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Does Distance Matter? Proximity to Exporting Firms on Child Labour and Education Rates: Evidence from Bangladesh

Aubrey Keeler Saunders
Samuel Brazys,
School of Politics and International Relations,
and Geary Institute for Public Policy,
University College Dublin

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Does Distance Matter? Proximity to Exporting Firms on Child Labour and Education Rates: Evidence from Bangladesh.[1]

Aubrey Keeler Saunders
Samuel Brazys[2]

Abstract

Child labour continues to be a major concern in developing countries. One of the main issues with child labour is that it interferes with a child's right to education as the majority of child labourers do not attend school due to employment. In this study, we consider the issue in Bangladesh where education rates have recently stagnated despite economic growth, which typically leads to an increase of education rates. The Bangladeshi economy is driven by its export sector, which relies on low-cost labour and it is plausible that children are not attending school in order to work. To test the claim, we combine novel spatial data on the locations over 11,000 exporting firms with over 95,000 similarly geo-located child survey responses from three waves of the Bangladesh Household Income and Expenditure Survey. Using matching techniques, we show that, when controlling for external factors, such as household income, students living closer to an exporting firm are more likely to report work and less likely to report attending school, providing evidence to suggest that the exporting sector may be influencing macro trends in Bangladesh school attendance.

Keywords: Child Labour; Education; Bangladesh; Export; Spatial

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[1] World Count: 8674

[2] Aubrey Saunders (aubrey.saunders@ucdconnect.ie) is a graduate of the Masters in Public Administration – Development Practice at University College Dublin. Samuel Brazys (samuel.brazys@ucd.ie) is Associate Professor in the School of Politics and International Relations at University College Dublin. This study received generous funding from the Irish Research Council Laureate Programme ("TRADE ME") grant no. IRCLA/2017/092. The authors thank Doris Aja, Oisin Joyce, Patrick Mascott, Tianyang Song and Daniel Noble Stairs for excellent research assistance with this project.

Introduction

Child labour is a global concern that affects about 150 million children worldwide, impacting nearly 10% of the world's children (International Labour Office, 2014). Child labour has been linked to a number of socio-economic and physical consequences (Beegle et al. 2008; Posso 2019) and, resultantly, is a widely condemned practice. The Labour Organization Convention has held two major conventions on the topic of child labour—the Minimum Age Convention in 1973 and the Worst Forms of Child Labour Convention in 1999. The UN Convention on the Rights of the Child declared child labour as a human rights issue and outlined the need for its elimination (Bangladesh Bureau of Statistics, 2015).

Not only does child labour exploit and harm the health and wellbeing of children, it is also a critical barrier to development. Employment interferes with a child's education, often causing children to drop out early or to never begin attending school, thus impeding chances to gain valuable skills and knowledge necessary to secure well-paying jobs. Various international organizations have taken steps to combat child labour. Studies show that many families in developing countries, especially in rural locations, are more likely to encourage their children to work rather than attend school to provide additional income for the household (Banerjee et al. 2006; Edmonds, 2007). Convenience and proximity to employment opportunities is an additional reason children seek work (Kain, 1992; Ihlanfeldt and Sjoquist, 1998; Ong and Blumenberg, 1998; Allard and Danziger, 2002; Aslund et al. 2009). The most common place of work for child labourers is in a factory or workshop, and these locations account for about 38% of the total child workforce (Sikder, 2019).

While poverty is recognized as the primary reason that families underinvest in their children's education (Maitra, 2003), not all poor children leave school for work. In this paper, we investigate the extent to which *opportunity* for children to work determines if children trade school for labour. Using spatial data on both exporting firms and households in Bangladesh to assess this claim, we find that children who are closer to an exporting firm are less likely to attend school and more likely to report being employed. While somewhat intuitive, empirically establishing this connection has important implications. First, the findings speak to an increasing literature that considers heterogeneity in *sub*-national development outcomes. Child labour rates may vary considerably *within* a country which can have profound distributional consequences. Second, the findings illustrate that there may well be a trade-off, or an "educational Kuznets curve", wherein increased growth (especially locally) may lead to increases in child labour usage and decreased educational outcomes.

In the following sections, we first investigate the reasons for child labour usage, highlighting how these rationales may be dependent or conditional on *proximity* to work opportunities, and discuss how labour and education may act as substitutes. We then briefly describe the child labour and educational situations in Bangladesh, including a discussion of policies and programmes in both of these areas. We then use micro-level spatial data and matching techniques to evidence that relative proximity to exporting firms both increases the likelihood of children working but also decreases the likelihood of attending school. Finally, we conclude with thoughts on the implications of the study for broader questions in the field.

Child Labour: Causes and Consequences

Child labour—as defined by the ILO—is the exploitation of children through work that denies children their right to their childhood, is harmful in any way, and/or interferes with their ability to attend school (International Labour Office, 2004). Child labour is dangerous and, in many cases, harmful to children. It also negatively impacts societal development and a child's personal development. Child labourers experience strenuous, long working hours and suffer from physical, psychological, and emotional harm and abuse (Bangladesh Bureau of Statistics, 2015). These poor conditions are a threat to a child's basic rights and hinders their development, which jeopardises their future. Child labourers generally lose the ability to work at a young age due to health issues. Furthermore, employment interferes with a child's right to education, which is crucial in gaining human capital—or the valuable skills, knowledge, and experience an individual can acquire—and is especially important to secure better employment. Typically, child labourers come from low-income households, thus perpetuating the poverty cycle (Heltberg and Johannesen, 2002; Maitra, 2003; Shafiq, 2007a).

