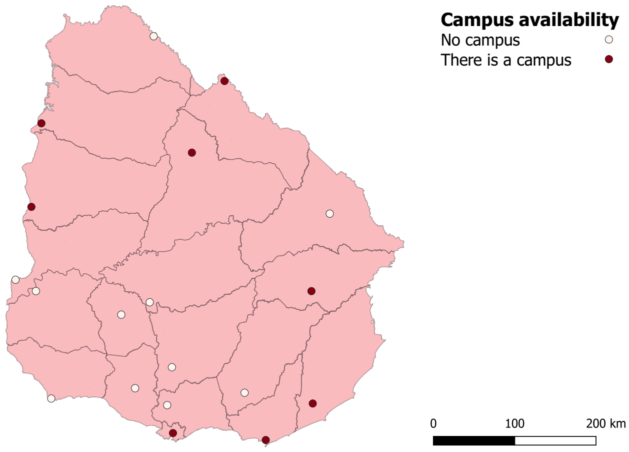
[7]Some postgraduate degrees have tuition fees but the majority are free of charge.

[8]Data obtained from the World Bank dataset (https://data.worldbank.org/indicator/SE.TER.ENRR)

[9]A map with density and total population per department is presented in the Appendix B.1

[10]The distance is calculated using the minimum distance from one point to the other. Therefore, I could be underestimating the commuting distance and time given that the roads in Uruguay were thought to connect different places with Montevideo, but less to connect other departments between each other

Figure 2.1: Presence of University by departments in 2017 onwards



Finally, it is worth mentioning that the general enrollment process of first-year students consists of attending the university in person during February, and the only requirement is to have finished high school. After enrollment, students register for those courses they would like to attend within the first year of their degree. Both annual and semestral courses coexist depending on the degree. The academic year starts in March and ends in December.

2.4.2 COVID-19 and institutional responses

The first COVID-19 patient detected in Uruguay was on the 13th of March of 2020, when courses at the university had just begun. By that date, the pandemic was already causing alarm around the world. Therefore, by mid-March, the university authorities decided to suspend courses for one month at the undergraduate and graduate levels. At the national level, the government did not impose a generalized lockdown in the country at any time, but one day after the university authorities' decisions, they decided to suspend the classes in all the educational system. In addition, teleworking was strongly suggested in private firms and mandatory in public offices.

In UDELAR the suspension of in-person classes continued, and by mid-April, courses started switching to virtual classes. The implementation of online teaching was defined at the course level and was not homogeneous between courses. However, to carry on the virtual learning process, the UDELAR used tools that it had previously developed and incorporated new ones. Specifically, 380 virtual teaching rooms were offered, with a capacity for up to 1000 students to be simultaneously connected and attending lessons. By May 2020, virtual tools were widespread and used in all university degrees. It is worth mentioning that over the last decades, a wide array of policies to foster the ICT sector was implemented in Uruguay to provide high-quality internet connection and guarantee digital inclusion in all the country. As a result, in 2021 86% of the population used the internet, a figure similar to European countries (87%) and close to the developed economies (90%).[11] In addition, for students' lack of access to technological devices, grants and equipment loans were provided in order to foster students' participation in the online courses.

Because COVID-19 broke out right after the start of the academic year, students' decisions about enrollment and registration for courses in the first semester were made before knowing that the classes were going to be online. In addition, the pandemic hit Uruguay more heavily in the second semester of the year; therefore, the virtual modality continued during that period. Moreover, by the end of 2020 and beginning of 2021, COVID-19 cases and deaths were at a peak, leading to the authorities' decision to continue with online courses also in 2021. In contrast with 2020, when enrollment was not affected by COVID-19 and online teaching, in 2021, new students could enroll and register for courses knowing that classes would be online at least for the first semester and with a hybrid modality for the second semester.

2.5 Data

2.5.1 Administrative records between 2017-2020

The data comes from different sources. On the one hand, I use administrative records from UDELAR for the period 2017 to 2020.[12] This information includes two different datasets of new enrollments. First, information from the registration form that students fill out when they enroll at the university at the beginning of the year. Completing the form is mandatory, and from there, I obtain students' socio-economic and sociodemographic characteristics, such as gender, age, the place where they studied high school, and if the institution was private or public. Second, a dataset with students' records of academic events, i.e., courses enrollment, courses approved, and grades. This information allows me to capture the academic trajectory of students over time. On the other hand, additional socio-economic characteristics such as parental education, students' parenthood, or the number of household members are obtained from a self-administered questionnaire collected yearly. Although completing this form is compulsory, due to the COVID-19 pandemic, the enforcement of this obligation was looser in 2020.

I combine the sources of information detailed before to obtain the final dataset of analysis. From the total population of new enrollments per year, I consider only freshmen in majors with more than 50 students enrolled per year. In addition, my main estimation is restricted to students below 30 years old (85% of the sample) and without any previous enrollment at university (65% of those). This decision is based on the fact that students that were previously enrolled at the university in another degree could potentially already be settled in the place where the campus is located. Because I am interested in analyzing decisions at the student level, if a student enrolled in more than one major, she is only considered in the degree in which she has more courses enrollment.

[11] The source of the figures is the International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database

[12] The information was provided by the General Planning Office from UDELAR, and was obtained from the Administrative Management System for Education.

I use these administrative records to obtain outcomes regarding academic performance. Firstly, I can observe whether students enrolled in the university but did not do any academic activity during the first year of university. I define the variable "No Activity" as a dummy that equals one if the student did not take any final or midterm evaluation during the academic year and zero otherwise. I conceptualized this variable as a measure of dropout. Secondly, I sum the number of courses for which the student took at least one evaluation test by the year, hereafter "Number of courses". As a third outcome, I sum the number of approved subjects during the year, "Number of approved subjects". Finally, I consider the "Mean Grade" as the average of all grades in the transcripts.

In Table 2.1, I present the main characteristics and the distribution of observations by year for the estimation sample. The first thing to notice is that in the analyzed period, the characteristics of students are stable across the years. 60% of students are women, and the mean age at enrollment is 19 years old. In addition, most university students come from public high school institutions. Considering only the administrative information from students, I have a sample of close to 14.000 students per year. The self-administered questionnaire shows that 80% of the students are white, the vast majority do not have kids when entering university, 20% of the students work, and for 20% of students, at least one of their parents has a university degree. The average household size is 3. The information from the self-questionnaire is useful, but for 2020 and for 2017, there are many missing observations (12% compared with 5% for 2018 and 2019). The non-response to this questionnaire could be associated with less commitment to the university, generating a bias in the sample when considering the self-questionnaire control variables. Because the variables from the questionnaire could be predictors of my outcomes, I estimate the main results in two ways, first, using only the administrative controls and then considering both administrative and self-questionnaire controls.[13]

[13]For the rest of the tables, I only present the results with administrative controls, but the results are similar when adding the self-questionnaire controls

Table 2.1: Descriptive statistics of control variables

	2017	2018	2019	2020	Total
Gender(1=Woman)	61.0	60.7	60.1	60.0	60.4
Age at enrollment (degree)	19.5	19.5	19.4	19.4	19.5
Private high-school	23.0	21.7	21.5	19.6	21.4
Public high-school	75.3	76.1	75.9	77.0	76.1
High-school abroad	1.6	2.2	2.6	3.4	2.5
N obs with admin controls	13,892	14,036	14,646	14,650	57,224
Ethincity(1=Non-white)	19.2	19.5	20.8	21.0	20.1
No kids	98.0	97.6	97.5	97.9	97.7
1 Child	1.6	1.9	1.9	1.7	1.8
More than 1 child	0.4	0.5	0.6	0.5	0.5
Work	19.6	20.9	19.5	18.2	19.5
Father or mother with univ.	22.1	21.4	22.0	21.2	21.7
Household size	3.4	3.0	3.0	3.0	3.1
W/o self administred quest.	12.3	5.1	5.6	11.6	8.6
N obs with full controls	11,974	13,088	13,422	12,733	51,217

Notes: The table shows the percentage of students according to the characteristics defined in the first column by year and total, except rows "N obs with admin controls" and "N obs with full controls", which are the number of observations by year and total.

2.5.2 Enrollment at the locality level for 2021

The data from administrative records give me information regarding the students that decided to enroll at university. However, to analyze the effect of online learning on the decision to attend university, I also need information on those who decided not to enroll. Because I miss this information, I do the analysis at a more aggregate level (locality) measuring changes in enrollment rates that could reflect changes in individual decisions. As mentioned before, localities are geographical units defined in terms of clearly and precisely delimited territories made up of clusters of buildings and therefore reflect the representation of landscape changes. They are characterized by a concentration of population and dwellings.[14]

To compute the enrollment rates, I combine two sources of information. First, the enrollment information comes from the registration form detailed above for the period 2017-2021. I aggregate enrollment by localities and obtain the number of new students enrolled in the university by locality and year. Second, I compute the total number of individuals between 17 and 29 by locality using the Uruguayan Census from 2011, the last one available. I merge both sources of information and compute the share of enrollment on population by locality and year.

2.5.3 Treatment variable: campus availability

As mentioned before, treatment is given by the fact that for the treated group, COVID-19 and the subsequent switch to online learning, implied the possibility of returning to (or avoiding leaving) their hometowns and/or reducing commuting long distances. Because I do not have information on where they lived in

[14] More information about localities is presented in Appendix B.1

the previous year, I define which students are in the treated or control groups based on where they did the last year of high school. To do this, I recover the high school's locality using the institution's name. Given that the average age of entrance is 19 years old (Table 2.1), the high school institution should be a good proxy for residence before university.

Based on the previous information, I compute three alternative definitions according to the distance to the campus (*Campus*). First, I consider as treated those students living outside a locality with a campus for their last year of high school (*Outsideloc.*). Second, I consider as treated those students living more than 20 Km from a campus (>20Km). Third, I consider as treated the students living more than 50 Km from a university (>50Km) and as controls the students living less than 20 Km from campus (I do not consider students living between 20 and 50 Km because it is not clear if they are treated or control students). Table 2.2 shows the distribution of the treated group over time and the total students considered in both the treatment and control groups. As the Table shows, close to 40% of students studied high school in a locality without a university campus, and of those students that did high school living less than 20 Km or more than 50 Km, only 29% are treated.

Table 2.2: Treatment variable - Student level

	2017	2018	2019	2020	Total
Outside loc.					
Treated	42	43	43	44	43
Total N	13,892	14,036	14,648	14,650	71,154
>20 Km					
Treated	37	38	38	38	38
Total N	13,892	14,036	14,648	14,650	71,154
>50 Km					
Treated	29	29	29	29	29
Total N	12,283	12,359	12,819	12,697	62,245

Notes: The Table shows the percentage of treated (Treated) students and the number of observations in the treated and control groups (Total N) according to different definitions of treatment by year and total. *Outsideloc.* defines treatment considering if students did their high school in a locality without a university campus (treated) and 0 otherwise (controls). >20Km considers as treated students that did high school more than 20 Km from campus and 0 otherwise. >50Km define as treated students those who did high school more than 50 Km from a university campus and controls the students who did high school less than 20 Km from campus.

To analyze enrollment in 2021, I construct the same variables at the locality level. For my main estimation, I used those localities for which at least one student registered at university in the period 2017-2020. Table 2.3 presents the distribution of treatment at the locality level. Because there are only eight localities with a university campus (the capitals of the eight departments with a university campus), the control group represents only 1% of total localities in the first approach. In addition, I also estimate the regression using all localities with at least 5,000 (the threshold for a place to be considered urban) or 2,000 inhabitants according to the 2011 Census.[15]

[15]In these specifications I ease the restriction of considering localities for which at least one student registered to university. This means that I also use as treatment group places where any student enrolled at the university never for the whole period of analysis.

Table 2.3: Treatment variable - Locality level

	2017	2018	2019	2020	Total
Outside loc.					
Treated	99	99	99	99	99
Total N	541	541	541	541	2,705
>20 Km					
Treated	87	87	87	87	87
Total N	541	541	541	541	2,705
>50 Km					
Treated	83	83	83	83	83
Total N	421	421	421	421	2,105

Notes: The Table shows the percentage of treated localities (Treated) and the number of observations in the treated and control groups (Total N) according to different definitions of treatment by year and total. *Outsideloc.* defines as treated localities those with a university campus. In the >20Km case, localities with a campus more than 20Km away are treated, and localities with a campus less than 20 Km are controls. >50Km define as treated those localities with a campus more than 50 Km away and controls the localities with a campus less than 20 Km away.

2.6 Empirical Strategy

To estimate the differential effect of the COVID-19 pandemic and the shift to online learning on students' academic outcomes among the treated and control group, I follow Rodríguez-Planas (2022a) framework and estimate the following difference-in-differences model:

$$y_{il} = \beta_0 + \beta_1 Year2020 + \beta_2(Year2020 * Campus_l) + \gamma_l + \beta_4 X_{il} + \epsilon_{il} \quad (2.1)$$

where y_{il} is the outcome of interest for student i in locality l[16]. $Year2020$ is a dummy equal to one for 2020 and 0 before that year. $Campus_l$ is an indicator variable with value one for the treated group, as mentioned before. γ_l represents the locality fixed effects, and X_{il} are the control variables from the registration form (gender, age at enrollment, and type of high school institution) and the self-administered questionnaire (ethnicity, categorical variable for number of kids, it the student has a job, if at least one of the student parents went to the university, and the household size) defined in Section 2.5. I cluster standard errors at the locality level.

The coefficient of interest, β_2, captures the differential post-pandemic effect on the outcome, y_{il}, for students that are from localities where there is no university campus relative to peers from localities where there is a campus. Because I include locality fixed effects to control for time-invariant observable and unobservable characteristics at that level, the campus indicator is omitted The

[16]My data is a pool of repeated cross-section for different years, therefore, I do not include the subindex t in the specification, as each student is observed only once

coefficient β_1 captures the changes in the outcome variables in 2020. Including the control variables allow me to control for observed characteristics of the students.

The empirical strategy of difference-in-differences relies on the identifying assumption of parallel trends across groups. To assess the validity of this assumption, I estimate the following equation using the event study framework to check for preexisting trends:

$$y_{il} = \mu_0 + \sum_{t=2017}^{2020} \mu_t Year_t + \sum_{t=2017}^{2020} \rho_t (Year_t * Campus_l) + \gamma_l + \mu_4 X_{il} + \epsilon_{il} \quad (2.2)$$

where $Year_t$ is a dummy that takes value one for the year when the outcome was observed and zero otherwise. The $Year_{2019}$ dummy is the reference category. The rest of the variables are defined as before. In the absence of preexisting differential pre-trends, the ρ_t estimated coefficients of years before 2020 should not be statistically different from zero.

To asses if there are differences in the enrollment rate in 2021 I follow a similar strategy, but at the locality level. First, I estimate the following equation:

$$ShEnrollment_{lt} = \theta_0 + \theta_1 Year2021 + \theta_2 (Year2021 * Campus_l) + \gamma_l + \epsilon_{lt} \quad (2.3)$$

where $ShEnrollment_{lt}$ is the outcome of interest, the share of students enrolled, in locality l and year t. $Year2021$ is a dummy equal to one if the outcome measure is for 2021 and zero before that year. $Campus_l$ is the treatment measure as defined in the previous section, and γ_l represents the locality fixed effects.

In this case, the coefficient of interest, θ_2, captures the differential post-pandemic effect on the outcome, $ShEnrollment_{lt}$, for treated localities relative to control localities. Once again, because I include locality fixed effects to control for time-invariant observable and unobservable characteristics at that level, the campus indicator is omitted.

In addition, I estimate the following equation using the event study framework to assess the validity of the parallel trend assumption:

$$ShEnrollment_{lt} = \sigma_0 + \sum_{t=2017}^{2021} \sigma_t Year_t + \sum_{t=2017}^{2021} \kappa_t (Year_t * Campus_l) + \gamma_l + \epsilon_{lt} \quad (2.4)$$

where $Year_t$ is a dummy that takes value one for the year when the outcome was observed and zero otherwise. The $Year2020$ dummy is the omitted category. The rest of the variables are defined as before. In the absence of preexisting differential trends, the estimated coefficients of the year previous to 2020 should not be statistically different from zero.

Finally, it is worth mentioning one limitation of this strategy. Because treatment turns on simultaneously with the pandemic, treatment and pandemic are not distinguishable in the regression. If the pandemic differentially affected students from localities with and without a university campus by another channel different from online learning, I am capturing both effects. However, the pandemic did not hit Uruguay in terms of infections until the end of 2020, and by the beginning of 2021, the situation was relatively similar across departments[17]. In addition, most of the decisions regarding public policy on the pandemic were taken at the country government level. With respect to the consequences of the economic shock, data constraints makes difficult to measure economic rates at the locality level. However, the distribution at the department level comparing 2020 with 2019 provided by CED (2022) is in line with the parallel trend assumption. Overall, it is plausible to believe that my results are mainly driven by the differential effects of the pandemic on tertiary educational outcomes derived from the online learning opportunity.

2.7 Results

In this section, I present the results of the analysis. First, I show the results of the effects on the academic outcomes for new first-year students up to 29 years old. I also present a heterogeneous effects analysis. Second, I follow the same order to show the results on the enrollment rates by localities.

2.7.1 Academic outcomes 2020

In Table 2.4 I present the main results regarding the effects of COVID-19 and online learning on the academic outcomes of freshmen under 30. In the first place, it is worth mentioning that the pandemic affected all first-year students. According to Panel a, there was an increase of 5.7 pp of enrolled students that did not do any activity, i.e., that dropout from university. Whereas this coefficient shows the effect of COVID-19 on the outcomes, the interaction term reflects the differences due to treatment. Then, the treatment softened the negative impact of the pandemic on the treated group by 1.5 pp compared to the control students. In other words, students from localities far away from the campus, that could potentially return home or commute less, had a lower dropout rate than students from localities where there was already a university campus. Regarding the academic outcomes, conditional on continuing studying, the pandemic had a positive effect on the number of approved subjects (one-third of a course more) and the mean grade (0.6 on a scale that goes from 0 to 12), but there was no differential effect according to treatment. The results hold when including sociodemographic controls obtained from the self-reported questionnaire.