Beyond its direct impact on children, child labour also an economic threat to countries. Child labour prevents the fulfilment of the 2030 Agenda for Sustainable Development Goals (SDG) Goal 4, "ensure inclusive and quality education for all" (United Nations, 2020). According to a study by the International Labour Organization (ILO), eliminating child labour and providing education for all children produces a predicted gain of an estimated US$5 trillion over 20 years (International Labour Office and International Programme on the Elimination of Child Labour (IPEC), 2004). The study also found that providing quality education for all children predicted an increase in innovation rates, productivity rates, and economic competition in a country.

There are various push and pull factors that lead to children seeking employment. One of the main push factors is poverty. Poverty is the primary reason that families underinvest in their child's education (Maitra, 2003; Shafiq, 2007b). Udry (2006, p.

243) argues that child labour is “a symptom of poverty” that can only be eradicated or dramatically decreased by the reduction of poverty. Poverty and child labour are linked to education as not sending children to school prevents families from receiving the higher wages that coincide with educational attainment, which in the long term could help families fight the poverty cycle (Shafiq, 2007b; Mukherje and Das, 2008). However, on many occasions, the immediate household need of child labour wages is perceived as greater than the long-term reward. Banerjee and Benabou (2006, p. 3) write that the concern with child labour is the “sacrifice of a child’s future welfare in exchange for a current benefit to the household.” Many families in developing countries, especially in rural areas, are more likely to have children that engage in child labour for survival reasons (Edmonds, 2007).

In contrast, higher income is generally due to the higher education level of both parents, which also contributes to education promotion (Khanam, 2008). Edmonds (2001), Admassie (2002), Wahba (2006), and Tuttle et al. (2001) found that an increase in household income, particularly when acquired by the parents, is associated with a decrease of child labour and increase in school enrolment. This is called the “positive income effect” (Banerjee and Benabou, 2006). Kana et al. (2010) and Rosati and Tzannatos (2006) also found a “positive income effect” even if only the mother was educated. While Sultan et al. (2021) find that adolescents in poor areas of Dhaka have high educational *aspirations*, those are not always translated into educational outcomes with poverty acting as a barrier to realizing those goals. Studies have shown that the investment in education is worth the trade-off, for both individuals and their household, of not being employed and acquiring income as a child, due to the increase in human capital (Basu and Van, 1999; Dessy, 2000; Razzaz, 2001; Hazan and Berdugo, 2001; Emerson and Souza, 2003; Bell and Gersbach, 2009).

Poor quality and high costs of education are also push factors for child labour. In some cases, due to the low quality of schools in rural or poorer areas, the costs of education do not match the expected benefit of graduates, and employment is a more enticing option (PROBE Team, 1999; Ray, 2002; Mukherje and Das, 2008). Although many countries have abolished tuition fees, there are still many hidden costs that prohibit households from being able to afford basic education (Grenze, 2007). These additional expenditures include examination fees, activity costs, and private tutors (Ahmed, Ahmed, Khan, Ahmed, 2007; Trines, 2019). Unlike primary school, secondary school is often not free and therefore is much more expensive due to tuition fees and uniform costs (Grenze, 2007). These high educational costs make it difficult for households to afford the annual fees, which cause many students to work rather than enrol in school or to drop out during the school year.

Geographical distance to employment is the main pull factor for poorer households. When considering adult employment, several studies find that proximity to employment opportunities increases employability of an individual (McQuaid and Lindsay, 2005) and likelihood that the individual will work (Kain, 1992; Ihlanfeldt and Sjoquist, 1998; Ong and Blumenberg, 1998; Allard and Danziger, 2002; Aslund, Osth and Zenou, 2009). Fafchamps and Wahba (2006) found that children living near or inside urban centres spend more time working in the industry sector than those in more rural locations. Fafchamps and Shilpi (2003) also found that in Nepal, employment in the industry sector increased near local market centres, although not as much as it increased near urban centres.

Child labour is especially enticing for exporting firms from an economic perspective because it is much cheaper than adult labour (Levison, 1996; Anker, Ashraf, and Barge, 1998; Lansky, 2000; Basu, 2003). In jobs that do not require high skill or expertise, adult and child labour are interchangeable and many firms are more inclined to save costs by employing child labourers. This results in exporting firms seeking child labourers, which is an additional pull factor.

Child Labour and Education in Bangladesh

Bangladesh is a useful country for examining the relationship between child labour and education for several reasons. First, child labour remains a considerable problem in Bangladesh. While the International Labour Standards (International Labour Office, 2017) defines child labour as working at age 15 years and under, the Bangladesh government defines child labour as children employed as workers at age 14 years and under (Ministry of Law, Justice and Parliamentary Affairs, 2006; Bangladesh Bureau of Statistics, 2015). In addition, in Bangladesh, children under the age of 14 are allowed to engage in a maximum of 28 hours of domestic work per week without being considered child labourers. As of 2013, there were approximately 3.45 million children under the age of 18 that work, 1.70 million of these are child labourers, which is about 4.3% of the total child population in Bangladesh (Ministry of Law, Justice and Parliamentary Affairs, 2006; Bangladesh Bureau of Statistics, 2015). Of these child labourers, 1.28 million reported working in hazardous labour, which is defined as labour that involves dangerous or unhealthy conditions due to a lack of safety and health precautions that can lead to injury, illness, or death. One of the most common hazardous labour sectors is manufacturing.

Child labour in Bangladesh is largely driven by labour demand from its booming export sector, particularly in textiles. As mentioned above, child labour demand in these industries stems from the relative cost of child and adult labour. Based on data from the most recent Household Income and Expenditure Survey (HIES) conducted in

Bangladesh in 2016, the average monthly wage for individuals that completed secondary school or higher was TK17,000 per month for salaried employees and about TK450 per day for daily wages. For individuals that only completed primary school, the average is much lower, at about TK9,000 per month and TK350 per day. Comparatively, child labourers receive less compensation on average than adults with similar educational attainment. The Child Labour Survey conducted in 2013 showed that on average child labourers only received TK5,800 per month and about 87% of children under the age of 13 received less than TK5,000 (Bangladesh Bureau of Statistics, 2015).

Due, in part, to this cheap supply of labour, Bangladesh has become the world's second largest textile exporter, which has caused dramatic economic growth (Sikder, 2019). The country's yearly Gross Domestic Product (GDP) growth has risen from 5.3% in 2000 to an impressive 7.1% in 2016 and steadily increased each year prior to the COVID-19 pandemic, reaching 8.15% in 2019 (World Bank and OECD, 2020). The industrial sector accounts for about 30% of the country's GDP, which was an increase from about 20% in 2000. Yet, despite these increases in GDP, education rates are not improving and poverty is still a huge concern. In 2016, 24.3% of the country's population was living under the national poverty line (Roser and Ortiz-Ospina, 2013). At the household level, poverty appears to remain a key driver of child labour in Bangladesh. According to the Bangladesh Child Labour Survey (2015), most child labours either dropped out of school or never attended in the first place due to expense and/or to support their family income.

Since Bangladesh ratified the ILO Convention on the Worst Forms of Child Labour in 2001, there have been a number of mandatory regulations and voluntary policy guidelines targeting child labour including the Labour Act of 2006 (amended in 2018), the 2010 National Child Labour Elimination Policy, the 2015 Domestic Workers Protection and Welfare Policy, the Child Labour National Plan of Action (2012–2021) and subsequent Draft: National Plan of Action to Eliminate Child Labour (2020-2025), and the Seventh Five Year Plan (2016-2020), published by the General Economics Division. These regulations and policy guidelines include strategies to eliminate child labour, focusing on child domestic workers. While these policies coincide with overall reductions in child labour since 2001, data are irregular and infrequent, and it is highly likely that hundreds of thousands of children are still at work in Bangladesh today, many in hazardous occupations.[3]

[3] Where the 2003 and 2013 Child Labour Surveys (CLS), reported 7.42 and 3.45 million child laborers, respectively. However, the 2013 CLS reported 1.28 million children working in "hazardous work" a drop from only 1.29 million in 2003. https://mole.portal.gov.bd/sites/default/files/files/mole.portal.gov.bd/project/6038e47e_5792_45f4_8fc0_958f113443f9/NPA.pdf accessed 11-10-2021.

With respect to education, the Bangladesh Constitution of 1972 included Article 17, which guaranteed that "free and compulsory education [would be provided] to all children to such stage as may be determined by law" (The Constitution of the People's Republic of Bangladesh: Free and Compulsory Education, 1972). However, it was not until decades later in the 1990s that policies were implemented to clarify this constitutional statement on who should receive free and compulsory education. In 1990, the United Nations Educational, Scientific and Cultural Organization (UNESCO) held a World Conference on Education for All and presented a framework called Education for All (EFA). During this conference, Bangladesh signed the EFA, and later that year instituted the Compulsory Primary Education Act of 1990 (Ministry of Primary and Mass Education (MoPME), 1990). This Act was officially implemented two years later in 1992, abolishing primary school tuition fees and making primary education compulsory and free to all children. Education policies remained unchanged until 2010, when the Ministry of Education (MoE) introduced The National Education Policy. This outlined new guidelines and strategies, but—most importantly—extended free, compulsory primary education from Class 5 to Class 8 (National Education Policy, 2010).

Education rates in Bangladesh have improved since these policy changes in the 1990s. School enrolment rates are determined by the net enrolment rate, which is the percentage of the total population in a specific age group for a particular level of education that is enrolled in the appropriate education level. Net enrolment rates for primary school made a dramatic increase from about 75% in 1990 to 93.69% in 2005; before levelling off at 90.53% in 2010 (UNESCO Institute for Statistics, 2019; World Bank and UNESCO, 2020) although more recent statistics suggest nearly universal primary enrolment.[4] Chowdhury, Nath, and Choudhury (2002) attribute these relatively high primary school enrolment rates—especially compared to neighbouring countries—to education promotion campaigns and stipend programmes. Primary school enrolment rates in Bangladesh are higher than the average rates in South Asia (UNESCO Institute for Statistics, 2020b).

However, secondary school net enrolment rates in Bangladesh are much lower than primary school rates, mostly due to the high cost of secondary school. Between 2000 and 2012, enrolment rates consistently hovered between 45% and 50%, but have since increased to 65.22% in 2015 (UNESCO Institute for Statistics, 2019). Globally, the average secondary school net enrolment rate in 2016 was 65.82% meaning that Bangladesh is near the global average.

[4] https://www.trade.gov/country-commercial-guides/bangladesh-education accessed 24-08-2022

In addition, many students drop out of school or repeat the same grade. Dropout rates for primary school are about 2.2% and repetition rates are about 5.2%. The drop-out rate increases to 3.75% for lower secondary school, but the repetition rates of lower secondary decrease to about 2.25%. Dropout rates and repetition rates are worse in upper secondary school at about an 11.7% dropout rate and a 38.7% repetition rate. There is also a high percentage of children that do not attend school at all. Of primary-aged children, 13% are not attending school, while 26% of lower secondary school-aged children are not attending school. The Child Labour Survey (2015) analysed attendance rates of working children and found that only 30.9% of working children between the ages of 5 and 17 were attending school. Additionally, about 8% of working children reported having never attended school.