[17] For the distribution of COVID-19 cases in Uruguay: https://guiad-covid.github.io/evolucionP7.html

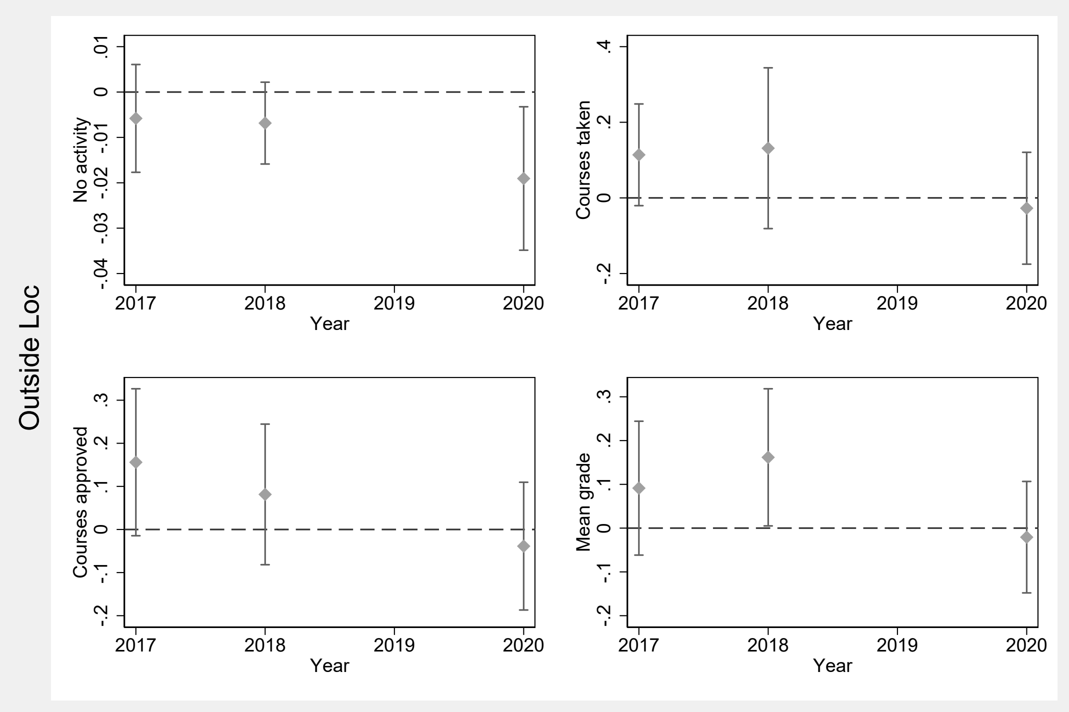
Table 2.4: Academic outcomes 2020

	No Activity (1)	Number of Courses (2)	Number of Approved subjects (3)	Mean Grade (4)
Panel a: New students up to 29 years old - Administrative controls				
Year2020	0.057***	-0.006	0.348***	0.608***
	(0.007)	(0.075)	(0.057)	(0.046)
	[0.000]	[0.941]	[0.000]	[0.000]
Year2020*Campus$_{\mathrm{L}}$	-0.015*	-0.108	-0.116	-0.103
	(0.008)	(0.084)	(0.071)	(0.067)
	[0.068]	[0.201]	[0.103]	[0.127]
N. Observations	55,342	50,746	50,746	44,153
Panel b: New students up to 29 years old - All controls				
Year2020	0.033***	0.079	0.513***	0.641***
	(0.006)	(0.073)	(0.054)	(0.049)
	[0.000]	[0.281]	[0.000]	[0.000]
Year2020*Campus$_{\mathrm{L}}$	-0.014*	-0.102	-0.076	-0.033
	(0.007)	(0.084)	(0.076)	(0.063)
	[0.053]	[0.223]	[0.320]	[0.595]
N. Observations	49,779	47,137	47,137	41,939

Notes: Reported estimates are obtained from an OLS regression, including locality fixed effects and student control variables. In Panel a, I only include the control variables from the administrative form: gender, age at enrollment, and type of high school institution. In Panel b, I also add the control variables from the self-administered questionnaire: ethnicity, categorical variable for the number of kids, if the student has a job, if at least one of the student's parents went to the university, and the household size. Standard errors reported in parentheses, clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing we use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (4) refer to the academic outcomes of students obtained from the administrative records as defined in Section 2.5.Year2020 is a dummy variable that equals 1 for students enrolled in 2020 and 0 otherwise. Year2020*Campus$_{\mathrm{L}}$ takes the value 1 for students enrolled in 2020 from the treated group defined as students that did high school in a locality without a university campus. The regression includes new students up to 29 years old.

As I mentioned in the empirical strategy, to show that the difference-in-differences strategy framework can be used in this setting, I present the results of the event study analysis. As figure 2.2 shows, there were no differences for previous years almost in any of the variables analyzed. Again, the only outcome affected by treatment was the decision of dropout.

Figure 2.2: Event study analysis for Academic outcomes 2020



Note: These figures plot the coefficients on the interaction between the year2020 and distance to campus treatment (and the 95% confidence intervals) from the regression of the model defined in equation 2.2. Students that did high school in a locality without a university campus are considered as treated students. Each figure represents the coefficients from the regression on the four different outcome variables considered in the analysis (No activity, Courses taken, Courses approved, and Mean grade). Standard errors clustered at the locality level using Liang-Zeger cluster robust standard errors.

As robustness checks, I also estimate the main equation but just considering degrees with more than 500 students and without degrees with restrictions for entrance or with changes in their curriculum in the period analyzed (Panel a and b of Table B1 respectively). In both cases, results are robust to these specifications.

Heterogeneous effects

First, I estimate the main equation using different distance variables as treatment (Table 2.5). The results when using as treated students those living more than 20 Km from a university campus are qualitatively similar to those from the main estimation. However, when considering as treated those students more than 50 Km from campus, the coefficient for the interaction doubled my main coefficient. This implies that for those students farthest away from campus, treatment softened dropout rates more pronouncedly.

Table 2.5: Academic outcomes 2020

	No Activity (1)	Number of Courses (2)	Number of Approved subjects (3)	Mean Grade (4)
Panel a: Treatment: >20Km				
Year2020	0.057***	-0.011	0.341***	0.596***
	(0.007)	(0.069)	(0.053)	(0.043)
	[0.000]	[0.874]	[0.000]	[0.000]
Year2020*Campus$_{\mathrm{L}}$	-0.016**	-0.111	-0.114	-0.085
	(0.008)	(0.083)	(0.071)	(0.069)
	[0.040]	[0.182]	[0.111]	[0.222]
N. Observations	55,342	50,746	50,746	44,153
Panel b: Treatment: >50Km				
Year2020	0.055***	-0.020	0.339***	0.596***
	(0.007)	(0.070)	(0.054)	(0.042)
	[0.000]	[0.776]	[0.000]	[0.000]
Year2020*Campus$_{\mathrm{L}}$	-0.027***	-0.124	-0.141*	-0.108
	(0.008)	(0.092)	(0.079)	(0.073)
	[0.001]	[0.183]	[0.075]	[0.144]
N. Observations	48,274	44,251	44,251	38,574

Notes: Reported estimates are obtained from an OLS regression, including locality fixed effects and student control variables (gender, age at enrollment, and type of high school institution). Standard errors reported in parentheses clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (4) refer to the academic outcomes of students obtained from the administrative records as defined in Section 2.5. Year2020 is a dummy variable that equals 1 for students enrolled in 2020 and 0 otherwise. Year2020*Campus$_{\mathrm{L}}$ takes the value 1 for students enrolled in 2020 from the treated group. In Panel a, the treated group consists of students that did high school more than 20 Km away from a university campus and the control group of other students. In Panel b, the treated group is composed of students living more than 50 Km away from a university campus, and the control group of students living less than 20 Km from a university campus. The regression includes new students up to 29 years old.

I also estimate the equation using different subsamples according to age and the previous institutional link with the university. Panel a from Table 2.6 shows the results for those new students up to 25 years old. The results are very similar to the results for the whole sample. On the opposite side, results differ when I consider the whole sample of first-year students enrolled in the university instead of only new students (as in my main estimation). First-year sample includes those students who enrolled in a career for the first time but could already have been enrolled in another career before. The results considering all students (Panel b and c) show that there is no differential effect of treatment in the dropout decisions, and I observe relatively slightly worst results for the other variables. This could be related to the fact that the treatment variable reflects the place where students did high school and not the previous residence. Including students previously enrolled at the university (as I do in Panel b and c) could mean that I am considering students already settled in a place with a university campus as treated.

Table 2.6: Academic outcomes 2020

	No Activity (1)	Number of Courses (2)	Number of Approved subjects (3)	Mean Grade (4)
Panel a: New students up to 25 years old				
Year2020	0.058***	-0.023	0.333***	0.582***
	(0.007)	(0.074)	(0.058)	(0.050)
	[0.000]	[0.754]	[0.000]	[0.000]
Year2020*Campus$_L$	-0.016*	-0.080	-0.094	-0.093
	(0.008)	(0.082)	(0.069)	(0.067)
	[0.054]	[0.329]	[0.175]	[0.171]
N. Observations	52,230	48,182	48,182	42,268
Panel b: All students up to 29 years old				
Year2020	0.051***	-0.480***	0.260***	0.873***
	(0.004)	(0.064)	(0.047)	(0.050)
	[0.000]	[0.000]	[0.000]	[0.000]
Year2020*Campus$_L$	-0.002	-0.150**	-0.146**	-0.161***
	(0.006)	(0.076)	(0.062)	(0.060)
	[0.769]	[0.049]	[0.020]	[0.008]
N. Observations	82,125	72,738	72,738	61,740
Panel c: All students up to 25 years old				
Year2020	0.053***	-0.462***	0.331***	0.919***
	(0.004)	(0.069)	(0.045)	(0.055)
	[0.000]	[0.000]	[0.000]	[0.000]
Year2020*Campus$_L$	-0.006	-0.113	-0.128**	-0.153**
	(0.007)	(0.077)	(0.060)	(0.062)
	[0.406]	[0.145]	[0.036]	[0.014]
N. Observations	73,437	66,055	66,055	56,876

Notes: Reported estimates are obtained from an OLS regression, including locality fixed effects and student control variables (gender, age at enrollment, and type of high school institution). Standard errors reported in parentheses clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (4) refer to the academic outcomes of students obtained from the administrative records as defined in Section 2.5. Year2020 is a dummy variable that equals 1 for students enrolled in 2020 and 0 otherwise. Year2020*Campus$_L$ takes the value 1 for students enrolled in 2020 from the treated group defined as students that did high school in a locality without a university campus. In Panel a, the regression only includes new students up to 25 years old. In Panel b, the regression includes all students up to 29 years old. In Panel c, the regression includes all students up to 25 years old.

Previous literature analyzing the effects of the pandemic shows that there could be differences according to gender and socioeconomic background of students. Therefore, I run the main equation separately for boys and girls to capture differences by gender. Table B2 shows that when considering those students living outside a locality with a campus, dropout results are qualitatively similar to the main estimation in terms of the coefficient magnitude but only significant for girls. However, when I consider being more than 20 Km away from campus as treatment the effect, the effect is similar for girls and becomes significant and more pronounced for boys (Table B3). The more pronounced positive effect for girls goes in line with some of the papers studying the impact of online learning during COVID-19 by gender (Aucejo et al. (2020); Kofoed et al. (2021). These papers find that girls prefer online learning more than boys. However, my results when the treatment variable considered being more than 20 Km away could suggest that distance may become online learning a solution for everyone.

To measure the socioeconomic background, I use the type of high school institution (private or public) where the student did secondary education. I observe that for both treatment variables, the differential effect of treatment in the decrease of dropout is driven mainly by students from public high schools (Table B4 and Table B5). This could suggest that students from less affluent socioeconomic backgrounds respond more to a reduction in costs associated with distance to a university campus. However, it is worth mentioning that enrollment in private high schools is particularly low in the treated group (6% of treated students).

2.7.2 Enrollment in 2021

As I mentioned, in 2021, both the enrollment and courses were online since the beginning of the year, and this decision was communicated and disseminated institutionally. The possibility of enrolling and attending classes virtually could have led to an increase in enrollment in places far away from campuses. In this section, I present the results of that analysis.

Table 2.7 shows the estimated results of equation 2.3, where I measure the differential effect of the pandemic and online learning on the share of enrollment of new students up to 29 years old by locality. Results show an increase of 0.4 pp in the share of enrollment in localities without a university campus. This effect represents an increase of 13% in the share of enrollment of the treated localities. When analyzing the results according to the distance to campus, I observe that the effect is stable for all treatment variables. Results suggest that online learning leads to an increase in university enrollment, thus building on the idea that distance matters in students' enrollment decisions.

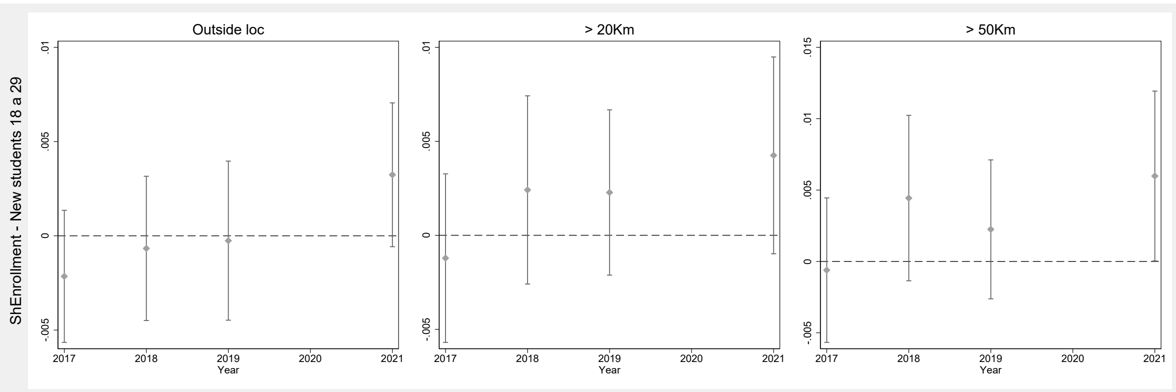
Table 2.7: Enrollment 2021 - New students up to 29 years old

	Share of enrollment		
	Outside loc	> 20Km	> 50Km
	(1)	(2)	(3)
	Outside loc	> 20Km	> 50Km
Year2021	-0.001	0.000	0.000
	(0.001)	(0.002)	(0.002)
	[0.107]	[0.930]	[0.930]
Year2021*Campus$_{\mathrm{L}}$	0.004**	0.003	0.004*
	(0.002)	(0.002)	(0.003)
	[0.012]	[0.154]	[0.092]
N. Observations	645	645	490

Notes: Reported estimates are obtained from an OLS regression, including locality fixed effects. Standard errors reported in parentheses clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome variable is the share of enrollment of students by locality defined as explained in Section 2.5. The share of enrollment is computed using all students up to 29 years old. Columns (1) to (3) differ in how the treatment groups are composed. In (1), the treated group consists of students that did high school in a locality without a university campus. In (2), the treated students are students that did high school more than 20 Km away from a university campus, and the control group by the other students. In (3), the treated group is composed of students living more than 50 Km away from a university campus, and the control group of students living less than 20 Km from a university campus. Year2021 is a dummy variable that equals 1 for localities in 2021 and 0 otherwise. Year2021*Campus$_{\mathrm{L}}$ takes the value of one for localities in 2021 from the treated group defined as explained before. The regression includes all localities for which at least one student enrolled in 2017-2021.

Figure 2.3 shows the event study analysis to provide evidence in favor of the parallel trends assumption.

Figure 2.3: Event study analysis for Enrollment 2021



Notes: These figures plot the coefficients on the interaction between the year2021 and distance to campus treatment (and the 95% confidence intervals) from the regression of the model defined in equation 2.4 where the outcome variable is the share of enrollment. Each figure considers a different definition of distance to campus. The first one considered as treated, localities where the university campus is outside the locality. The one in the middle considers as treated localities more than 20 Km away from a university campus. The third figure considers as treatment the localities more than 50Km away from a university campus and as control localities less than 20 Km away from a university campus. Standard errors clustered at the locality level using Liang-Zeger cluster robust standard errors.

Heterogeneous effects

As before, I analyze if there are differences according to age or previous link with the university. To do this, I compute the enrollment rates by localities considering enrollment of the different analyzed groups. Panel a of Table 2.8 shows that if I consider all students up to 29 years old and not only those without previous enrollment in the university, the effects are more pronounced and significant for all the treatment definitions. This could be capturing the fact that the switch to online courses widens the degree offer also for students with a previous linkage with UDELAR. On the other side, Panel b shows that the effect is similar for new students up to 25 than those up to 29.

Table 2.8: Enrollment 2021

	Campus distance		
	Outside loc	> 20Km	> 50Km
	(1)	(2)	(3)
Panel a: All students up to 29 years old			
	Outside loc	> 20Km	> 50Km
Year2021	0.002^{*}	0.003^{*}	0.003^{*}
	(0.001)	(0.002)	(0.002)
	[0.064]	[0.082]	[0.083]
Year2021*$\mathrm{Campus_L}$	0.005^{***}	0.005^{**}	0.006^{**}
	(0.002)	(0.002)	(0.003)
	[0.007]	[0.046]	[0.047]
N. Observations	645	645	490
Panel b: New students up to 25 years old			
	Outside loc	> 20Km	> 50Km
Year2021	-0.001^{*}	0.000	0.000
	(0.001)	(0.002)	(0.002)
	[0.082]	[0.839]	[0.839]
Year2021*$\mathrm{Campus_L}$	0.005^{**}	0.003	0.005
	(0.002)	(0.003)	(0.003)
	[0.021]	[0.260]	[0.146]
N. Observations	645	645	490

Notes: Reported estimates are obtained from an OLS regression, including locality fixed effects. Standard errors reported in parentheses clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome variable is the share of enrollment of students by locality defined as explained in Section 2.5. In Panel a, the share of enrollment is computed using all students up to 29 years old. In Panel b, the share of enrollment is computed using new students up to 25 years old. Columns (1) to (3) differ in how the treatment groups are composed. In (1), the treated group consists of students that did high school in a locality without a university campus. In (2), the treated students are students that did high school more than 20 Km away from a university campus, and the control group by the other students. In (3), the treated group is composed of students living more than 50 Km away from a university campus, and the control group of students living less than 20 Km from a university campus. Year2021 is a dummy variable that equals 1 for localities in 2021 and 0 otherwise. Year2021*$\mathrm{Campus_L}$ takes the value of one localities in 2021 from the treated group defined as explained before. The regression includes all localities for which there is at least one student enrolled in 2017-2021.

In addition, I estimate the main results considering all urban localities (Table B6) and localities of more than 2000 inhabitants (Table B7). In these specifications, and differently than in my main estimation, I also include localities without any students enrolled in the 2017-2021 period. This implies that in the treated group, I include localities with enrolment rates equal to zero for the whole period. When including these changes, the results remain stable when considering treatment as having a university campus in the locality. However, I do not observe any effect when accounting for distance in the treatment. This could suggest the relevance of knowing older university students when deciding to continue studying. In line with this idea, Pistolesi (2022) stress the importance of peer effects in the decision of enrollment to university, and Bobonis and Finan (2009) for secondary school enrollment.

2.8 Final Remarks

Using administrative data from a public university in Uruguay, I analyze the differential effect of COVID-19 and the consequent online learning shift on freshman academic outcomes students according to the distance from the university. This setting allows me to contribute to understanding the potential benefits of online learning in reducing the distance (or commuting time) to university.

I find that the pandemic increased dropouts, but students that now could avoid being far away from home had a lower dropout rate. This effect holds when using different measure of distances as the treatment variable. In addition, conditional on continuing the university, there is no systematic effect on other academic outcomes (such as the number of courses, approved subjects or mean grade). In addition, I analyze the effect on the decision to attend university. To do this, I aggregate the information at the locality level to compute enrollment rates by locality and year. I find that there was an increase in the enrollment rate in those localities without a university campus. Again, this stress the importance of distances in the decision of university enrollment and online learning as a potential solution.