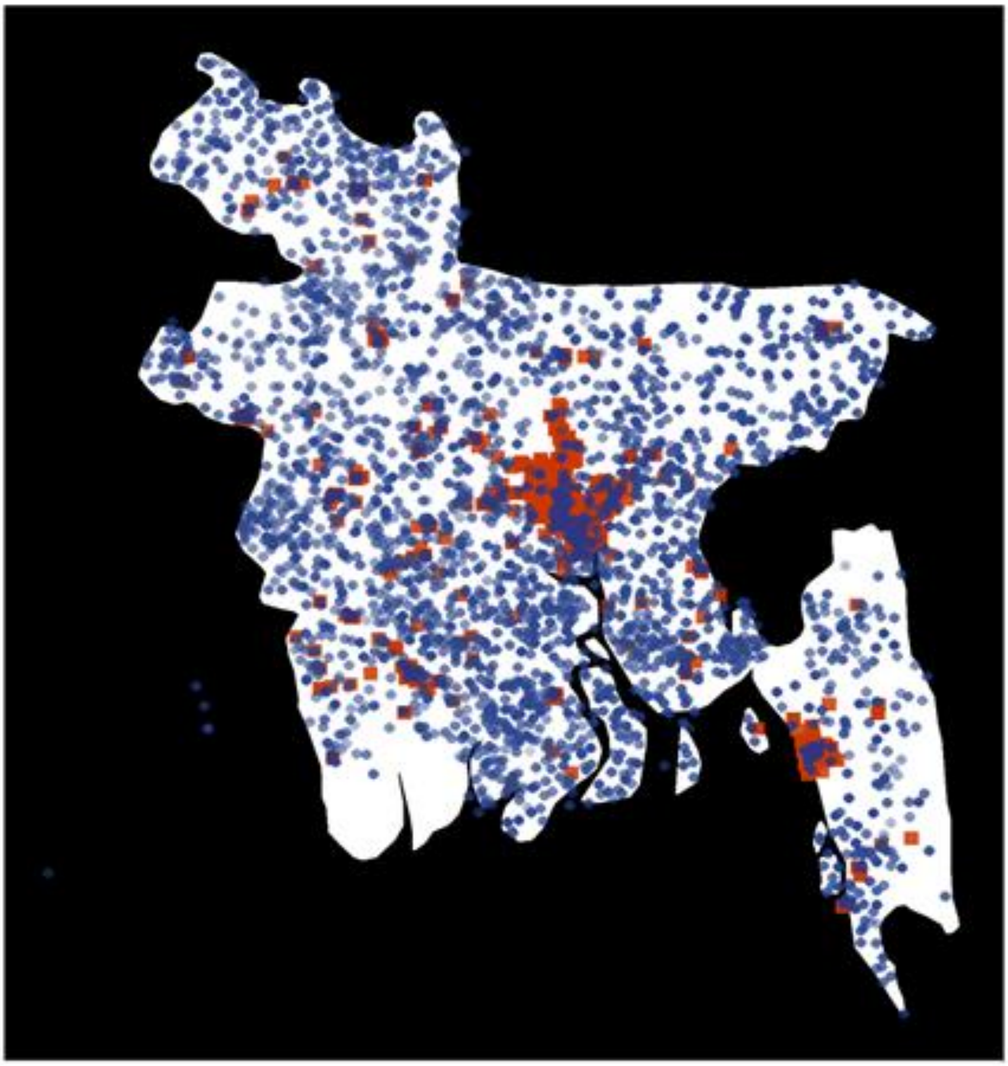
Based on the discussion above, we present two hypotheses. First, we expect that children that are in relative proximity to exporting firms will be less likely to attend school compared to their compatriots who live further away. Second, we also expect that those children in proximity to exporting firms will be more likely to be in full-time employment than those farther away.

Data and Methodology

In order to evaluate these hypotheses, we utilise data from the Bangladesh Household Income and Expenditure Survey (HIES), which is a multi-stage, stratified, random sample survey conducted every few years in Bangladesh by the Bangladesh Bureau of Statistics (BBS) and the World Bank. This survey provides detailed person, household, and community-level data on education, health, employment, housing, agriculture, assets, income, consumption, and expenditures. Specifically, the survey data used for this study was combined from three separate years of the survey: 2005, 2010, and 2016. The HIES 2005 consists of 10,080 sample households and 48,998 individuals. The HIES 2010 consists of 12,240 households and 55,605 individuals. The HIES 2016 consists of 46,080 households and 186,239 individuals. The total number of households is 64,800 with a total of 290,924 individuals. For this study, a sub-sample of school-aged individuals (5 to 19 years), also referenced as students, was identified, totalling 95,395 individuals from 50,254 households.

In order to employ our spatial empirical strategy, we needed to geo-code the HIES surveys. While the surveys did not collect precise geographic information on the respondents, i.e. latitude and longitude coordinates, the survey respondents were coded using the Geocodes from the Bangladesh Bureau of Statistics. These codes included information to the Mouza level – a geographic unit roughly corresponding to a village and more precise than the Union (ADM4) level. In the first step, we collected the full name of the location from the geo-code, i.e. District (ADM1), Zila (ADM2), Upazila/Thana (ADM3), Union (ADM4), and Mouza. We then used the Google geo-code application programming interface (API) to retrieve latitude and longitude coordinates for these location names.[5] We then checked the validity by ensuring that the location coordinates for the Mouza were within the ADM4 units by utilising an ADM4 shapefile.[6] For coordinates that did not meet this criteria, we hand-checked the coordinates using Google Maps and Open Street Maps to identify the Mouza location. In all, for our 95,395 student respondents, we identified 3,080 unique Mouza locations

Map 1: HIES and Firm Locations



Orange squares indicate firm location, blue circles, HIES household survey locations.

From the HIES, we chose three questions to form outcome variables to evaluate the impact the location of exporting firms has on both education and child employment.