These findings shed light on a possible answer to reducing geographical inequalities in access to tertiary education. This is particularly relevant for the developing world, where tertiary education rates are lower. However, it is worth mentioning that connectivity throughout the territory is needed to take advantage of online learning. Uruguay constitutes an interesting case to study because it is a developing country with tertiary enrollment rates that are still below developed economies but with a high internet connectivity figure. The economy of scale of providing access to tertiary education via online learning for those far away from a university campus is a feasible requirement. Therefore, digital inclusion efforts could also increase tertiary education enrollment rates. However, because literature also has shown adverse effects of online learning compared to live teaching (Figlio et al., 2013; Kofoed et al., 2021; De Paola et al., 2022; Bird et al., 2022) and Bettinger et al. (2017), placing online learning as a substitute for in-person classes could also have disadvantages. Overall, there is space to continue contributing to the design of policies to take advantage of new technologies and tackle their drawbacks in the educational system.

Chapter 3

Labor share and innovation in a developing country

3.1 Introduction[1]

The analysis of the functional distribution of income was a major question for classical economists. With the consolidation of the neoclassical theoretical framework and the Kaldor fact of constant labor share, the interest shifted from the functional to the personal income distribution. However, in the last decades, the analysis of factor share distribution gained attention again, mainly due to the observed decline in the labor share for developed countries (Karabarbounis and Neiman, 2012; Autor et al., 2017; Kehrig and Vincent, 2021;Grossman and Oberfield, 2021 among others). The analysis for developing countries also shows a decline in the labor share but with more dispersion across countries and time (Dao et al., 2017, Stockhammer, 2013, among others). As Atkinson (2009) argues, the analysis of the factor share distribution dynamics is relevant to better understand the dynamics of the personal distribution of income but also to tackling inequality.

Among several potential causes proposed to understand the labor share dynamics (such as globalization, market power, or changes in workforce composition), many researchers paid particular attention to the technological change explanations (Grossman and Oberfield, 2021). Some researchers focused on the decline in the relative price of capital and the consequent increase in capital use. Other researchers investigate the role of particular types of technical change, such as improvements in ICTs, or the development of new types of capital (e.g., robots) that may substitute labor (Grossman and Oberfield, 2021). In addition, according to Schumpeterian perspectives, innovation could generate a rent of innovation derived from the possibility of setting a markup over the marginal cost of products. If the firms' owners appropriate all the innovation rent, they

[1]I presented a similar version of this paper in the VI EQUALITAS Workshop, the 12th RGS Doctoral Conference in Economics, the Workshop on Latin American Theories from the Young Scholar Initiative and the 27th Meeting on Public Economics. I want to thank all the comments and suggestions in those instances. In addition, I want to thanks the Research Institute in Economics from UDELAR and the Tax Office in Uruguay for the provision of data.

will increase the profit and decline the labor share of the firm (Schumpeter, 1934).

In this chapter, I focus the analysis on the labor share for Uruguay, a developing Latin-American country. I describe the evolution of the labor share at the micro-level, and the relationship between innovation and the labor share. To do this, I combine survey data from an innovation and an economic activity survey and create a panel of firms for the period 2009-2015. I estimate a pooled OLS and a fixed effect regression. Besides, to account for possible bias due to unobservables, I follow the Oster approach for evaluating robustness to omitted variable bias (Oster, 2019). To account for the potential differential relationship according to the type of innovation, I disaggregate innovation into three different categories: intangibles, capital and training.

The results show in the first place that, as in other previous studies, the labor share at the micro-level performs differently than at the aggregate level. Regarding innovation, I find a negative correlation between innovation and the labor share when the innovation is in intangibles. The correlation is positive when firms innovate in activities related to training. In addition, related to other potential causes of labor share movements, I observe that firms with more concentration of sales in the industry have less labor share than firms with less market concentration.

This analysis relates to the literature that studies the labor share determinants, which I briefly present in the next section. Particularly, I am close to the strand of literature that poses technological change and innovation as a potential explanation. It is worth mentioning that most of this literature is rooted in firm-level behaviour but mostly analyzed empirically at a macro-level aggregation (Kehrig and Vincent, 2021). Therefore, using firm-level data allows me to contribute to the analysis by following a microeconomic approach, complementing the macro perspective on the topic. More importantly, the literature for developing, particularly Latin-American countries, is scarce. The specificities and differences these types of countries have with respect to developed economies make a differentiated analysis necessary. On one side, the movements of the labor share for these countries are more dispersed. On the other side, the reduction of inequality is a challenge for the majority of developing countries. Moreover, innovation is proposed in Latin-American countries as a particularly relevant factor for development (see, for example, Moreno-Brid et al., 2013) with public policies focusing on promoting innovation. Understanding the relationship between innovation and labor share is relevant to designing public policies aiming to achieve growth and equality by taking advantage of innovation.

The remainder of the chapter is structured as follows. Section 3.2 presents a brief summary of the literature on the topic, and section 3.3 synthesizes the conceptual framework. Section 3.4 and 3.5 present the data and empirical strategy. Section 3.6 shows the results, and Section 3.7 presents some final remarks.

3.2 Literature review

In this section, I present a brief review of the theoretical and empirical studies that analyze the labor share determinants. It is worth mentioning that, although these explanations are presented separately, disentangling one cause from the other is difficult, not only theoretically but mainly empirically, given that exogenous sources of variation are scarce in this literature.[2]

One branch of the literature relates the movements of the labor share with technological change and the production function. Karabarbounis and Neiman (2012), Neiman and Karabarbounis (2015) propose an explanation related to the fall in the price of investment goods relative to the price of consumption goods. Considering a CES production function, a decline in prices induce producers to shift from labor toward capital. Acemoglu and Restrepo (2018a) analyze the introduction of technology in a framework where technology automated tasks performed by labor but also creates new versions of existing tasks with comparative labor advantages. According to the model where the capital is fixed and technology exogenous, automation negatively affects labor share while the creation of new tasks has the opposite effects. In Acemoglu et al. (2020), the authors show that the adoption of robots coincides with declines in labor share in the French economy. Using Danish data, Humlum (2022) studies robot adoption by firms, finding that robot adopters increased their sales more than the increase in wage bills, decreasing the labor share. In addition, he finds that adopters reduced production workers but increased the employment of technical workers. Koh et al. (2020) incorporate the intellectual property products (IPP) to the analysis and argue that for the US, the shift to a more IPP capital-intensive economy is the cause of the decline of the labor share in that country, considering that capital and labor are more than Cobb-Douglas substitutes.

Other studies propose technological change as a reason for a reallocation of resources toward larger firms that concentrate more market. Autor et al. (2017) propose a superstar firm model that emphasizes the role of firm heterogeneity in the dynamics of the aggregate labor share. They suggest the concentration of sales in large firms with lower labor shares. Using data from developed countries, they present evidence that supports their model, finding that concentration can explain a proportion of the fall of the labor share. These firms have seen faster total factor productivity growth and a greater increase in patenting, suggesting that these firms benefited disproportionately from innovation. Lashkari et al. (2022) propose a model to analyze the role of ICTs prices on concentration and composition of shares and use French data for the calibration. In their model, when the elasticity of substitution between ICTs inputs and labor is less than one, there could be a positive effect of ICTs on returns to scale and labor share. But, according to the predictions, the fall in the price of ICTs also results in a reallocation toward firms with larger sizes and lower levels of labor share, canceling the positive effect.

[2] As an example, the development of modern communication technologies (associated with innovation and technological change) makes feasible the increase of international production networks. Therefore, the role of globalization and the role of technological change on the dynamics of the labor share is not easily differentiable (Dao et al., 2017).

Also related to imperfect competition, Barkai (2020) shows that the decrease in the labor share occurs jointly with an increase in profits. The author proposes competition as the main driver, developing a model where imperfect competition and an increase of markup among firms, make the labor share decrease jointly with an increase in profits. Regarding markups, De Loecker et al. (2020) show evidence in favor of an increasing trend of markups, driven mainly by the upper tail of the markup distribution. According to the authors, this result could explain the declining labor share. González and Trivín (2017) relates the fall of the labor share with the rise of corporate market valuations through a slowdown of corporate investment.

Globalization and international trade have been proposed as well as explanatory factors of the movements of the labor share. As Grossman and Oberfield (2021) summarize, the offshoring of activities and imports of labor-intensive consumer products could shift the composition of output from industries with higher to lower labor shares. In addition, the rising prices of traded raw materials could reduce the labor share if materials and labor are complements in production. Stockhammer (2013) also points out that financial integration that promotes fewer barriers to capital mobility could induce a lower bargaining position for labor and deepening of capital use, potentially inducing substitution of capital for labor. Empirically, Elsby et al. (2013) analyze the role of import exposure at an industry level and find that this factor explained an important part of the decline in the US payroll share over the past quarter-century. Jayadev (2007) analyses the role of capital account openness, finding a negative correlation between the labor share and the degree of openness, although this effect is not found for low-income countries. For developing economies, Sun (2020) considers the reduction in barriers to multinational production using a cross-section of industries and countries. He finds that larger firms and firms from more capital-abundant home countries use more capital-intensive technologies. Using a quantitative model of multinational production, the author shows that the liberalization of multilateral production contributes to the decline of the labor share. On the other hand, Leblebicioğlu and Weinberger (2021) analyze the particular case of Indian trade reform and find that in a cross-section framework, more openness to trade is correlated with a larger ratio of the labor share to the capital share. Doan and Wan (2017) focus on the impacts of trade openness and foreign direct investments (FDI) on the labor share, finding that trade is a significant determinant of labor share with exports decreasing the labor share and imports increasing it. Concerning the FDI, they find no impact of this variable in the labor share. Decreuse and Maarek (2015) find that FDI decreased the labor share for developing countries after controlling for trade and financial openness. Stockhammer (2013) finds that for developing countries, the relevant variable for explaining the change in the wage share was financialization, with globalization and welfare state retrenchment having more modest negative effects.

The majority of the papers regarding labor share analysis are at a macroeconomic level, mostly at the country and sector level. This allows a better understanding of the general equilibrium effects of labor share determinants. However, as Kehrig and Vincent (2021) point out, this literature is rooted in firm-level behavior. Therefore, understanding the labor share dynamics at the firm level is also relevant for the discussion. The authors use microeconomic data for the manufacturing plants in the US and find that the decline of the aggregate labor share occurs with an increase of the labor share at the median establishment level. Their explanation for reconciling both facts is related to the reallocation of production towards hyper-productive plants and a downward adjustment of the labor share of those firms over time. The decrease in the labor share of those hyper-productive plants is associated with an increase of value-added driven by an increase in prices over movements in employment or wages. A different picture is observed in Switzerland, where Siegenthaler and Stucki (2015) use firm-level data to understand the determinants of the constant labor share in that country. They find that the firm's share of workers using information and communication technology was the main factor decreasing the labor share. However, Switzerland's labor share remained almost constant due to a relatively slow rate of technological progress and sectoral reallocation toward industries with above-average labor shares. Miyoshi (2021) replicates Kehrig and Vincent (2021) and Autor et al. (2017) using Japanese data finding similar results as the US in terms of a slower decline rate of the median firm compared to the overall rate. In addition, as in the US, the firms with low labor share increased. However, in contrast to that country, the role of firms with an extremely low labor share is limited in Japan, and firms with a large value-added share are lowering their labor share.

The evidence for Latin-American countries is less abundant. The study by Abeles et al. (2014) presents a detailed description of the labor share movements finding a decline in the majority of countries. The case of Uruguay is particularly interesting since the labor share decreased in the end of the 90's and the beginning of the 2000's but increased after that period. In a report by De Rosa et al. (2017), they also analyze the labor share for a more extended period (1997-2014), finding similar results. They find differences in the labor share between industries and within industries. Industries with higher labor share are industries with higher levels of wages but also steeper salary structures. The increase of the labor share during the last decade was also associated with an increasing minimum wage regulation and the restoration of tripartite negotiation in 2005.

Overall, the literature on the topic points out that technological change can be a potential explanation for the movements of the labor share not only by the potential substitution of labor but also generating imperfect market competition. This explanation is complemented by other explanations related to trade, globalization, or the increase of firms' market power. As mentioned before, although the micro-level analysis has been increasing, most papers are at a sector o country level. In addition, the studies for developing economies, particularly for Latin-American economies, are less abundant.

3.3 Conceptual framework

As mentioned and presented in the literature review, the idea that innovation could affect the labor share and, therefore, inequality is not new. As an example, according to Schumpeterian perspectives, innovation can generate an extra rent that goes to the firms that innovate. If this extra rent, which increases the value-added by the firms, goes to profits at a higher rate than rising wages, then the labor share will decline. The duration of this advantageous situation for the firm depends on the ability of other firms to imitate the innovation.

Recent papers use the previous idea to point out that innovation could negatively affect the labor share or inequality. Guellec (2020) analyzes the importance of digital innovation on inequality using a Schumpeterian framework where digital innovation gives rise to "winner-take-all" market structures. This structure stimulates higher rates of creative destruction and higher risk for firms, with higher risk premia for investors. Rents from digital innovation affect income distribution because they are mainly shared among shareholders and investors or top executives and key employees of the winning firms. As a result, there is an increased dispersion in profits and capital share across firms.

Aghion et al. (2018) propose a model where innovation increases the capital and reduces the labor share due to the increase of markups related to the benefits of innovation. They develop a model where innovating allows the technological leader to charge a higher markup temporarily. Since markups are more significant in sectors with new technologies, aggregate income shifts from workers to entrepreneurs in relative terms whenever the equilibrium fraction of products with new technologies increases. Thus, the model derives that the share of wage income in total income decreases with the fraction of high markup sectors and, consequently, with the innovation intensities. They empirical evidence is nor related with the labor share, but suggests that innovation is temporary associated with top income inequality, rather than broad measures of inequality.

Kehrig and Vincent (2021) also propose technology as a potential driver of the labor share trend. In their conceptual framework, with a Cobb-Douglas production function, a positive technology shock can lower marginal costs and increase average labor productivity so that these changes cancel each other. According to their perspective, higher total factor productivity does not directly affect the unit's labor share, but it can increase the firm's market share. The effect is different if producers do not pass through all the cost savings. Under this scenario, technological change will move unit i's labor share and market share in opposite directions decreasing the former and increasing the latter.

Overall, the theoretical literature suggests that innovation could affect the labor share negatively. In this analysis I describe the relationship using survey data on innovation for a developing country. The analysis do not allow me to establish any causal relationship nor understand the mechanisms behind the potential effect. However, given the lack of studies for developing economies, and the challenges regarding inequalities for those countries, I consider that providing descriptive evidence on this topic is one step to better understanding the problem.

3.4 Data

To do the analysis, I use different sources of Uruguayan data. First, I use administrative records from the Tax office to describe the evolution of the aggregate and firm labor share. Then, I use survey data to better understand the relationship between innovation and the labor share. A caveat that should be mentioned is that both administrative records and survey data do not account for the country's informal economy.[3]

The administrative records were provided by the Tax Office in Uruguay and represent approximately 10.000 firms per year with turnovers of more than four million local Indexed Units during the period 2009-2017. These firms have to inform about their accounting to determine the amount of the Business Activities Tax they will have to pay. Therefore, the information comes from the firm balance sheet providing administrative records of sales, investment, production costs, and payment of salaries, among others. Based on this data, I compute the value-added and the labor share of the firm.

Regarding the survey data, I combine the Firm Innovation Survey, which provides information on innovation, and the Economic Activity Survey, from where I obtain the labor share information. The Firm Innovation Survey (FIS) is conducted by the National Institute of Statistics and the National Agency of Research and Innovation and collects firms' data for the manufacturing and various services sectors.[4] The goal of the survey is to collect information about the innovation activities of the firm. To do this, the survey follows the Bogota Manual. This manual combines definitions of the Oslo Manual with the particularities of Latin-American countries to measure innovation activities. The Bogota Manual (OEA/RICYT, 2001) proposes different innovation activities: R&D expenditure; acquisition of disembodied technology and know-how; acquisition of embodied technology; industrial engineering, industrial design, and production start-up, training; and marketing for technologically new or improved products. Besides, the survey asks for general information of the firm, such as the number of employees and the volume and destination of sales. The survey sampling frame is based on the sampling frame of the Economic Activity Survey (EAS). It is a stratified random design, with mandatory inclusion for prominent firms in terms of the number of employees or total sales. The FIS is collected every three years, but in the last editions, firms are asked about innovation information not only for the survey year but also for the previous ones. This question allows building panel data information for 2009-2015.

As mentioned, I combine the FIS with the Economic Activity Survey (EAS), an annual survey designed and implemented also by the NIS to collect information about the situation of firms in the Uruguayan economy. The survey gathers firms' characteristic information, property, number of workers, and gross production value, among others. The survey is available from 1998 to 2015.[5] Because the EAS is a cross-section survey with compulsory inclusion of big firms, I work with those firms of mandatory inclusion in order to create panel data at

[3]According to Amarante and Gómez (2016) the informality rate was 31.6% in 2009 and 23.5 in 2015. Caño-Guiral (2015) measures the non-observed economy in terms of value-added finding that in 2010 represented 16.1% in the Gross Domestic Product.

[4]The service sectors included were: Supply of electricity, gas, steam and hot water; Water Collection, Depuration and Distribution; Hotels and restaurants; Transportation by land and by pipeline; Water transportation; Transportation by Air; Transport, ancillary and complementary activities; Posts and Telecommunications; Rental of Machinery and Equipment, Personal Effects and Domestic Appliances; Computer and related activities; Research and development; Services Provided to Companies; Activities related to Human Health.

[5] In 2011, the application form was reduced, only collecting the main economic variables such as value-added, sales, and labor compensation.

the firm level. However, this implies that the findings are representative only of big firms in sectors included in the surveys during the whole period. Although my analysis is not representative of the entire sample frame of the surveys, these firms represent a considerable proportion of aggregate employment (30%) and value-added (50%) measured by the survey.

3.4.1 Measurement of Firm Labor Shares and innovation

The labor share is measured as the ratio of total labor cost to value-added. The value-added is computed as the difference between the earnings at producer prices minus intermediate inputs other than employee compensation, adjusted by inventory growth. The total labor cost (annual payroll), like in the national accounts, includes all forms of paid compensation (including non-wage expenses, such as employee contributions to pension plans and social security taxes). In my main estimation I winsorize the labor share at the 99th percentile to avoid outliers driving the results.[6] I ease these restrictions in the robustness checks.

The variables related to innovation are obtained from the FIS. The survey asks whether the firm did activities to obtain a product, process, organizational or marketing innovations and, if so, the amount of investment. Using this information, I define an indicator variable of innovation that takes the value of one if the firm did innovation activities and zero otherwise. In addition, I use the standardized variable of the amount of money invested in innovation activities. The same question is asked separately for eight types of innovation activities: internal R&D, external R&D, acquisition of capital goods, ICTs, technology transfer and consultancies, engineering and industrial design activities, organizational design and management activities, and training activities. I regrouped these different types of innovation into three categories. The innovation in intangibles accounts for innovation activities related to internal R&D, external R&D, ICTs, technology transfer and consultancies, and/or engineering and industrial design activities. Capital innovation measures innovation activities of acquiring capital goods. Finally, training activities innovations are related to training activities, organizational design, and innovation in management activities. As for the aggregate innovation measurement, I compute an indicator variable and the standardized variable of the amount of money invested for each of the three previous categories. I present the descriptive statistics of the innovation variables in Appendix C.1

3.5 Empirical Strategy

To analyze the relationship between innovation and labor share, I estimate the following regression at the firm level:

$$labsh_{it} = \beta_0 + \beta_1 * Innov_{it} + \beta_2 X_{it} + \lambda_t + \mu_l + \epsilon_{it} \tag{3.1}$$

[6] The ratio is usually between 0 and 1, but it could be more than one if the labor share is higher than the value-added or negative if the value-added is negative. In the cases where the value-added is negative, I impute the maximum positive value of the labor share to those observations

where the dependent variable is the labor share ($labsh_{it}$), measured as defined before, for a firm i at time t. The innovation variable ($Innov_{\text{it}}$) captures if the firm innovates or not according to the questions asked in the FIS. I use both an indicator variable that takes value one if the firm innovates and zero otherwise and the standarized variable of the money invested for innovation. In addition, I differentiate according to the type of innovation considering the three categories defined before (Innov $\text{intangibles}_{\text{it}}$, Innov $\text{capital}_{\text{it}}$ and Innov $\text{training}_{\text{it}}$).

As control variables (X_{it}), I include all variables that account for the other different explanations affecting the labor share presented in the literature review and that the survey allows to measure. These variables are the concentration of sales (sales of the firm over total sales of the industry), exports (exports over total sales of the firm), the percentage of foreign capital, and the number of employees. I also include indicator variables for the type of firm, classified as capitalist firms, cooperatives firms, foreign companies, and others.[7] In addition, I include an indicator variable for firms that have negative value added. Finally, I include year (λ_t) and sector fixed effects (μ_l).

First, I estimate the Pooled OLS regression. In the second place, to avoid bias due to time-invariant unobservable variables, I estimate a firm fixed effect estimation.[8] Due to the length of the period used, the firm's risk aversion and the fixed (organizational and locative) structure could be captured by this term. I clustered standard errors at the firm level.

However, the strategy could suffer from time-varying omitted variables bias (i.e., changes in the board of directors). To attenuate this limitation, I follow Oster (2019) strategy. Using this procedure, I estimate bounds for my main coefficients. To estimate these bounds, the author suggests assuming bounds for delta and R^2 parameters. The delta parameter indicates how much more the selection would have to be explained by unobservables for the true effect to be zero. Oster proposes a delta value equal to one as a reasonable upper bound. I define the lower bound as delta equal to minus one. The R^2 maximum that can be achieved in a regression is one. Therefore I use this value as the bound for maximum R^2. [9]

3.6 Results

Before analyzing the relationship between innovation and labor share results, I present descriptive statistics regarding the importance of understanding the micro-level analysis when studying the labor share.

Figure 3.1 shows the aggregate labor share and the mean labor share by year. The aggregate labor share results from the ratio of the total amount of payroll income (adding up firms' individual payroll for all firms) and the total amount of value-added (adding up firms' individual value-added for all firms). The mean

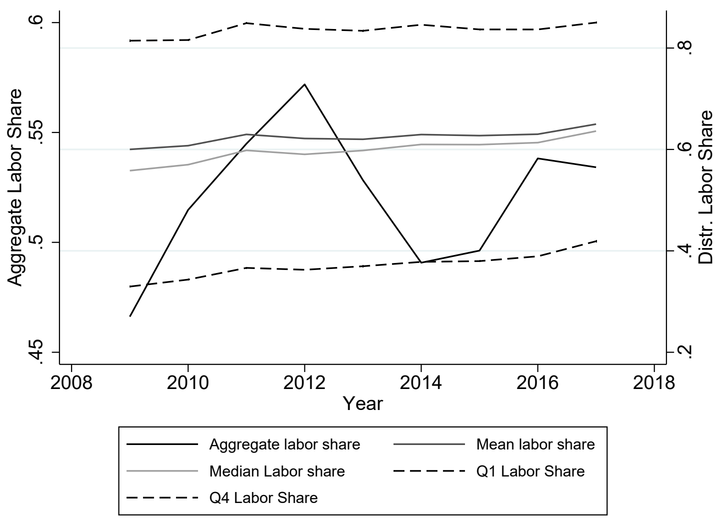
[7] I exclude public companies from the sample because their dynamics, objectives and regulations are very different from the other types of firms.

[8] The Hausman test was performed in order to discard the random effect model as the appropriate one.

[9] The maximum R^2 is the one that would result if all unobservables were to be included in the regression.

of the labor share is the mean of the firms' labor share. As can be seen, the comparison between the aggregate and the mean labor share shows dispersion of the labor share by firms. If all firms had identical labor share, both measures would have been the same. Besides, the trends of the variables are also slightly different. The micro-level results from this figure are relatively similar to Kehrig and Vincent (2021) results for the US; however, the aggregate labor share for Uruguay shows an unclear trend, while for the US, it is decreasing.

Figure 3.1: Aggregate and mean labor share

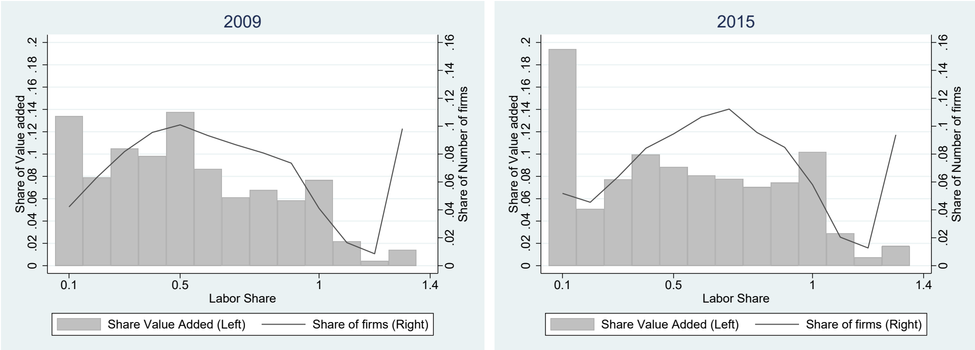


Source: Own calculation based on administrative records from the Tax Office in Uruguay.

In addition, Figure 3.2 presents the raw distribution of labor shares (solid black line) and value-added (grey bars) across firms for 2009 and 2015. I observe a slight polarization pattern of the share of value-added by labor share, with a more pronounced shift to the left. This means that there was a reallocation of value-added toward the low end of the labor share distribution: the share of value added of firms with labor share less than 0.1 was 0.13 if 2009 and increased to 0.19 if 2015. On the other side, the distribution of firms by labor share show a soft concentration in central values of labor share and the weight of firms with labor share more than 1 remains stable. In addition, comparing 2015 in Uruguay with 2012 in the US, the share of low-firm value added is slightly lower (19% in Uruguay and 22% in the US) and the distribution is less shifted to the left in Uruguay than in the US.[10]

[10] Again, I use Kehrig and Vincent (2021) information. His figures are from 1967 and 2012. Therefore I only compare the 2012 data. In addition, in his paper, he trims observations with negative value-added and outliers; instead, I winsorize them.

Figure 3.2: Distributions of Labor Shares and Value Added



Source: Own calculation based on administrative records from the Tax Office in Uruguay.

The dispersion of the labor share points out the importance of a micro-level analysis of the topic. As Adrjan (2018) notes, the technologically-efficient input allocation of profit-maximizing firms would be the same in a framework of competitive markets and free mobility of homogeneous input factors. Under this framework, the labor share will be equal across firms since each factor will be paid its marginal product, and the firm-level analysis will not be of particular interest. However, complementing Figure 3.1, Table 3.1 shows measures of between-firm and within-firm variation in the labor share. Using the random effect model: $x_{it} = \alpha + u_i + \epsilon_{it}$, between-firm variation is defined as the standard deviation of the error term u_i and within-firm variation as the standard deviation of ϵ_{it}, both normalized by their mean. The results from the random effect model, including year and sector fixed effects, show that both between and within variation contribute to the dispersion of the labor share, being almost half of the variance derived from differences across firms (47% in the labor share before taxes and 45% of the labour share after taxes)

Table 3.1: Labor share dispersion

	Between firms	Within firms	Within %
Labor share before taxes	0.64	0.68	0.47
Labor share after taxes	0.61	0.67	0.45

Notes: The table shows the dispersion for the labor share before and after taxes in levels. The between-firm variation (σ_μ) and the within-firm variation (σ_ϵ) are estimated standard deviations of the error terms from the random-effects model and adding year and two-digit sector fixed effects. The last column shows the proportion of variance due to differences across firms ($\rho = \sigma_\mu^2/(\sigma_\mu^2 + \sigma_\mu^2)$).

This descriptive analysis of the labor share provides evidence of the importance of a firm-level analysis to understand the dynamics of the labor share.

3.6.1 Labor share and innovation

In Table 3.2 I present the main results of the analysis. For all the columns, the outcome variable is the labor share of the firm. In the first and third columns I present the results of the OLS regression considering innovation as an indicator variable and as the standardized variable of the money invested, respectively. In the second and fourth columns, I do the same analysis but with the firm fixed effect regression. Panel a of Table 3.2 shows a negative relationship between innovation an labor share. Considering the OLS regression, I observe that innovation is associated with 6 pp less of the labor share. The coefficients are non-significant for the money invested variable and for the fixed effect regression.

Panel b shows the results for each of the three categories of innovation defined in Section 3.4. The results show that the association differs depending on which type of innovation the firms invest in. First, considering the OLS estimation, the results show that firms that innovate in intangibles have 9.5 pp less labor share than firms that do not innovate in intangibles. Similar results are observed for an increase of 1SD of the amount of money invested. If I consider innovation in capital goods, then the OLS results also suggest a negative relationship but with coefficients that are half of the previous ones. In addition, the results are non-significant for the amount of money invested. Finally, innovation in training activities shows a positive relationship with the labor share, being the coefficients of similar magnitude to the innovation in intangibles.

When analysing the results of Panel b with the fixed effect strategy, I observe that the negative relationship of innovation in intangibles remains both for the indicator and the amount of money invested. In addition, the magnitude of the coefficients is similar. The positive coefficient for innovation in training activities also remains for the fixed effect strategy. However, for innovation in capital goods, the coefficients are not significant. The Oster analysis shows that for all the significant coefficients, the bounds for beta exclude zero (Table C1).

Table 3.2: Innovation and labor share

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
Panel a: Aggregate variable				
Innov_{it}	-0.060***	-0.030	0.002	0.007
	(0.020)	(0.022)	(0.008)	(0.006)
	[0.003]	[0.180]	[0.811]	[0.254]
R^2	0.784	0.796	0.784	0.796
N. Observations	4,302	4,302	4,302	4,302
Panel b: Types of innovation				
$\text{Innov intangibles}_{\text{it}}$	-0.095***	-0.094***	-0.013**	-0.017***
	(0.024)	(0.025)	(0.006)	(0.006)
	[0.000]	[0.000]	[0.031]	[0.005]
$\text{Innov capital}_{\text{it}}$	-0.044*	0.004	-0.001	0.005
	(0.024)	(0.028)	(0.007)	(0.006)
	[0.074]	[0.890]	[0.876]	[0.353]
$\text{Innov training}_{\text{it}}$	0.074***	0.054**	0.015*	0.019**
	(0.025)	(0.026)	(0.008)	(0.008)
	[0.003]	[0.035]	[0.073]	[0.020]
R^2	0.785	0.797	0.784	0.797
N. Observations	4,302	4,302	4,302	4,302

Notes: Reported estimates are obtained from an OLS regression(Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In Panel a, I regress the labor share on innovation as an indicator variable with a value of one if the firm innovates in period t and zero otherwise. In Panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations I include as controls the variables defined in Section 3.4, year and two-digit sector fixed effects. Standard errors are reported in parentheses and clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added before taxes. The sample includes firms of mandatory inclusion for at least one year.

In addition, in Table C2, I present the coefficients from the same specifications as before, but for the control variables that aim to capture other possible variables affecting the labor share. As the table shows, concentration is negatively associated with the labor share. An increase in 10 pp of the ratio of sales of the firm over the total sales of the two-digit industry implies a reduction of 5 pp of the labor share. This negative coefficient also results from the fixed effect regression but is non-significant. This could be due to the fact that the concentration of sales by a firm may be a process that could take time to be consolidated.

Overall, these results align with the conceptual framework, and with papers that point out the importance of intangibles in the movements of the labor share. Although the way of measuring innovation is different across studies, the negative relationship between the labor share and the use of ICT in Switzerland (Siegenthaler and Stucki, 2015), the negative association with digital technologies in Guellec (2020) or the potential negative impact of technology automated tasks as in Acemoglu and Restrepo (2018b), could be associated with my measure of intangible innovation. The innovation in training activities could reflect the idea of complementarities and the creation of new existing tasks that positively relate to the labor share as in Acemoglu and Restrepo (2018b).

3.6.2 Robustness

To check the robustness of my results, I estimate different additional regressions. The sample of the main results includes firms of mandatory inclusion for at least one year. I check the validity of using other samples. First, I present the results when considering only firms of mandatory inclusion during the whole period (C3). Conversely, in Table C4, I present the results when I include all firms for which I have information in both surveys (without restricting the mandatory inclusion criteria). In both cases, results remain similar regarding the negative association of innovation in intangibles and the positive association with innovation in training. The results for innovation in capital goods are less stable.

Besides, I analyze the results by computing the labor share differently. My main estimation uses the labor share as the ratio of total labor cost to value-added before taxes. In Table C5, I present the results for the labor share computed by considering the value-added after taxes. In addition, I try different treatments of outliers. First, as Kehrig and Vincent (2021), I drop observations with negative value added and in the top 1 percentile of labor share (Table C6). Second, I winsorize the labor share to a value of 3 and impute that value when the value-added is negative (Table C7). Third, I do the same procedure as before but winzorizing to a value of 1 (Table C8). In all the specifications, the results remain qualitatively similar.

3.7 Final Remarks

As Atkinson (2009) argues, the analysis of the factor share distribution dynamics is relevant to better understand the dynamics of the personal distribution of income but also to tackling inequality. Because capital income tends to be concentrated in few and richer people while labor income is more evenly distributed, studying the dynamics of labor and capital share is relevant for understanding inequality (Schlenker and Schmid, 2015). Furthermore, empirical evidence suggests that the factor distribution of income is an essential determinant of the personal distribution of income (Daudey and García-Peñalosa, 2007, Checchi and García-Peñalosa, 2010). In this analysis, I present descriptive evidence of the movements of the labor share for Uruguay, a developing and Latin-American country, and about the relationship between the labor share and innovation.

To describe the labor share in Uruguay, I use administrative records from the Tax Office in Uruguay for the period 2009-2017. In addition, I combine two sources of survey data to create a panel of firms with information both about labor share and innovation activities. I estimate a pooled OLS and a firm FE regression and compute Oster bounds (Oster, 2019) to measure the bias on unobservables. The results show that the micro-level behavior of the labor share is more stable than the aggregate figure and that there is dispersion in the labor share by firms. In addition, by the end of the period, there was an increase in the value-added share by firms with low labor shares. Regarding the relationship between innovation and the labor share, I find a negative association between innovation and the labor share, mainly driven by innovation in intangibles. On the other side, innovation in training activities is positively associated with the labor share. These results are in line with other papers in the literature.

As mentioned, innovation at the firm level and policies with the objective to foster innovation are crucial for development and growth. In addition, inequality is a major issue for developing, particularly Latin-American, economies, and the labor share is one relevant determinant. My findings suggest the relevance of policy design that accounts for potential negative spillover of innovation to obtain economic development together without an increase in inequality. According to my results, innovation that reinforces the role of labor in the productive processes (as the training activities innovation) could be one of the paths to reconcile both objectives.

Some caveats are worth to be mentioned. First, I cannot claim any causal effects. Second, I am not considering the informal economy, which in developing countries is not disregardable. Third, I do not account for the aggregate macroeconomic effects. However, describing the relationship between the labor share and innovation, contributes to deepening knowledge on the topic. First, by providing evidence at the micro-level. In addition, and most importantly, by analyzing a non-developed economy. Future steps of this project involve merging survey data with administrative data to extend the number of observations and period of analysis and to obtain detailed balance-sheet information together with the innovation activities. This new dataset will allow for improving the current analysis. Given the lack of studies for developing economies and the challenges regarding inequalities for those countries, efforts on a better comprehension are essential.

Concluding remarks and future research

With this dissertation, I aim to contribute to understanding how new technologies affect our lives by analysing relevant dimensions for the discussion. In particular, I provide evidence on (i) the effects of high-speed internet on early childhood development, (ii) the effect of COVID-19 and the shift to online learning on academic outcomes and enrollment rates for students living far away from a university, and (iii) the relationship between innovation and the labor share from a micro-level firm perspective.

The first chapter combines an exogenous source of variation in the deployment of FTTH with child developmental tests representative of the urban population aged 0 to 5 in Uruguay. This allows us to estimate the causal effect of high-speed internet on child development delays in early childhood. Results show a deterioration in children's outcomes caused by an increase in high-speed internet accessibility. The test score decreased for communication, problem solving, personal-social and socio-emotional skills, and for the probability of developing within normal ranges for communication and socio-emotional skills. The heterogeneous effects and mechanisms analysis suggest the importance of the opportunity costs of screen exposure and the caregivers' behavior to explain the results. This study contributes to the academic literature and to the public discussion on the topic. To the best of our knowledge, this is the first study that analyses the effect of exposure to modern media during early childhood on cognitive and non-cognitive skills, using an exogenous source of variation. Further research is needed to identify the long-run effects of exposure in early childhood and to fully understand which exposure practices are more beneficial for the development of future generations of children.

In line with this research agenda, we continue investigating the topic in two ongoing projects. First, to account for the long-run effects of early childhood exposure to high-speed internet, we will follow a similar empirical strategy to analyze the impacts on administrative records for school attendance and transcripts. This will inform about the lasting effects of high-speed internet on child development. Second, to understand the role of parental practices in the use of technologies, we are conducting an information experiment on parental beliefs regarding screen exposure in early childhood. The project aims to analyze the effects of providing information to parents on the quality of screen exposure in early childhood. We randomly provide information on the regulation of media time and recommendations on best practices during exposure to parents of children between 0 and 5 years of age. Additionally, we will gather parental practices and beliefs regarding screen exposure through an online survey. This will allow us to identify the causal effect of an information policy on parental beliefs and decisions regarding early screen exposure. Finally, the FTTH deployment database that we constructed for this project is also suitable for analyzing the effect of high-speed internet on other outcomes. We are currently studying the effects of FTTH on youth mental health and well-being using this setting.