[5] https://developers.google.com/maps/documentation/geocoding/overview?_ga=2.188378669.-484578848.1662023371 accessed 01-09-2022

[6] Retrieved from https://gadm.org/download_country_v3.html, accessed 10-10-2020.

The educational outcome variables come from a question about current school attendance, "Are you currently attending school/educational institution?" and a question which captures if children have *completed* any school. For the former variable, we code a binary indicator variable as "1" if the respondent answered "yes". Of our sample, 95,316 students responded to this question with 70,375 (74%) indicating they were currently attending school. This figure is significantly lower than the official enrolment rate cited above. This suggests that while some students may be officially enrolled, they are not actually attending school. For the latter variable, we utilise the question "What was the highest class that you completed" where we code a binary indicator "1" if the respondent answered, "No class passed." Of our sample, 84,685 students that responded to this question with 16,487 (19%) reporting not completing any class or only pre-schooling.

For the labour outcome variable, we are interested in children who are in continuous (rather than seasonal) employment. Accordingly, we create a binary indicator that equals "1" if a child answered "12 months" to the question "How many months did you do this activity in the last 12 months?" which followed on from an answer to the question "What economic activities did you do in the past 12 months?" which indicated that the child had been involved in work over the previous 12 months. From our sample 94,036 children answered the first question, with 5,280 (5.6%) indicating they were involved in full-time work. Each of these questions were identically posed across each wave of the HIES survey.

Our primary explanatory variable comes from a novel geo-referenced directory of the population of 11,124 exporting firms sourced from the Bangladesh Export Promotion Bureau. This directory was received as a scanned PDF file and contained the name and address information for each firm. This data was first extracted into a machine-readable format and was again geo-coded with Google's geo-coding API. The API was run twice, once using all information available for a given entry and then with the information of the most specific geographic unit in the address (mouza, city, district, division). The two coding methods were then compared and, where discrepancies existed, they were checked and reconciled by trained research assistants. These efforts ultimately yielded specific geo-location information for 11,115 firms (99.9%). The directory also contained information regarding the firm sector. The sector with the largest number of firms was the ready-made garment sector with 8,297 (75%) firms. Other sectors included software with 667 (6%) firms, food-related products with 523 (5%), handicrafts with 441 (4%) firms, and 1,187 (10%) in other sectors. Map 1 provides a visual of the geographic distributions of both the exporting firms, represented by the orange squares, and child HIES respondent locations from the HIES data, represented by the blue circles. The map illustrates the high concentration of firms around Dhaka, Chittagong, and Khulna but also shows that there is still a considerable number of firms dispersed throughout the entire country as well as the geographically representative HIES survey locations. Full summary statistics for all variables are available in the appendix.

Estimation Approach

To evaluate our hypotheses, we utilise the spatial nature of our data to employ a matching approach as our data is not panel at the individual level. Likewise, unfortunately, our firm directory does not contain temporal information regarding the firms, that is, we do not have information on when firms were established. The lack of temporal information mean that we cannot employ a difference-in-difference like estimator wherein we might compare respondents near an "active" firm (i.e. one that is operating at the time of the survey) to respondents at sites where a firm is not yet, but will be, operating ("inactive"), as first used in Knutsen et el. (2017) but since widely employed in spatial studies.

Beyond this, the spatial location of exporting firms is not random, and indeed may be biased when considered with other individual-level confounders that might influence school attendance or work. Accordingly, as our primary approach, we use a Propensity Score Matching (PSM) technique. PSM has been used in previous studies in Bangladesh which utilises cross-sectional household survey information, including in a study on the adoption of agricultural technology (Mendola, 2007) and is a well-established approach for evaluating (pooled) cross-section observational data. Matching techniques are employed when treatment has not been randomly assigned and therefore confounders may differ between the "treatment" and "control" groups resulting in bias which hinders accurate identification of a treatment effect. If "treated" units are instead matched with a control group on the observed confounders, then the conditional independence assumption holds and any differences in outcome can be attributed to the treatment. When cohorts need to be matched on a large number of confounders, matching techniques face the "curse of dimensionality" and propensity scores, i.e. the probability of participating in a treatment program based on a vector of observed participant characteristic (Caliendo and Kopeinig 2008). Formally, this approach was described by Rosenbaum and Rubin (1983) where selection into treatment $T=1$, for individual i, is based on some vector of observed covariates, X:

$$\Pr\,(T_i=1 \mid X_i)$$

and then where the average treatment effect (ATE) is given by the conventional difference in mean outcomes, Y, between the treated (=1) and the control (=0) conditional on the observed covariate selection:

$$E(Y_1\text{-}Y_0 \mid T=1) = E(Y_1 \mid T=1) - E(Y_0 \mid T=1)$$

We estimate the ATE rather than the average treatment effect of the treated (ATT) as there is no delineation or selection in our design between those who were eligible for treatment and those who received treatment. All units in the relative proximity of the firm are considered treated. Five observed confounders that may result in bias on our educational outcomes are gender, age, household wealth, survey year and location. We proxy household wealth with household access to mobile phones, the internet, and electricity, while we use the household survey coordinates for location. For the employment outcome, we drop the household wealth covariates as these are potentially correlated with post-treatment outcome. The respective covariates are used to generate the propensity scores which are then used to balance the cohorts and retrieve an estimate of the average treatment effect. We use Mahalanobis matching (1936) with Abadie-Imbens (2004) standard errors in our models.