In the second chapter, I analyze the effects of COVID-19 and the induced shift to online learning to show that online learning could be a potential solution to reduce geographical inequalities in access to tertiary education. I do this by exploiting an advantageous institutional setting in Uruguay and following a difference-in-differences strategy. The main findings of that chapter show a positive effect on students from localities without university campuses in two dimensions. First, the dropout rate during 2020 was lower for treated students. Second, enrollment rates of localities without university campuses were higher after the shift. This suggests that online learning implied a reduction in the cost of attending university, changing the students' enrollment behaviour. This study contributes to the literature in different ways. First, to the literature that analyses the role of distance in academic outcomes and decisions of students. Second, to the literature on the COVID-19 effects on education. Third, by analyzing the case of a developing country. However, further research is needed on this topic. The literature also has shown adverse effects of online learning compared to live teaching, therefore, understanding the medium and long-term effects of online learning as a solution to distance is crucial. In this regard, my participation in a research project that will follow the students of my sample in the next years will allow me to account for the medium and long-run effects on academic outcomes[11].

The third chapter provides descriptive evidence about the functional distribution of income in Uruguay, particularly on the labor share, and the relationship with innovation. I use administrative records and survey data to estimate an Ordinary Least Square and firm fixed effects regression. The analysis of the labor share in Uruguay shows that, as in other studies for developed economies, the micro-level behavior of the labor share is different from the aggregate figure. The labor share is more stable at the firm level, but by the end of the period, there was an increase in the value-added share by firms with low labor shares. In addition, I find a negative association between innovation and the labor share, mainly driven by innovation in intangibles. Contrary to this, innovation in training activities is positively associated with the labor share. This paper contributes to the literature by analyzing the labor share dynamics for a Latin-American country. Because exogenous variations are difficult to find in this literature, improving and deepening the descriptive analysis is crucial. In addition, the particularities of developing economies, alongside their challenges regarding inequality and growth, turns the analysis for these countries essential. I contribute towards that path. In order to continue with this research, I aim to merge administrative records with the innovation survey for an extended period. This would improve the precision of the estimations and allow me to

[11]The analysis of trajectories of these students is a joint project together with Alina Machado and Nicolás Fiori from Universidad de la República

apply techniques that demand data for longer periods.

Altogether, this dissertation shows that technologies could have both benefits and risks and points out the importance of understanding how to use them to gain all their benefits and reduce their risks. I consider these results to be relevant for the academic literature and, in particular, for the public debate and informed decision making in policy design

Appendix A

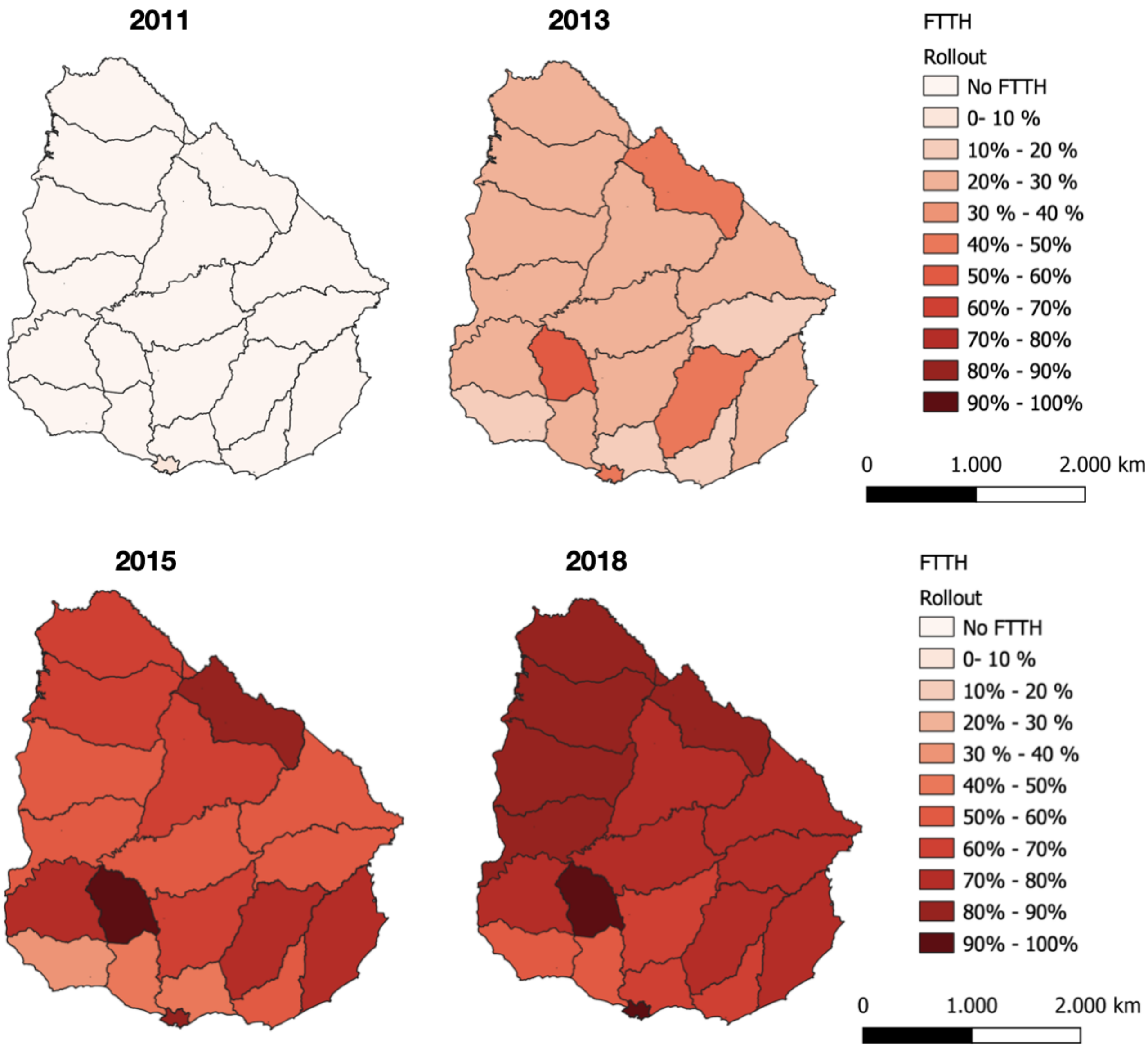
A.1 Data sources

Table A.1: Sources of information

Name	Description	Variables obtained
ANTEL administrative data	Data on the proportion of fixed telephone lines with FTTH connection by year and department for the period 2012-2018 and data on FTTH availability at block level for 2020	FTTH deployment at neighborhood and department level
Internet Archive on ANTEL's web page	Information on the geographic deployment of FTTH at block level for the period 2011-2012	FTTH deployment at neighborhood level
2011 Census	Country Census	FTTH deployment at neighborhood level and
Nutrition, Child Development and Health Survey (NCDHS)	Survey to study the situation of early childhood in Uruguay	Outcome variables, control variables, mechanisms
Continuous Household Survey (CHS)	Survey to study socioeconomic and sociodemographic characteristics of Uruguayan households	Control variables and mechanisms

A.2 FTTH Deployment

Figure A.1: FTTH Rollout by Department



Source: Own computations based on ANTEL data.

A.3 Neighbourhood imputation

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:

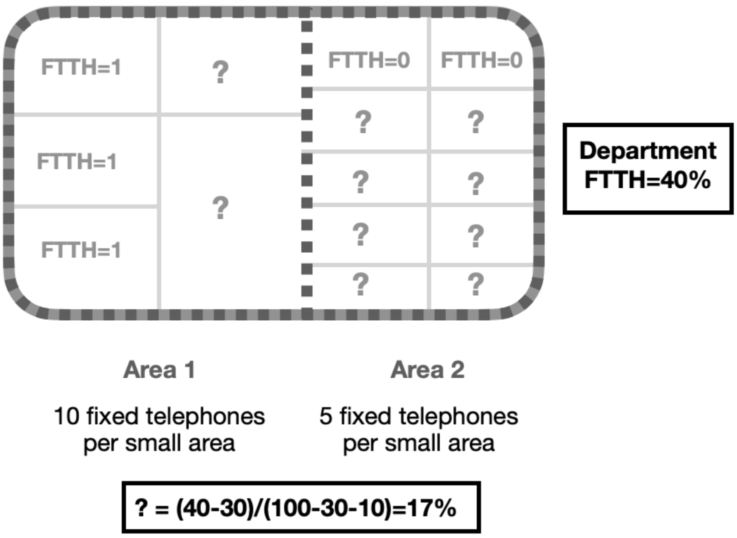
- $a_{d,y} \in A_1 : FTTH_{2012} = 1 \;\; \rightarrow \;\; FTTH_t = 1, t \in [2012, 2018]$
- $a_{d,y} \in A_2 : FTTH_{2020} = 0 \;\; \rightarrow \;\; FTTH_t = 0, t \in [2012, 2018]$
- $a_{d,y} \in A_3 : max(FTTH_t = 1), t \in [2012, 2018]$

Using the number of landlines phones by small geographical areas in 2011, $q\_tel_{d,2011}$, we impute an adjusted probability of FTTH for the areas without accurate information, those belonging to A_3, in the following way:

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

An example of this procedure is presented in figure A.2. Suppose that the information provided by ANTEL for a particular department and year is 40% (meaning that 40% of landlines had access to FTTH), and that this department contains 15 small geographical areas. For three of those areas, we know that for 2012-2018 they had FTTH with probability one, and for two of those, 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 A.2: Example - FTTH Neighbourhood level



A.4 Nutrition, Child Development and Health Survey (NCDHS)

A.4.1 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.

A.4.2 Descriptive Statistics

Table A.2: Basic Descriptive Statistics

Variables	2015		2018	
	Mean	SD	Mean	SD
Monthly Income per capita	528.52	546.87	486.24	620.43
Living in Montevideo	0.47	0.50	0.45	0.50
Gender of the child (males)	0.52	0.50	0.51	0.50
Age in months	49.52	13.93	29.62	17.29
Ethnicity	0.07	0.26	0.13	0.33
Maternal age	29	8	28	7
Insufficient prenatal care	0.16	0.37	0.15	0.36
Premature	0.11	0.31	0.08	0.27
Weight at birth (grs.)	3,295	559	3,289	562
Low birth weight	0.06	0.24	0.06	0.25
Exclusive breastfeeding	0.64	0.48	0.61	0.49
Cohabitation with parents	0.72	0.45	0.77	0.42
Preschool attendance	0.78	0.41	0.56	0.50
Caregiver's educational level	10.52	3.95	9.8	4.53
Nº of observations	2,611		2,598	

Source: Own calculations based on NCDHS 2015 and 2018 using survey weights. Notes: Household income per capita is expressed in April 2020 dollars. To compute it, all income sources available in the survey were used, including labor income from the first and second occupation, retirement, pensions and other personal and household income transfers. Ethnicity is a binary variable for ethnic origin other than white. Maternal age indicates the mother's age when the child was born. Insufficient prenatal care is a binary variable indicating either having the first doctor visit after the third month of pregnancy and/or having five or less visits. Premature is a binary variable indicating children born before week 37. Low birth weight is a binary variable identifying children 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. Cohabitation with parents is a binary variable indicating a child that lives with both parents.

A.4.3 Sample Questions for the ASQ-3 and ASQ-SE

ASQ-3 - 15 and 16 Months Questionnaire

1. Communication
   (a) Does your child point to, pat, or try to pick up pictures in a book?
   (b) Does your child say four or more words in addition to "Mama" and "Dada"?
   (c) When your child wants something, does she tell you by pointing to it?
   (d) When you ask your child to, does he go into another room to find a familiar toy or object? (You might ask, "Where is your ball?" or say, "Bring me your coat," or "Go get your blanket.")

   (e) Does your child imitate a two-word sentence? For example, when you say a two-word phrase, such as “Mama eat,” “Daddy play,” “Go home,” or “What’s this?” does your child say both words back to you? (Mark “yes” even if her words are difficult to understand.)
   (f) Does your child say eight or more words in addition to “Mama” and “Dada”?

2. Gross Motor
   (a) Does your child stand up in the middle of the floor by herself and take several steps forward?
   (b) Does your child climb onto furniture or other large objects, such as large climbing blocks?
   (c) Does your child bend over or squat to pick up an object from the floor and then stand up again without any support?
   (d) Does your child move around by walking, rather than crawling on her hands and knees?
   (e) Does your child walk well and seldom fall?
   (f) Does your child climb on an object such as a chair to reach something he wants (for example, to get a toy on a counter or to “help” you in the kitchen)?

3. Fine Motor
   (a) Does your child help turn the pages of a book? (You may lift a page for her to grasp.)
   (b) Does your child throw a small ball with a forward arm motion? (If he simply drops the ball, mark “not yet” for this item.)
   (c) Does your child stack a small block or toy on top of another one? (You could also use spools of thread, small boxes, or toys that are about 1 inch in size.)
   (d) Does your child stack three small blocks or toys on top of each other by herself?
   (e) Does your child make a mark on the paper with the tip of a crayon (or pencil or pen) when trying to draw?
   (f) Does your child turn the pages of a book by herself? (He may turn more than one page at a time.)

4. Problem Solving
   (a) After you scribble back and forth on paper with a crayon (or pencil or pen), does your child copy you by scribbling? (If she already scribbles on her own, mark “yes” for this item.)
   (b) Can your child drop a crumb or Cheerio into a small, clear bottle (such as a plastic soda-pop bottle or baby bottle)?

(c) Does your child drop several small toys, one after another, into a con- tainer like a bowl or box? (You may show him how to do it.)

(d) After you have shown your child how, does she try to get a small toy that is slightly out of reach by using a spoon, stick, or similar tool?

(e) Without your showing him how, does your child scribble back and forth when you give him a crayon (or pencil or pen)?

(f) After a crumb or Cheerio is dropped into a small, clear bottle, does your child turn the bottle upside down to dump it out? (You may show her how.)

5. Personal-Social

    (a) Does your child feed herself with a spoon, even though he may spill some food?

    (b) Does your child help undress herself by taking off clothes like socks, hat, shoes, or mittens?

    (c) Does your child play with a doll or stuffed animal by hugging it?

    (d) While looking at herself in the mirror, does your child offer a toy to her own image?

    (e) Does your child get your attention or try to show you something by pulling on your hand or clothes?

    (f) Does your child come to you when she needs help, such as with winding up a toy or unscrewing a lid from a jar?

ASQ-SE - 21 to 26 Months Questionnaire

1. Does your child look at you when you talk to him?
2. Does your child seem too friendly with strangers?
3. Does your child laugh or smile when you play with her?
4. Is your child's body relaxed?
5. When you leave, does your child stay upset and cry for more than an hour?
6. Does your child greet or say hello to familiar adults?
7. Does your child like to be hugged or cuddled?
8. When upset, can your child calm down within 15 minutes?
9. Does your child stiffen and arch her back when picked up?
10. Is your child interested in things around her, such as people, toys, and foods?
11. Does your child cry, scream, or have tantrums for long periods of time?
12. Do you and your child enjoy mealtimes together?

13. Does your child have eating problems? For example, does he stuff food, vomit, or eat things that are not food? (Please describe.)
14. Does your child sleep at least 10 hours in a 24-hour period?
15. When you point something, does your child look in the direction you are pointing?
16. Does your child have trouble falling asleep at naptime or at night?
17. Does your child get constipated or have diarrhea?
18. Does your child follow simple directions? For example, does she sit down when asked?
19. Does your child let you know how he is feeling with words or gestures? For example, does he let you know when he is hungry, hurt, or tired?
20. Does your child check to make sure you are near when exploring new places, such as a park or a friend's home?
21. Does your child do things over and over and get upset when you try to stop her? For example, does she rock, flap her hands, or spin? (Please describe.)
22. Does your child like to hear stories or sing songs?
23. Does your child hurt herself on purpose?
24. Does your child like to be around other children? For example, does she move close to or look at other children?
25. Does your child try to hurt other children, adults, or animals (for example, by kicking or biting)?
26. Does your child try to show you things by pointing at them and looking back at you?
27. Does your child play with objects by pretending? For example, does your child pretend to talk on the phone, feed a doll, or fly a toy airplane?
28. Does your child wake three or more times during the night?
29. Does your child respond to her name when you call him? For example, does he turn her head and look at you?
30. Is your child too worried or fearful? If "sometimes" or "often or always," please describe.
31. Has anyone shared concerns about your child's behaviors? If "sometimes" or "often or always," please explain.

A.4.4 NCHDS Questions on Secondary Outcomes

1. <u>Direct effect on the child</u>
   (a) Screen time of the child

- Wave 2018: During yesterday, how much time did [child's name] spend in front of a screen such as TV, computer, tablet, video games, cell phone?
  - Write down the number of hours and minutes.
- Wave 2015: How much time during the day is [child's name] in front of a screen such as TV, computer, tablet, cell phone video games?
  - Select one of the following categories: $<$ 1 hour, 1 to 2 hours, 3 to 4 hours, $>$ 4 hours.

(b) Quality of screen exposure of the child

- Wave 2015 & 2018: Leaving kids in front of the TV for a long period of time is a solution when mothers are busy.
  - Select one of the following categories: Yes, No.

2. Substitution effect of the child

(a) Tell stories to the child.

- Wave 2015: Do you or any other adult in the household usually tell stories you know or make up to [child's name]?
  - Select one of the following categories: Yes, No.
- Wave 2018: In the past 3 days, did anyone in the household, over the age of 15, tell stories to [child's name]?
  - Select one of the following categories: Yes, No.

(b) Sing Songs with Child.

- Wave 2015: Do you or any other adult in the household sing songs to [child's name]?
  - Select one of the following categories: Yes, No.
- Wave 2018: In the past 3 days, did anyone in the household, over the age of 15, participate sang songs or sang with [child's name], even a lullaby?
  - Select one of the following categories: Yes, No.

(c) Sing Songs with Child.

- Wave 2015: Approximately how many children's books are in your home? (include those that are borrowed)
  - Select one of the following categories: 0, 1 to 10, 11 to 20, 21 to 30, More than 30.
- Wave 2018: How many children's books or picture books do you have for [child's name]?
  - Select one of the following categories: 0, 1 to 9, 10 or more.

3. Effect through the Caregiver
   (a) Internet use of the caregiver
      - Wave 2015 & 2018: Did you use internet in the last month?
         - Select one of the following categories: Yes, No.
      - Wave 2015 & 2018: How often did you use internet?
         - Select one of the following categories: Daily, At least once a week but not daily, At least once a month but not weekly.
   (b) Child-rearing practices
      - Wave 2015 & 2018: These are phrases that are said about children. They have two possible answers: yes or no. If in any case it seems to you that the answer is neither yes nor no, choose the one that is closer to what you think.
         - The only thing that being with other kids is good for is to learn how to fight.
         - If a child does not yet speak, it is impossible to know what he/she wants.
         - If a child asks how babies are born, you have to tell him the truth.
         - Even if they are very young, being with other kids helps them grow better.
         - Many times kids' whims get on your nerves and you end up hitting and yelling at them.
         - The child who needs an adult to do something for him to fall asleep (read him a story, sing him a song, rock him, etc.) is spoiled.
         - Babies who touch everything are not spoiled, they are learning.
         - To teach them to eat on their own, you need to let them get dirty and play with the spoon.
         - Boys need to be educated so that they know how to be in charge at home.
         - Sometimes, in order for them to understand, even if they are little, there is no other choice but to hit them.
         - To love a child more is to let him do whatever he wants to do.
         - Boys have to be taught to take care of themselves and girls have to be taken care of.
         - For kids to eat they should be fed always at any time.
         - Kids learn to behave well when you talk to them and are patient with them.
         - If kids do not like the food you have cooked for them, you must force them to eat it.
         - Girls should be taught that a woman's place is in the home.
         - A good spanking once in a while is good for them.
         - For kids to stop having tantrums, you have to wait for them to calm down on their own without paying too much attention to them.

- It is better to talk to kids about how babies are born when they are already in school.
- To get kids to stop crying, let them cry until they get tired.
- Kids eat better when you are patient with them and give them something to play with and entertain themselves.
- In order for kids to learn to obey, they need to know what they can and cannot do.

A.5 Control Variables

Table A.3: 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 the gender of the child. 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. Source: NCDHS.
Child Control	Cohabitation with both parents	Both parents living with the child.	Indicator variable for a child living with both parents. Source: NCDHS.

A.6 Evidence for Conditional Exogeneity

To assess the conditional exogeneity of FTTH rollout, we applied a Principal Component Analysis (PCA) to summarize FTTH rollout in 2012-2018 at the department and neighborhood level. The main variables that explain the deployment at the department level are sanitation (percentage of households with flush to piped sewer system) and population density in urban localities, while at the neighborhood level the main variables are sanitation and income per capita. These two variables have an explanatory power of 92% and 61% at the department and neighborhood level, respectively. This percentage is computed by regressing the 1st component of the PCA on the two variables and estimating the R^2, weighting each geographic unit (departments or neighborhoods) by the proportion of fixed telephone lines before the treatment assignment. In addition, we regress the residuals of the previous regression against other relevant variables finding almost no correlation.

Figure A.3: Residuals Against Relevant Variables - Department level

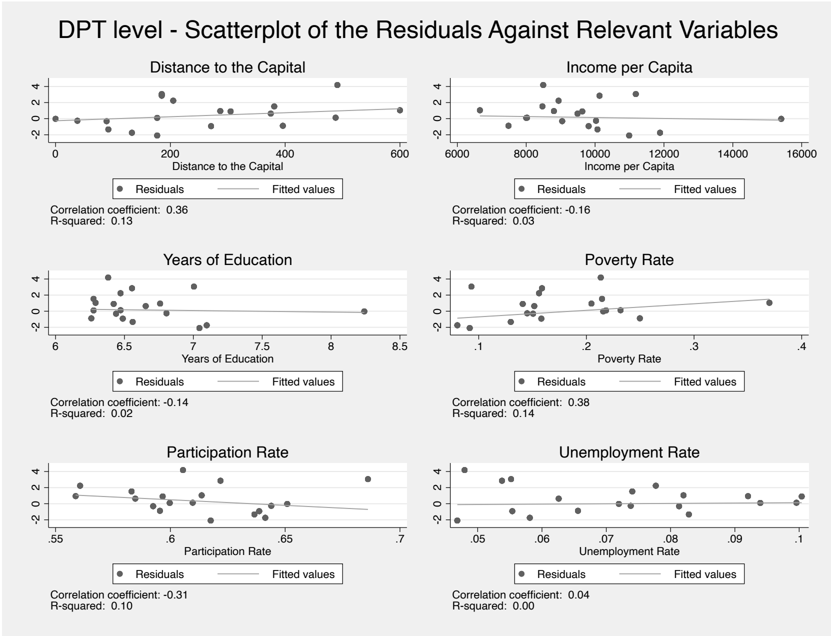
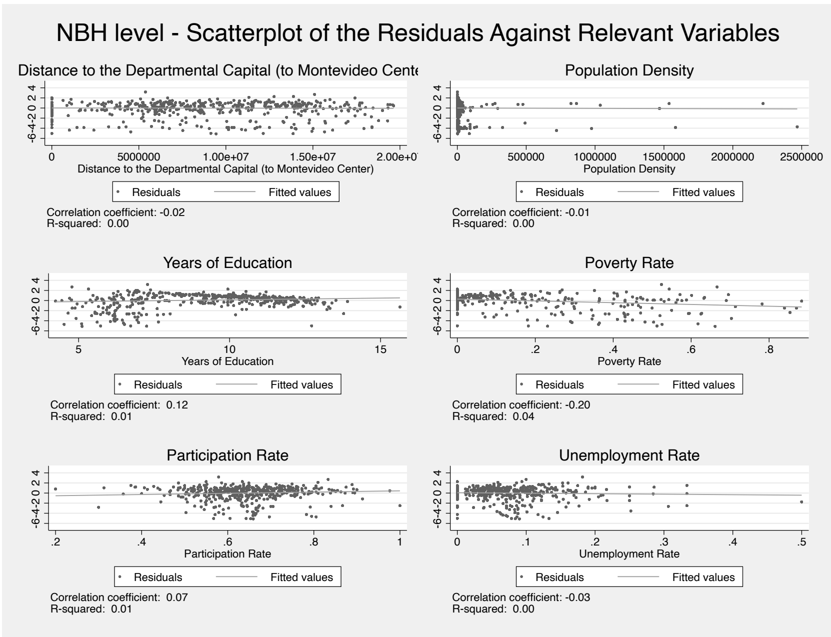


Figure A.4: Residuals Against Relevant Variables - Neighborhood level



A.7 Robustness Checks

Table A.4: Effects of FTTH Exposure Controlling for Age Differences

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
Panel a: Continuous Outcomes						
FTTH Exposure	-1.60***	-0.31	0.66	-1.07**	-0.69*	-0.86**
	(0.48)	(0.37)	(0.41)	(0.42)	(0.43)	(0.36)
P-value	0.00	0.41	0.11	0.01	0.11	0.02
P-value WCB	0.00	0.43	0.11	0.02	0.09	0.02
Lower bound WCB	-2.52	-1.02	-0.20	-1.87	-1.49	-1.53
Upper bound WCB	-0.65	0.41	1.47	-0.23	0.18	-0.17
N	5,035	5,035	4,027	5,034	5,033	4,909
Panel b: Categorical Outcomes						
FTTH Exposure	-0.36**	-0.08	0.03	-0.06	0.06	-0.36**
	(0.13)	(0.10)	(0.18)	(0.15)	(0.12)	(0.16)
P-value	0.01	0.45	0.89	0.71	0.58	0.02
P-value WCB	0.01	0.48	0.88	0.68	0.59	0.02
Lower bound WCB	-0.62	-0.29	-0.37	-0.35	-0.15	-0.65
Upper bound WCB	-0.09	0.11	0.40	0.24	0.30	-0.06
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, 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.5: Effects of FTTH Exposure W/O 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.6: Effects of FTTH Exposure W/O Sample Weights

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-1.44***	0.01	0.55	-1.15***	-0.80*	-0.63*
	(0.43)	(0.40)	(0.41)	(0.43)	(0.44)	(0.34)
P-value	0.00	0.99	0.18	0.01	0.08	0.07
P-value WCB	0.00	0.98	0.18	0.01	0.07	0.05
Lower bound WCB	-2.29	-0.81	-0.26	-1.96	-1.68	-1.26
Upper bound WCB	-0.58	0.81	1.36	-0.28	0.06	0.01
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 A.7: Effects of FTTH Exposure for 2013-2015-2018

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-0.66*	-0.15	0.30	-0.72*	-0.55*	-0.32
	(0.38)	(0.23)	(0.33)	(0.34)	(0.30)	(0.27)
P-value	0.08	0.52	0.36	0.04	0.07	0.24
P-value WCB	0.10	0.54	0.39	0.07	0.06	0.24
Lower bound WCB	-1.45	-0.61	-0.35	-1.39	-1.10	-0.80
Upper bound WCB	0.09	0.30	1.10	0.08	0.03	0.24
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 A.8: Effects of FTTH Exposure using the Balanced Panel

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
FTTH Exposure	-2.02***	-0.52	0.22	-1.36***	-0.94**	-1.02**
	(0.49)	(0.39)	(0.41)	(0.43)	(0.44)	(0.39)
P-value	0.00	0.19	0.60	0.00	0.04	0.01
P-value WCB	0.00	0.21	0.63	0.00	0.05	0.02
Lower bound WCB	-3.03	-1.32	-0.66	-2.27	-1.80	-1.78
Upper bound WCB	-1.02	0.26	1.04	-0.47	-0.02	-0.26
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 A.9: Effects of FTTH Exposure W/0 Always and Never Treated Neighbourhoods

	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	-3.88	-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 without FTTH accessibility in 2018.

Table A.10: Effects of FTTH Exposure W/0 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	-0.74
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.

Table A.11: Effects of FTTH Exposure W/0 One-Year-Old Children

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	ASQ-SE
FTTH Exposure	-1.77***	-0.47	0.39	-1.48***	-0.91**	-0.83**
	(0.50)	(0.39)	(0.43)	(0.44)	(0.44)	(0.34)
P-value	0.00	0.23	0.37	0.00	0.04	0.02
P-value WCB	0.00	0.25	0.37	0.00	0.04	0.01
Lower bound WCB	-2.78	-1.23	-0.53	-2.35	-1.74	-1.46
Upper bound WCB	-0.80	0.27	1.23	-0.58	-0.05	-0.19
N	4,454	4,454	3,446	4,453	4,452	4,449

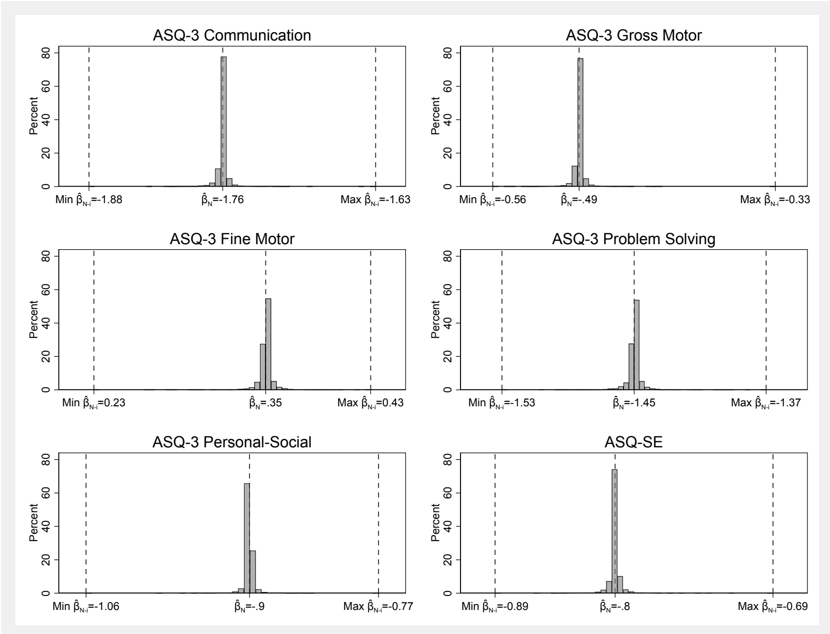
Notes: Reported estimates are obtained from an OLS regression including neighborhood/age and survey year fixed effects, linear trends in sanitation and income per capita by neighborhood, and child controls (gender and caregiver's educational level for the ASQ-3 tests, and ethnicity, maternal age at birth, 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 A.12: DFBETA Analysis

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
$\|DFBETA_i\| > 1$	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$\|DFBETA_i\| > 2/\sqrt{N}$	0.03%	0.03%	0.03%	0.03%	0.03%	0.04%

Notes: The table shows the percentage of observations with a dfbeta greater than 1 or 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 analogus coefficient when the ith observation is excluded, scaled by the estimated standard error.

Figure A.5: 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.13: 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	-5.53	-3.11	-4.38
Upper bound WCB	.	.	.	.	.	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.14: 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	-1.80***	-0.46	0.41	-1.34**	-0.87*	-0.82**
	(0.54)	(0.44)	(0.46)	(0.49)	(0.44)	(0.35)
P-value	0.00	0.29	0.37	0.01	0.05	0.02
P-value WCB	0.00	0.33	0.38	0.02	0.05	0.02
Lower bound WCB	-2.96	-1.38	-0.55	-2.31	-1.72	-1.48
Upper bound WCB	-0.70	0.40	1.31	-0.30	0.01	-0.15
N	5,035	5,035	4,027	5,034	5,033	4,909
FTTH Exposure Opt. 2						
FTTH Exposure	-1.76***	-0.49	0.35	-1.45***	-0.90**	-0.80**
	(0.49)	(0.39)	(0.44)	(0.46)	(0.44)	(0.34)
P-value	0.00	0.21	0.42	0.00	0.04	0.02
P-value WCB	0.00	0.22	0.43	0.00	0.04	0.02
Lower bound WCB	-2.76	-1.24	-0.58	-2.35	-1.73	-1.43
Upper bound WCB	-0.79	0.25	1.22	-0.52	-0.04	-0.17
N	5,035	5,035	4,027	5,034	5,033	4,909
FTTH Exposure Opt. 3						
FTTH Exposure	-1.80***	-0.46	0.41	-1.34**	-0.87*	-0.82**
	(0.54)	(0.44)	(0.46)	(0.49)	(0.44)	(0.35)
P-value	0.00	0.29	0.37	0.01	0.05	0.02
P-value WCB	0.00	0.33	0.38	0.02	0.05	0.02
Lower bound WCB	-2.96	-1.38	-0.55	-2.31	-1.72	-1.48
Upper bound WCB	-0.70	0.40	1.31	-0.30	0.01	-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, 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. For FTTH exposure Opt 2, we use the distribution of fixed telephones from the Census 2011 and applied it to the total number of landlines provided by the administrative data for the imputation. For FTTH exposure Opt. 3, we use both Opt. 1 and Opt. 2.

Table A.15: Effects of Binary FTTH Exposure

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
Binary FTTH Exposure	-0.70***	-0.21	0.20	-0.47	0.02	-0.54*
	(0.25)	(0.28)	(0.26)	(0.28)	(0.25)	(0.26)
P-value	0.01	0.46	0.45	0.10	0.93	0.04
P-value WCB	0.01	0.47	0.50	0.10	0.90	0.06
Lower bound WCB	-1.42	-0.90	-0.23	-1.16	-0.51	-1.09
Upper bound WCB	-0.21	0.46	0.90	0.12	0.59	0.03
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.16: 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	0.46	0.64	0.08	0.93	0.03
N	3,486	3,486	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	3,363	3,363	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

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. 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, and 3 we also exclude children in groups with negative weights according to (de Chaisemartin and D'Haultfœuille, 2020) procedure.

Table A.17: Heterogeneous Effects of FTTH Exposure on Categorical Outcomes

	Comm.	Gross Motor	Fine Motor	Problem Solving	Personal Social	Socio Emotional
Panel a: Gender						
Girls	-0.39***	-0.14	-0.08	-0.23	0.01	-0.31**
Boys	-0.40***	-0.12	-0.03	-0.11	0.01	-0.26*
P-value girls-boys	0.87	0.46	0.33	0.01	0.96	0.39
N	5,035	5,035	4,027	5,034	5,033	4,904
Panel b: Caregiver's educational level						
Primary	-0.34**	-0.16	0.02	-0.05	-0.05	-0.26
Lower secondary	-0.29**	-0.06	0.02	-0.11	0.07	-0.21
Upper secondary	-0.42***	-0.12	-0.07	-0.17	0.01	-0.33**
Tertiary	-0.45***	-0.15	-0.12	-0.25*	0.03	-0.28**
P-value primary-lower sec.	0.46	0.10	0.98	0.44	0.11	0.53
P-value primary-upper sec.	0.18	0.45	0.28	0.12	0.41	0.44
P-value primary-tertiary sec.	0.05	0.90	0.11	0.00	0.27	0.84
N	5,005	5,005	3,998	5,004	5,003	4,874
Panel c: Region of residence						
Capital	-0.52**	-0.23*	-0.10	-0.44**	-0.15	-0.20
Rest of the country	-0.39***	-0.13	-0.06	-0.18	0.01	-0.29**
P-value capital-rest	0.30	0.16	0.79	0.11	0.09	0.58
N	5,035	5,035	4,027	5,034	5,033	4,904

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 wegiths 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. 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. 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.

Table A.18: Reference Values - Mechanisms

	Screen Time $\geq$ 1hr	TV as a solution	Activities with parents	Number of books	Daily use Adults	Weekly use Adults	Risk in p.p.
2015	0.25	0.39	1.67	1.4	0.17	0.53	4.44
2018	0.43	0.36	1.50	1.29	0.06	0.86	3.94
N	5,037	4,941	5,036	5,036	11,111	11,111	4,941

Notes: Mean for 2015 and 2018 using sample weights

Appendix B

B.1 Geographic details of Uruguay

B.1.1 Information at the department level

Uruguay's surface is 176.215 Km^2, and it has different geographical divisions. The more aggregate geographical divisions are departments, of which there are 19. Figure B.1 shows the division of Uruguay according to the departments and the total population per department. Figure B.3 shows the density by department.

Figure B.1: Total population by department

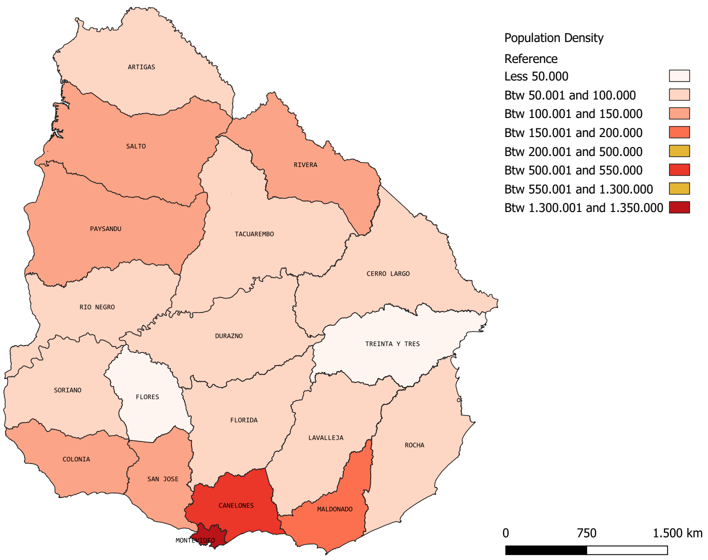
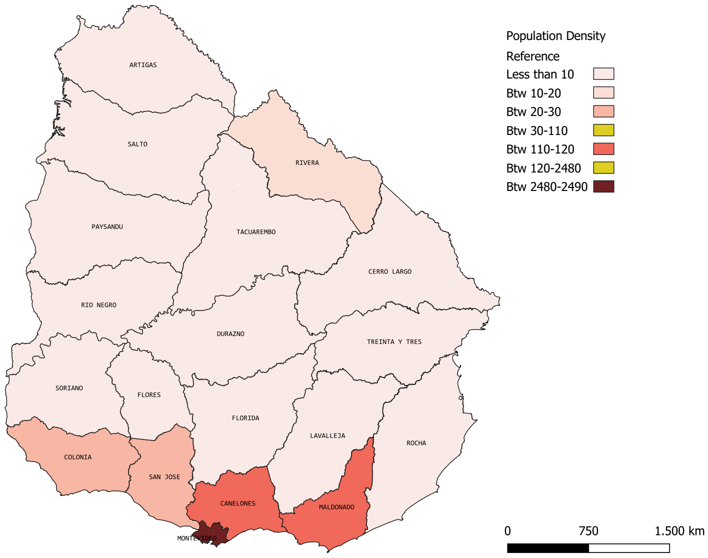


Figure B.2: Density by department

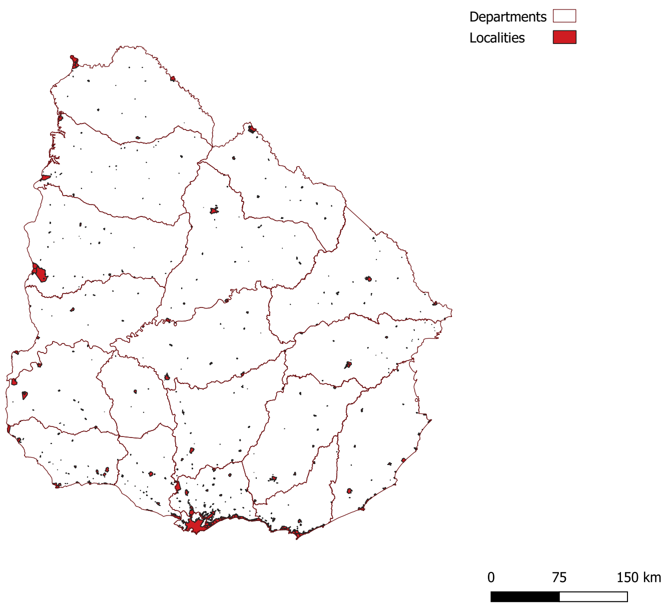


B.1.2 Information at the locality level

According to the National Institute of Statistics, geographical localities (or census localities) are defined in terms of clearly and precisely delimited territories made up of clusters of buildings and therefore reflect the representation of landscape changes. A Census Locality corresponds to a set of census tracts characterized by a concentration of population and dwellings.