Table 1: Treatment Percentiles and Distance to Firms (Excluding Cities)

Percentile	Distance Treated (N)	Distance Control (N)
10/90	<0.49 km (10,926)	> 34.19 km (9,523)
15/85	<1.11 km (14,330)	> 29.59 km (14,298)
25/75	<4.75 km (23,872)	>22.75 km (23,845)
50/50	<12.88 km (47,713)	>12.89 km (47,682)

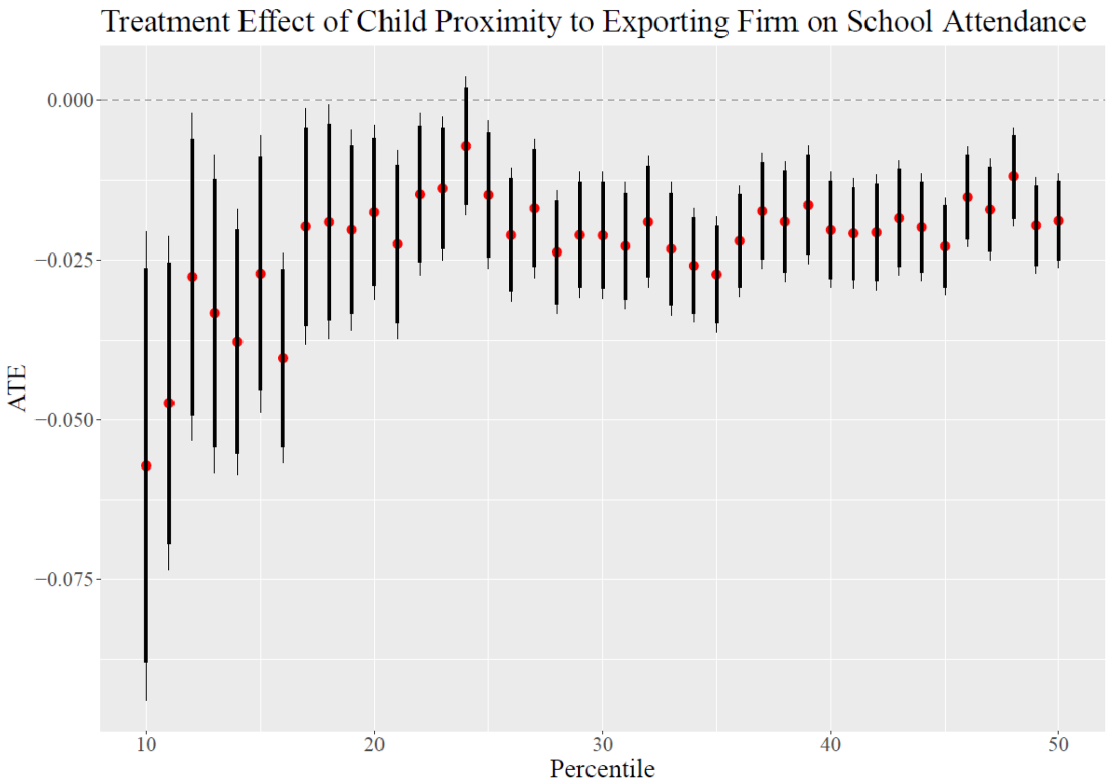
Number of observations given in parentheses

Treatment status is assigned based on the proximity to the nearest exporting firm. In order to generate this variable, we first determined the Euclidean distance between each survey respondent and the nearest exporting firm. We then assigned treatment to the respondents that are closer to the exporting firm. As we do not expect a discrete cut-off for the spatial effect, we run a range of models where the treatment groups are assigned by percentile distance. Assigning “too many” households to treatment status risks attenuation bias, however assigning “too few” households potentially increases noise due to the small number of treated units. The whole sample is employed when assigning treatment at the median, but then only mirrored subsets are assigned when using other percentiles. For instance, when assigning the treated cohort as only those respondents within the 25th percentile of distance, the control cohort are only respondents in the 75th percentile and above, where the remaining respondents are excluded from the analysis. Percentiles and the respective cut-off distances for the treated and control cohorts are given in Table 1 along with the number of observations in each corresponding sample. Post-matching balance statistics and diagnostics are available in Appendix I for the 15th percentile treatment sample.

Results

As we run each outcome model over all percentiles from the 10th to the 50th and presenting the results in tabular form would be unfeasible, we instead present our findings in a series of graphs which plot the results. Figure 1 presents the result of firm proximity to self-reported school attendance. As seen there, and as expected, when assigning treatment status at a lower percentile, the magnitude of results is larger, but the estimates are considerably nosier as there are far fewer treated children. However, in all treatment percentile samples the result is in the expected direction (negative) and is also significant at the $p<0.05$ level for nearly all samples.