Uruguay has 615 localities based on the information of 2011 Census from the National Institute of Statistics. These localities have a median of 296 inhabitants with a high level of dispersion. The mean is 5057 inhabitants. The mean of department localities is 32, with Montevideo in the lower tail (only one locality for the whole department) and Canelones in the upper tail (with 117 localities).

Figure B.3: Localities geographical distribution



B.2 Other estimations for academic outcomes 2020

Table B1: New students up to 29 years old

	No Activity (1)	Number of Courses (2)	Number of Approved subjects (3)	Mean Grade (4)
Panel a: Only degrees of more than 500 students				
Year2020	0.067***	0.039	0.538***	0.698***
	(0.007)	(0.109)	(0.066)	(0.053)
	[0.000]	[0.717]	[0.000]	[0.000]
Year2020*Campus$_L$	-0.018*	-0.159	-0.201**	-0.120*
	(0.010)	(0.148)	(0.086)	(0.061)
	[0.067]	[0.287]	[0.020]	[0.051]
N. Observations	39,161	35,990	35,990	32,060
Panel b: Only degrees without lottery for entrance neither changes in their curriculum				
Year2020	0.072***	-0.076	0.336***	0.716***
	(0.006)	(0.073)	(0.061)	(0.049)
	[0.000]	[0.302]	[0.000]	[0.000]
Year2020*Campus$_L$	-0.015*	-0.047	-0.039	-0.068
	(0.008)	(0.094)	(0.064)	(0.068)
	[0.062]	[0.618]	[0.539]	[0.320]
N. Observations	47,013	42,898	42,898	37,233

Notes: Reported estimates are obtained from an OLS regression including locality fixed effects and student control variables (gender, age at enrollment and type of high school institution). In Panel a, I only consider students registered in degrees of more than 500 students. In Panel b, I only consider students registered in degrees without a lottery for entrance and changes in the curriculum for 2017-2021. Standard errors reported in parentheses, clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (4) refer to the academic outcomes of students obtained from the administrative records as defined in section 2.5. Year2020 is a dummy variable that equals 1 for students enrolled in 2020 and 0 otherwise. Year2020*Campus$_L$ takes the value 1 for students enrolled in 2020 from the treated group defined as students that did high school in a locality without a university campus. The regression includes new students up to 29 years old.

Table B2: New students up to 29 years old by gender - Treatment: Outsise loc.

	No Activity (1)	Number of Courses (2)	Number of Approved subjects (3)	Mean Grade (4)
Panel a: Boys				
Year2020	0.076***	-0.061	0.256**	0.503***
	(0.007)	(0.074)	(0.099)	(0.052)
	[0.000]	[0.408]	[0.011]	[0.000]
Year2020*Campus$_{\mathrm{L}}$	-0.014	-0.182*	-0.132	-0.119
	(0.012)	(0.101)	(0.131)	(0.107)
	[0.258]	[0.074]	[0.314]	[0.265]
N. Observations	21,884	19,971	19,971	16,464
Panel b: Girls				
Year2020	0.044***	0.032	0.420***	0.683***
	(0.007)	(0.104)	(0.072)	(0.050)
	[0.000]	[0.759]	[0.000]	[0.000]
Year2020*Campus$_{\mathrm{L}}$	-0.013*	-0.075	-0.119*	-0.102
	(0.007)	(0.101)	(0.067)	(0.068)
	[0.082]	[0.456]	[0.079]	[0.139]
N. Observations	33,458	30,775	30,775	27,689

Notes: Reported estimates are obtained from an OLS regression including locality fixed effects and student control variables (gender, age at enrollment and type of high school institution). In Panel a, I run the regression only for boys, while in Panel b, I only include girls. Standard errors reported in parentheses, clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (4) refer to the academic outcomes of students obtained from the administrative records as defined in section 2.5. Year2020 is a dummy variable that equals 1 for students enrolled in 2020 and 0 otherwise. Year2020*Campus$_{\mathrm{L}}$ takes the value 1 for students enrolled in 2020 from the treated group defined as students that did high school in a locality without a university campus. The regression includes new students up to 29 years old.

Table B3: New students up to 29 years old by gender - Treatment: >20Km

	No Activity (1)	Number of Courses (2)	Number of Approved subjects (3)	Mean Grade (4)
Panel a: Boys - Treatment: >20Km				
Year2020	0.078***	-0.088	0.240**	0.486***
	(0.007)	(0.084)	(0.097)	(0.052)
	[0.000]	[0.293]	[0.015]	[0.000]
Year2020*Campus$_L$	-0.020*	-0.132	-0.107	-0.087
	(0.012)	(0.112)	(0.132)	(0.112)
	[0.084]	[0.241]	[0.419]	[0.441]
N. Observations	21,884	19,971	19,971	16,464
Panel b: Girls - Treatment: >20Km				
Year2020	0.043***	0.039	0.414***	0.672***
	(0.008)	(0.098)	(0.069)	(0.048)
	[0.000]	[0.695]	[0.000]	[0.000]
Year2020*Campus$_L$	-0.012	-0.106	-0.125*	-0.090
	(0.008)	(0.098)	(0.069)	(0.071)
	[0.130]	[0.282]	[0.071]	[0.208]
N. Observations	33,458	30,775	30,775	27,689

Notes: Reported estimates are obtained from an OLS regression including locality fixed effects and student control variables (gender, age at enrollment and type of high school institution). In Panel a, I run the regression only for boys, while in Panel b, I only include girls. Standard errors reported in parentheses, clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (4) refer to the academic outcomes of students obtained from the administrative records as defined in section 2.5. Year2020 is a dummy variable that equals 1 for students enrolled in 2020 and 0 otherwise. Year2020*Campus$_L$ takes the value 1 for students enrolled in 2020 from the treated group defined as students that did high school in a locality more than 20Km away from a university campus. The regression includes new students up to 29 years old.

Table B4: New students up to 29 years old by socioeconomic background - Treatment: Outsise loc.

	No Activity (1)	Number of Courses (2)	Number of Approved subjects (3)	Mean Grade (4)
Panel a: Public high school				
Year2020	0.062***	-0.115	0.296***	0.609***
	(0.010)	(0.104)	(0.075)	(0.060)
	[0.000]	[0.271]	[0.000]	[0.000]
Year2020*Campus$_L$	-0.017*	0.031	-0.030	-0.065
	(0.010)	(0.100)	(0.076)	(0.071)
	[0.097]	[0.757]	[0.692]	[0.358]
N. Observations	43,236	39,530	39,530	34,187
Panel b: Private high school				
Year2020	0.046***	0.176***	0.397***	0.532***
	(0.003)	(0.055)	(0.051)	(0.040)
	[0.000]	[0.004]	[0.000]	[0.000]
Year2020*Campus$_L$	-0.013	-0.097	-0.066	-0.008
	(0.024)	(0.141)	(0.257)	(0.302)
	[0.574]	[0.496]	[0.801]	[0.978]
N. Observations	12,106	11,216	11,216	9,966

Notes: Reported estimates are obtained from an OLS regression including locality fixed effects and student control variables (gender, age at enrollment and type of high school institution). In Panel a, I run the regression only for students that attended a public high school, while in Panel b, I only include students that attended a private high school. Standard errors reported in parentheses, clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (4) refer to the academic outcomes of students obtained from the administrative records as defined in section 2.5. Year2020 is a dummy variable that equals 1 for students enrolled in 2020 and 0 otherwise. Year2020*Campus$_L$ takes the value 1 for students enrolled in 2020 from the treated group defined as students that did high school in a locality without a university campus. The regression includes new students up to 29 years old.

Table B5: New students up to 29 years old by socioeconomic background - Treatment: Outsise >20Km

	No Activity (1)	Number of Courses (2)	Number of Approved subjects (3)	Mean Grade (4)
Panel a: Public high school - Treatment: >20Km				
Year2020	0.061***	-0.114	0.282***	0.585***
	(0.010)	(0.095)	(0.067)	(0.059)
	[0.000]	[0.229]	[0.000]	[0.000]
Year2020*Campus$_{\mathrm{L}}$	-0.019**	0.034	-0.004	-0.020
	(0.010)	(0.094)	(0.076)	(0.075)
	[0.050]	[0.720]	[0.959]	[0.789]
N. Observations	43,236	39,530	39,530	34,187
Panel b: Private high school - Treatment: >20Km				
Year2020	0.045***	0.191***	0.428***	0.559***
	(0.004)	(0.046)	(0.044)	(0.054)
	[0.000]	[0.000]	[0.000]	[0.000]
Year2020*Campus$_{\mathrm{L}}$	-0.007	-0.291***	-0.415*	-0.286
	(0.030)	(0.093)	(0.234)	(0.272)
	[0.821]	[0.005]	[0.090]	[0.305]
N. Observations	12,106	11,216	11,216	9,966

Notes: Reported estimates are obtained from an OLS regression including locality fixed effects and student control variables (gender, age at enrollment and type of high school institution). In Panel a, I run the regression only for students that attended a public high school, while in Panel b, I only include students that attended a private high school. Standard errors reported in parentheses, clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (4) refer to the academic outcomes of students obtained from the administrative records as defined in section 2.5. Year2020 is a dummy variable that equals 1 for students enrolled in 2020 and 0 otherwise. Year2020*Campus$_{\mathrm{L}}$ takes the value 1 for students enrolled in 2020 from the treated group defined as students that did high school in a locality more than 20Km away from a university campus. The regression includes new students up to 29 years old.

B.3 Other estimations for enrollment in 2021

Table B6: Enrollment 2021 for urban localities

	Campus distance		
	Outside loc	> 20Km	> 50Km
	(1)	(2)	(3)
Panel a: All students up to 29 years old			
	Outside loc	> 20Km	> 50Km
Year2021	-0.001	0.001*	0.001*
	(0.001)	(0.001)	(0.001)
	[0.111]	[0.091]	[0.093]
Year2021*Campus$_L$	0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
	[0.017]	[0.634]	[0.728]
N. Observations	335	335	255
Panel b: New students up to 25 years old			
	Outside loc	> 20Km	> 50Km
Year2021	-0.001*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)
	[0.086]	[0.061]	[0.063]
Year2021*Campus$_L$	0.003**	-0.001	-0.001
	(0.001)	(0.002)	(0.002)
	[0.021]	[0.465]	[0.580]
N. Observations	335	335	255

Notes: Reported estimates are obtained from an OLS regression including locality fixed effects. In Panel a, the outcome variable is the share of enrollment of new students up to 29 years of age over the total population from 17 to 29 years of age by locality. In Panel b, the outcome variable is the share of enrollment of new students up to 25 years of age over the total population from 17 to 29 years of age by locality. Standard errors reported in parentheses clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (3) differ in how the treatment groups is composed. In (1), the treated group consists of students that did high school in a locality without a university campus. In (2), the treated students are students that did high school more than 20 Km away from a university campus, and the control group by the other students. In (3), the treated group is composed of students living more than 50 Km away from a university campus, and the control group of students living less than 20 Km from a university campus. Year2021 is a dummy variable that equals 1 for localities in 2021 and 0 otherwise. Year2021*Campus$_L$ takes the value of one for localities in 2021 from the treated group defined as explained before. The regression includes all localities with more than 5,000 inhabitants (urban localities) in 2017-2021.

Table B7: Enrollment 2021 for localities with more than 2000 inhabitants

	Campus distance		
	Outside loc	> 20Km	> 50Km
	(1)	(2)	(3)
Panel a: New students up to 29 years old			
	Outside loc	> 20Km	> 50Km
Year2021	-0.001	0.001*	0.001*
	(0.001)	(0.001)	(0.001)
	[0.108]	[0.088]	[0.090]
Year2021*Campus$_L$	0.002**	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
	[0.020]	[0.704]	[0.693]
N. Observations	500	500	380
Panel b: New students up to 25 years old			
	Outside loc	> 20Km	> 50Km
Year2021	-0.001*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)
	[0.083]	[0.059]	[0.060]
Year2021*Campus$_L$	0.003**	-0.001	-0.001
	(0.001)	(0.002)	(0.002)
	[0.027]	[0.525]	[0.598]
N. Observations	500	500	380

Notes: Reported estimates are obtained from an OLS regression including locality fixed effects. In Panel a, the outcome variable is the share of enrollment of new students up to 29 years of age over the total population from 17 to 29 years of age by locality. In Panel b, the outcome variable is the share of enrollment of new students up to 25 years of age over the total population from 17 to 29 years of age by locality. Standard errors reported in parentheses clustered at the locality level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1) to (3) differ in how the treatment group is composed. In (1), the treated group consists of students that did high school in a locality without a university campus. In (2), the treated students are students that did high school more than 20 Km away from a university campus, and the control group by the other students. In (3), the treated group is composed of students living more than 50 Km away from a university campus, and the control group of students living less than 20 Km from a university campus. Year2021 is a dummy variable that equals 1 for localities in 2021 and 0 otherwise. Year2021*Campus$_L$ takes the value of one for localities in 2021 from the treated group defined as explained before. The regression includes all localities with more than 2,000 inhabitants.