Figure 1: ATE of Firm Proximity on School Attendance

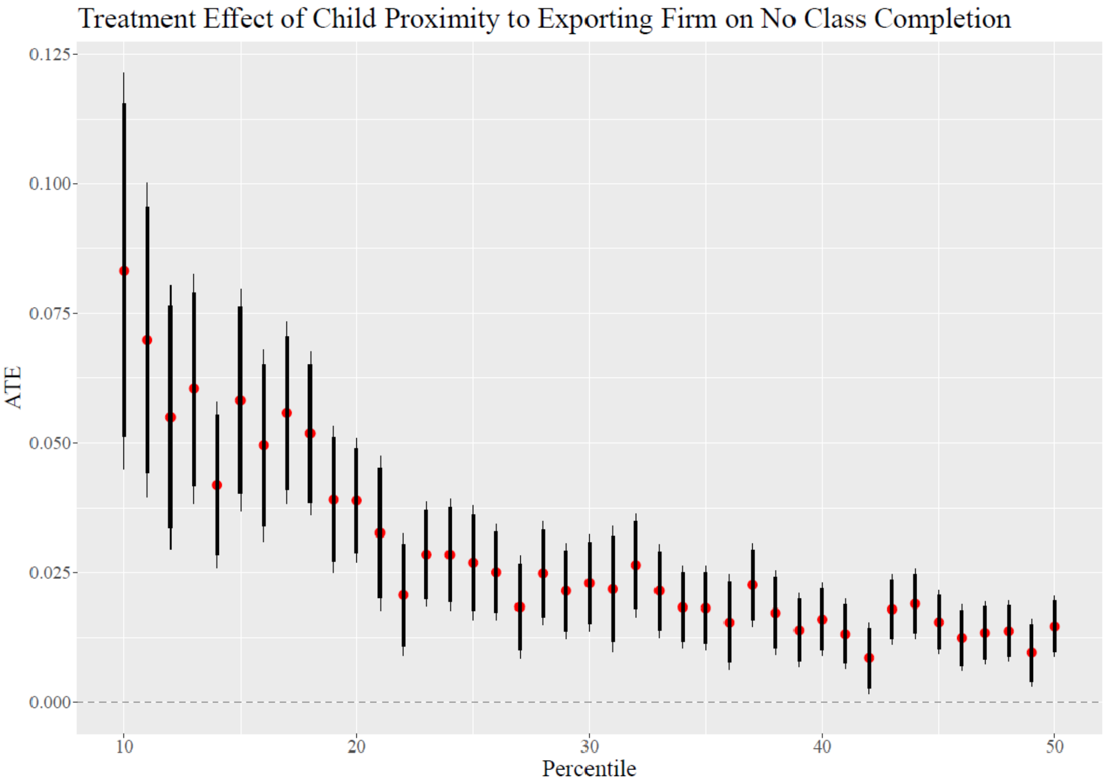


Average treatment effect given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

The magnitude of the impact varies between -0.057 and -0.012, or between a 5.7% (10th percentile) and 1.2% (48th percentile) reduction in reported school attendance. The probability of non-attendance in the 10th percentile sample is 29.65%, while it is 26.23% so the effect of proximity on non-attendance is equivalent to between roughly 4.5% and 19% of the underlying sample probabilities.

Similar results are found when considering children who reported never having attended school in Figure 2. Once again, we see larger, but noisier, estimates at the lower percentiles with smaller samples and fewer treated children. The results are again consistently in the expected direction (positive) and statistically significant at the p<0.05 level for all treatment percentile samples. The magnitude of the effect once again ranges substantially based on the treatment percentile, from 0.083 in the 10th percentile sample to 0.009 in the 42nd percentile sample. As the sample probability of never attending school is roughly 21% at the 10th percentile, and 19% at the 42nd percentile, this implies an effect that is equivalent to anywhere between 4.6% and 40% of the respective underlying sample probability.

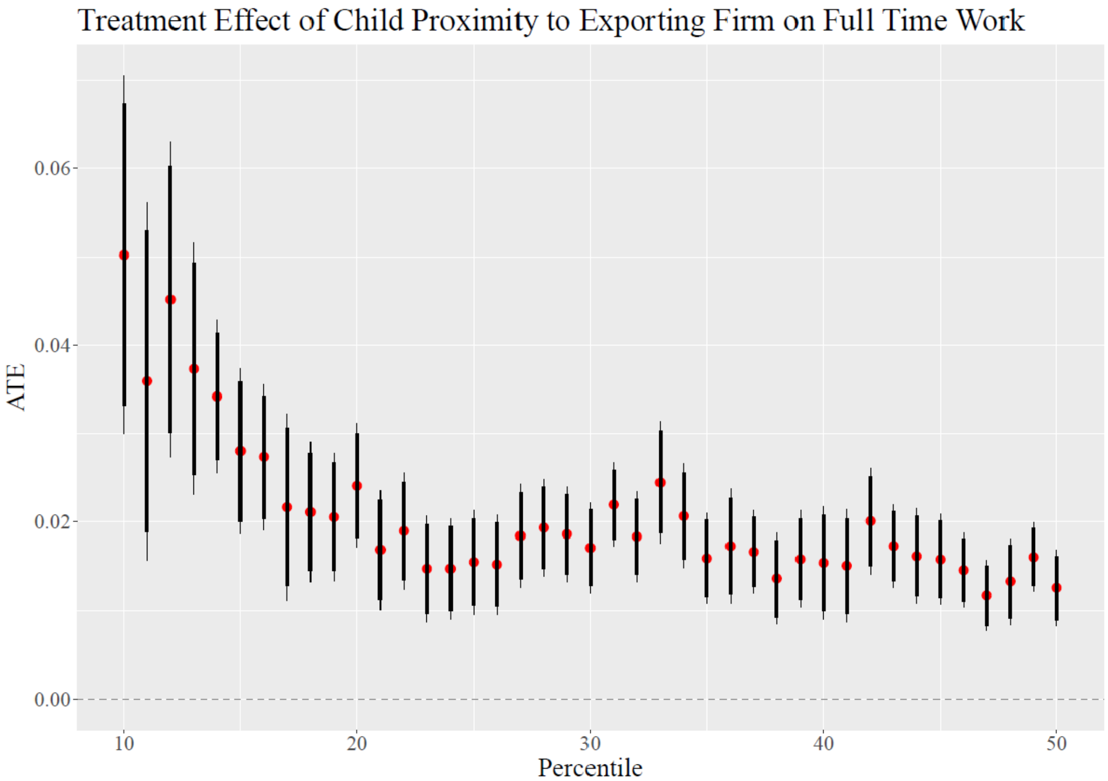
Figure 2: ATE of Firm Proximity on No Class Completion



Average treatment effect given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Finally, we turn to the impact of firm proximity on the likelihood that children report working full-time in Figure 3. As with the education models, our hypothesis is broadly supported, with an impact in the expected direction (positive) and statistically significant at the p<0.05 level for models at all treatment percentages. Also, like school attendance models, at lower percentiles the models are noisier. The magnitude of the impact again varies from 0.050 at the 5th percentile to 0.012 in the 47th percentile treatment. However, unlike the school attendance models, the baseline probability of working in the sample is much lower, at around 5%. Accordingly, the treatment effect ranges from about 25% to 100% of this underlying probability.