Appendix C

C.1 Descriptive statistics about innovation

Figure C.1: Percentage of firms that innovate

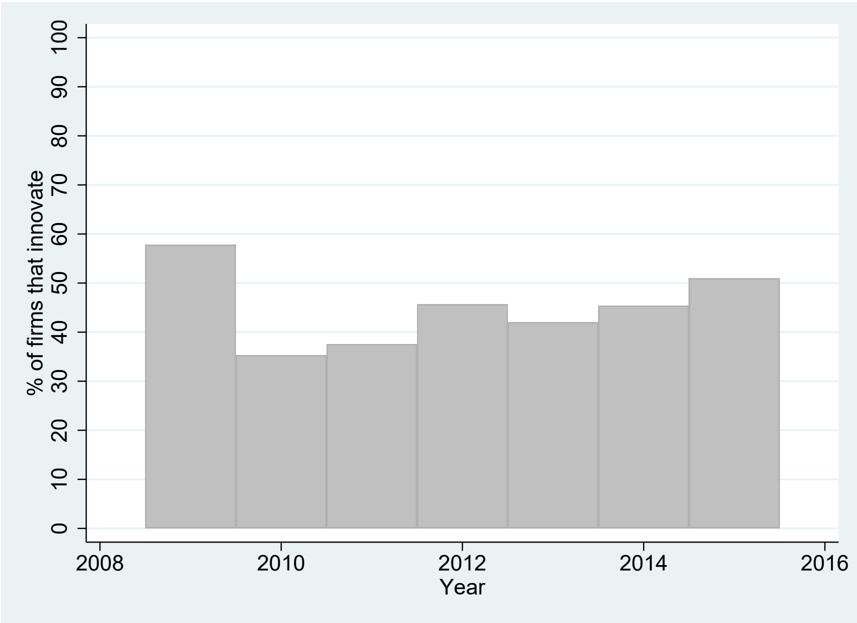


Figure C.2: Percentage of firms that innovate in intangibles

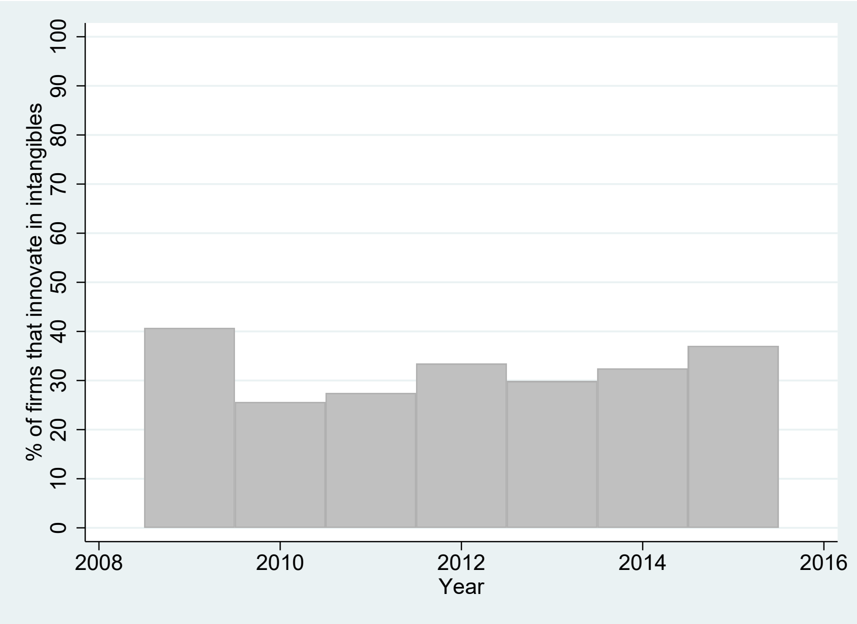


Figure C.3: Percentage of firms that innovate in capital goods

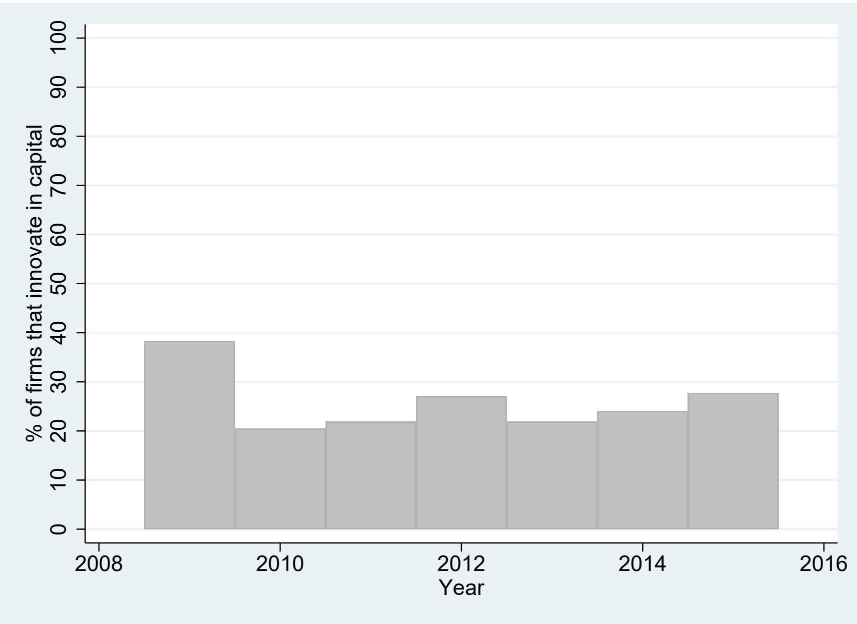


Figure C.4: Percentage of firms that innovate in training activities

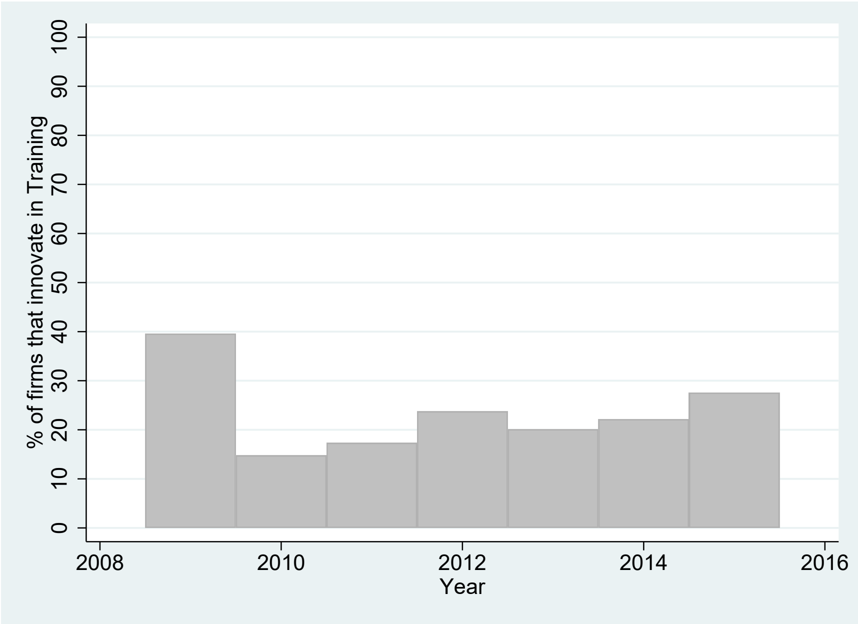
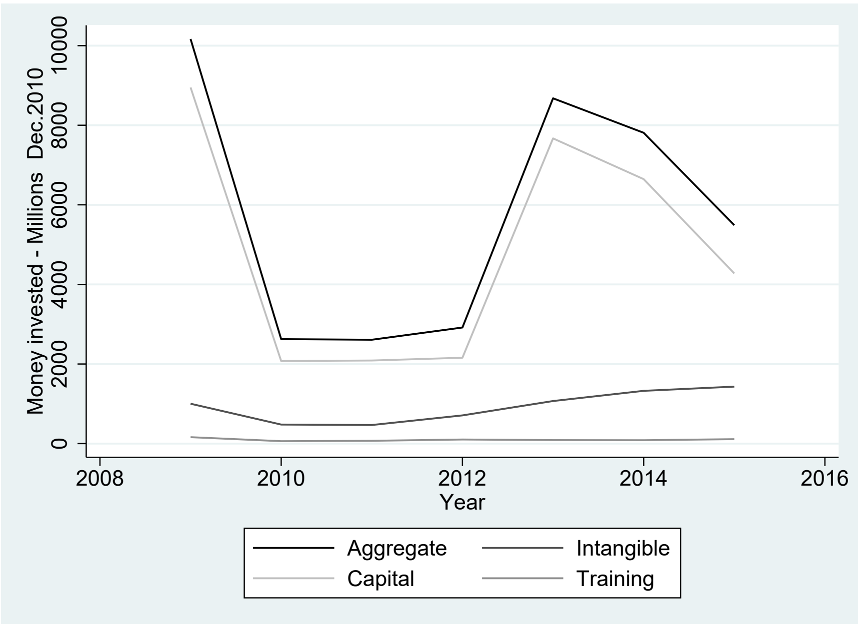


Figure C.5: Total amount of money invested



C.2 Oster analysis

Table C1: Innovation and labor share - Oster bounds

	Labor share							
	Indicator variable Innov.				Logarithm Innov.			
	(OLS)		(FE)		(OLS)		(FE)	
	Value of Delta							
	δ=-1	δ=1	δ=-1	δ=1	δ=-1	δ=1	δ=-1	δ=1
Innov_{it}	-0.065	-0.054	-0.055	-0.005	0.007	-0.004	0.005	0.009
$\text{Innov intangibles}_{\text{it}}$	-0.090	-0.102	-0.093	-0.096	-0.009	-0.018	-0.015	-0.019
$\text{Innov capital}_{\text{it}}$	-0.029	-0.061	-0.016	0.025	0.004	-0.007	0.001	0.009
$\text{Innov training}_{\text{it}}$	0.070	0.080	0.066	0.041	0.020	0.009	0.027	0.011

Notes: The table presents the bounds for beta for each of the regressions in the main table according to the Oster methodology Oster (2019). I use as -1 and 1 as the delta coefficients for the beta bounds. Delta is the coefficient of proportionality which estimates how big the selection on unobservables has to be relative to the selection on observables for the true effect to be zero. The author suggest δ=1 as a good value for imputing the beta bounds. Beta estimates are obtained using the Stata command psacalc. I use an Rmax equal to 1.

C.3 Control variables in main regression

Table C2: Innovation and labor share - Control variables

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
$\text{Concentration}_{\text{it}}$	-0.565***	-0.237	-0.595***	-0.257
	(0.109)	(0.220)	(0.116)	(0.224)
	[0.000]	[0.284]	[0.000]	[0.253]
$\text{Exports}_{\text{it}}$	-0.044	-0.038	-0.041	-0.039
	(0.036)	(0.076)	(0.037)	(0.076)
	[0.233]	[0.616]	[0.272]	[0.613]
$\text{Foreign capital}_{\text{it}}$	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
	[0.297]	[0.511]	[0.305]	[0.583]
Num of employees $_{\text{it}}$	0.000***	-0.000	0.000***	-0.000
	[0.000]	[0.427]	[0.000]	[0.430]
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Reported estimates are obtained from an OLS regression (Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In Panel a, I regress the labor share on innovation as an indicator variable with a value of one if the firm innovates in period t and zero otherwise. In Panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations I include as controls the variables defined in Section 3.4, year and two-digit sector fixed effects. Standard errors are reported in parentheses and clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added before taxes. The sample includes firms of mandatory inclusion for at least one year.

C.4 Robustness Checks

Table C3: Innovation and labor share - Mandatory firms all years

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
Panel a: Aggregate variable				
Innov_{it}	-0.045**	-0.031	0.003	0.008
	(0.022)	(0.026)	(0.007)	(0.006)
	[0.042]	[0.233]	[0.711]	[0.192]
R^2	0.789	0.798	0.789	0.798
N. Observations	3,659	3,659	3,659	3,659
Panel b: Types of innovation				
$\text{Innov intangibles}_{\text{it}}$	-0.079***	-0.105***	-0.013**	-0.016**
	(0.024)	(0.029)	(0.006)	(0.006)
	[0.001]	[0.000]	[0.029]	[0.013]
$\text{Innov capital}_{\text{it}}$	-0.023	0.018	0.001	0.006
	(0.026)	(0.032)	(0.007)	(0.006)
	[0.387]	[0.568]	[0.932]	[0.276]
$\text{Innov training}_{\text{it}}$	0.060**	0.046	0.014*	0.016**
	(0.025)	(0.029)	(0.008)	(0.008)
	[0.019]	[0.110]	[0.090]	[0.048]
R^2	0.790	0.799	0.789	0.798
N. Observations	3,659	3,659	3,659	3,659

Notes: Reported estimates are obtained from an OLS regression (Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In panel a, I regress the labor share on innovation as an indicator variable with a value of one if the firm innovates in period t and zero otherwise. In panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations, I include as controls the variables defined in section 3.4, year and two-digit sector fixed effects. Standard errors reported in parentheses, clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added before taxes. The sample includes all firms that are of mandatory inclusion for the whole period.

Table C4: Innovation and labor share - All firms with full information

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
Panel a: Aggregate variable				
Innov_{it}	-0.049***	-0.028	0.001	0.006
	(0.016)	(0.021)	(0.007)	(0.006)
	[0.002]	[0.179]	[0.853]	[0.349]
R^2	0.754	0.767	0.753	0.767
N. Observations	6,971	6,971	6,971	6,971
Panel b: Types of innovation				
Innov $\text{intangibles}_{\text{it}}$	-0.086***	-0.083***	-0.014**	-0.018***
	(0.019)	(0.021)	(0.006)	(0.006)
	[0.000]	[0.000]	[0.025]	[0.001]
Innov $\text{capital}_{\text{it}}$	-0.040**	0.001	-0.001	0.004
	(0.020)	(0.023)	(0.006)	(0.006)
	[0.047]	[0.980]	[0.840]	[0.422]
Innov $\text{training}_{\text{it}}$	0.082***	0.062***	0.015**	0.017**
	(0.023)	(0.024)	(0.008)	(0.007)
	[0.000]	[0.009]	[0.049]	[0.022]
R^2	0.755	0.768	0.754	0.768
N. Observations	6,971	6,971	6,971	6,971

Notes: Reported estimates are obtained from an OLS regression (Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In panel a, I regress the labor share on innovation as an indicator variable with a value of one if the firm innovates in period t and zero otherwise. In panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations, I include as controls the variables defined in section 3.4, year and two-digit sector fixed effects. Standard errors reported in parentheses, clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing I use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added before taxes. The sample considers all firms with data in both surveys without considering the restriction of mandatory inclusion.

Table C5: Innovation and labor share considering value added after taxes

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
Panel a: Aggregate variable				
Innov_{it}	-0.054	-0.048	0.017	0.010
	(0.038)	(0.046)	(0.016)	(0.013)
	[0.153]	[0.305]	[0.284]	[0.433]
R^2	0.692	0.687	0.692	0.687
N. Observations	4,302	4,302	4,302	4,302
Panel b: Types of innovation				
Innov $\text{intangibles}_{\text{it}}$	-0.104^{**}	-0.074	-0.008	-0.024
	(0.044)	(0.048)	(0.014)	(0.017)
	[0.020]	[0.129]	[0.562]	[0.163]
Innov $\text{capital}_{\text{it}}$	-0.046	-0.051	0.009	0.006
	(0.043)	(0.052)	(0.015)	(0.012)
	[0.280]	[0.331]	[0.564]	[0.614]
Innov $\text{training}_{\text{it}}$	0.108^{**}	0.109^{**}	0.025	0.031^{**}
	(0.046)	(0.050)	(0.016)	(0.015)
	[0.020]	[0.029]	[0.110]	[0.037]
R^2	0.692	0.687	0.692	0.687
N. Observations	4,302	4,302	4,302	4,302

Notes: Reported estimates are obtained from an OLS regression(Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In Panel a, I regress the labor share on innovation as an indicator variable with value one if the firm innovates in period t and zero otherwise. In panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations, I include as controls the variables defined in section 3.4, year and two-digit sector fixed effects. Standard errors reported in parentheses, clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing we use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added after taxes. The sample includes firms of mandatory inclusion for at least one year

Table C6: Innovation and labor share - Trimming the labor share

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
Panel a: Aggregate variable				
Innov_{it}	-0.047***	-0.030*	-0.003***	-0.002
	(0.017)	(0.018)	(0.001)	(0.001)
	[0.005]	[0.088]	[0.008]	[0.185]
R^2	0.669	0.697	0.668	0.697
N. Observations	4,351	4,351	4,351	4,351
Panel b: Types of innovation				
$\text{Innov intangibles}_{\text{it}}$	-0.071***	-0.073***	-0.004**	-0.005***
	(0.019)	(0.019)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.020]	[0.001]
$\text{Innov capital}_{\text{it}}$	-0.040**	0.004	-0.003**	0.000
	(0.020)	(0.021)	(0.001)	(0.001)
	[0.041]	[0.867]	[0.030]	[0.784]
$\text{Innov training}_{\text{it}}$	0.071***	0.037*	0.005***	0.003*
	(0.020)	(0.020)	(0.002)	(0.002)
	[0.000]	[0.065]	[0.003]	[0.062]
R^2	0.670	0.698	0.669	0.697
N. Observations	4,351	4,351	4,351	4,351

Notes: Reported estimates are obtained from an OLS regression (Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In Panel a, I regress the labor share on innovation as an indicator variable with a value one if the firm innovates in period t and zero otherwise. In panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations, I include as controls the variables defined in section 3.4, year and two-digit sector fixed effects. Standard errors reported in parentheses, clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing we use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added before taxes. The sample includes firms of mandatory inclusion for at least one year. I exclude firms with negative value added and the top 1 upper percentile of labor share distribution.

Table C7: Innovation and labor share - labor share winsorized to 3

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
Panel a: Aggregate variable				
Innov_{it}	-0.054***	-0.029	-0.001	0.005
	(0.016)	(0.018)	(0.007)	(0.006)
	[0.001]	[0.109]	[0.894]	[0.340]
R^2	0.674	0.698	0.672	0.698
N. Observations	4,302	4,302	4,302	4,302
Panel b: Types of innovation				
Innov $\text{intangibles}_{\text{it}}$	-0.077***	-0.074***	-0.013**	-0.015***
	(0.019)	(0.019)	(0.005)	(0.005)
	[0.000]	[0.000]	[0.017]	[0.002]
Innov $\text{capital}_{\text{it}}$	-0.042**	0.003	-0.002	0.005
	(0.020)	(0.021)	(0.006)	(0.005)
	[0.034]	[0.896]	[0.712]	[0.371]
Innov $\text{training}_{\text{it}}$	0.062***	0.037*	0.012*	0.013**
	(0.020)	(0.020)	(0.007)	(0.006)
	[0.002]	[0.064]	[0.075]	[0.045]
R^2	0.675	0.699	0.673	0.698
N. Observations	4,302	4,302	4,302	4,302

Notes: Reported estimates are obtained from an OLS regression (Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In Panel a, I regress the labor share on innovation as an indicator variable with a value one if the firm innovates in period t and zero otherwise. In panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations, I include as controls the variables defined in section 3.4, year and two-digit sector fixed effects. Standard errors reported in parentheses, clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing we use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added before taxes. If value-added is negative or labor share is higher than 3, I winsorize the data to the value of 3. The sample includes firms of mandatory inclusion for at least one year.

Table C8: Innovation and labor share - labor share winsorized to 1

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
Panel a: Aggregate variable				
Innov_{it}	-0.021^{**}	-0.009	-0.003	0.004
	(0.010)	(0.008)	(0.003)	(0.003)
	[0.034]	[0.281]	[0.343]	[0.139]
R^2	0.311	0.260	0.310	0.260
N. Observations	4,302	4,302	4,302	4,302
Panel b: Types of innovation				
$\text{Innov intangibles}_{\text{it}}$	-0.029^{**}	-0.030^{***}	-0.007^{*}	-0.005^{*}
	(0.012)	(0.010)	(0.004)	(0.003)
	[0.015]	[0.002]	[0.072]	[0.061]
$\text{Innov capital}_{\text{it}}$	-0.027^{**}	0.007	-0.003	0.004^{*}
	(0.012)	(0.010)	(0.003)	(0.003)
	[0.018]	[0.507]	[0.355]	[0.091]
$\text{Innov training}_{\text{it}}$	0.039^{***}	0.015	0.004	0.000
	(0.012)	(0.010)	(0.003)	(0.003)
	[0.001]	[0.137]	[0.154]	[0.999]
R^2	0.314	0.262	0.311	0.261
N. Observations	4,302	4,302	4,302	4,302

Notes: Reported estimates are obtained from an OLS regression (Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In Panel a, I regress the labor share on innovation as an indicator variable with a value of one if the firm innovates in period t and zero otherwise. In Panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations, I include as controls the variables defined in section 3.4, year and two-digit sector fixed effects. Standard errors reported in parentheses, clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing we use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added before taxes. If value-added is negative or labor share is higher than 1, I winsorize the data to the value of 1. The sample includes firms of mandatory inclusion for at least one year.

Table C9: Innovation and labor share - labor share with remunerations 2011

	Labor share			
	Indicator variable Innov.		Logarithm Innov.	
	(OLS)	(FE)	(OLS)	(FE)
Panel a: Aggregate variable				
Innov_{it}	-0.055***	-0.022	0.002	0.007
	(0.018)	(0.018)	(0.007)	(0.006)
	[0.002]	[0.223]	[0.796]	[0.247]
R^2	0.755	0.779	0.754	0.779
N. Observations	4,954	4,954	4,954	4,954
Panel b: Types of innovation				
Innov $\text{intangibles}_{\text{it}}$	-0.085***	-0.074***	-0.012**	-0.012**
	(0.021)	(0.020)	(0.006)	(0.005)
	[0.000]	[0.000]	[0.036]	[0.021]
Innov $\text{capital}_{\text{it}}$	-0.038*	0.001	-0.001	0.005
	(0.021)	(0.023)	(0.006)	(0.005)
	[0.073]	[0.976]	[0.900]	[0.383]
Innov $\text{training}_{\text{it}}$	0.066***	0.041*	0.012	0.013*
	(0.022)	(0.021)	(0.007)	(0.007)
	[0.003]	[0.057]	[0.102]	[0.056]
R^2	0.756	0.779	0.755	0.779
N. Observations	4,954	4,954	4,954	4,954

Notes: Reported estimates are obtained from an OLS regression (Columns 1 and 3) and a firm fixed effects regression (Columns 2 and 4). In Panel a, I regress the labor share on innovation as an indicator variable with a value of one if the firm innovates in period t and zero otherwise. In Panel b, I regress the labor share on three categories of innovation: innovation in intangibles, innovation in capital goods, and innovation in training activities. In both equations, I include as controls the variables defined in section 3.4, year and two-digit sector fixed effects. Standard errors reported in parentheses, clustered at the firm level using Liang-Zeger cluster robust standard errors. P-Values are reported in square brackets and obtained using Liang-Zeger cluster robust standard errors. For hypothesis testing we use P-values with significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The labor share is computed as the ratio of total labor cost to value-added before taxes, including observations for the year 2011. If value-added is negative or labor share is higher than 1, I winsorize the data to the value of 1. The sample includes firms of mandatory inclusion for at least one year.

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