Figure 3: ATE of Firm Proximity on Full Time Work



Average treatment effect given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Robustness

As discussed above, our empirical strategy relies on *spatial* identification, namely the proximity between child survey respondents and exporting firms. While this approach is a useful method for testing our hypotheses, it is potentially problematic in geographically concentrated urban areas which also have a high number of firms, as nearly all children will be relatively proximate to a firm, especially compared to rural areas. While we include location in our matching models above, as a first robustness check we exclude the three main metropolitan areas (Dhaka, Chittagong and Khulna – "cities") from our sample. This exclusion leaves us with a sample population of 80,871 individuals aged 5 to 19 years old. As shown in figures AII.1, AII.5 and AII.9 in Appendix II, while the effect estimates are noisier than when we include the cities, they are all substantively consistent with the results and significant at the $p<0.05$ level for a wide many of the treatment percentiles.

In our second and third set of robustness checks, we use ordinary least squares (OLS) and logit models, respectively, where we include our matching covariates directly into the models as controls. In the absence of matching, these models are likely to be biased, but using these models allows us to cluster the standards errors at the ADM4 level. These results are presented in Appendix II in figures 2, 3, 6, 7, 10 and 11. While the presence of attenuation bias is more noticeable in these models, with many of the estimates being no longer different from zero at the $p<0.05$ level for higher treatment percentiles, these models are still substantively consistent with our main results and the estimates are statistically significant at the lower treatment percentiles.

While our data is not panel at the respondent level, in our final robustness check we take advantage of the fact that our survey data does have panel observations at the ADM4 level. As such, we collapse our individual-level responses at the mean by ADM4 unit for a panel of ADM4 observations. We assign the treatment variable as equal to "1" if more than 50% of the respondents in the ADM4 unit were considered proximate to an exporting firm at the respective treatment level. We again estimate these models using OLS with standard errors clustered at the ADM4 level. As shown in figures AII.4, AII.8 and AII.12, these results are strongly consistent with our main individual-level results and the effect estimates are significant at the $p<0.05$ level for all three outcome variables across nearly the entire range of treatment percentiles.

Discussion and Conclusions

The overall aim of this study was to analyse the impact of the proximity of exporting firms on a child's likelihood to attend school or work. Bangladesh has experienced a massive increase in the number of exporting firms in the last few years, which has led to a dramatic increase in GDP. Typically, an increase of GDP correlates with an increase of education rates; however, education rates in Bangladesh stagnated in the 2010s. The two main reasons a child seeks work are because of poverty and proximity to employment opportunities. The purpose of this study was to show that, regardless of external factors, proximity to an exporting firm has an impact on child labour and education rates.

The results presented in this study provide a new perspective of the effects of the proximity to exporting firms on child labour and education rates in Bangladesh. Although Bangladesh has a relatively high enrolment rate, the actual school attendance rate is comparatively lower. The results from this study show that students living closer to an exporting firm were more likely on average to report not currently attending school and also never having completed any grade level. Failure to attend school affects students' ability to pass classes.

The Child Labour Survey (2015) found that low attendance and completion rates are due to students being unable to afford the cost of school and engagement in child labour. That survey discovered that 61.1% of child labourers were not attending school. These insights are consistent with the results of this study. Students living closer to an exporting firm were more likely on average to report working full time. In general, samples which assigned the firm proximity "treatment" at a closer distance yielded larger average treatment effects, a result that is both consistent with our theoretical expectation and the presence of attenuation bias in spatial approaches were the strength of the treatment effect dissipates over distance.

This study employed propensity score matching (PSM) techniques to evaluate these relationships. These approaches can help mitigate bias when attempting to identify a treatment effect with cross-section, observational data. However, it should be noted that these methods rely on the conditional independence assumption which, in turn, relies on the selection bias originating from *observed* covariates. As such, these approaches can be limited when treatment selection occurs on *unobservable* covariates, and we cannot rule that out entirely. Further studies which employ spatial-*temporal* observations approaches, and or randomized control trials (RCTs) would be useful to further confirm the findings in this manuscript.

Several studies have shown that the main factor pushing children to work rather than attend school is poverty. This study shows that the impact of the export sector is not merely concentrated in urban centres, but in any location that has an exporting firm. As other developing countries seek to emulate Bangladesh's export-oriented development success, the results in this paper suggest that such gains can come at a cost to childhood education and potentially risk pushing (some) children out of school and into work.

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Appendix I: Descriptive Statistics

Table A.1 Descriptive Statistics

Variable	Source	Mean	Min	Max	N
School Attendance	HIES (2005, 2010, 2016)	0.74	0	1	95,316
No Class Completion	HIES (2005, 2010, 2016)	0.19	0	1	84,685
Full Time Work	HIES (2005, 2010, 2016)	0.06	0	1	94,036
Latitude	HIES (2005, 2010, 2016)	23.81	20.77	26.52	95,395
Longitude	HIES (2005, 2010, 2016)	90.23	87.51	92.56	95,395
Male	HIES (2005, 2010, 2016)	0.52	0	1	95,395
Age	HIES (2005, 2010, 2016)	11.75	5	19	95,395
Electricity	HIES (2005, 2010, 2016)	0.21	0	1	95,395
Internet	HIES (2005, 2010, 2016)	0.004	0	1	95,395
Mobile Phone	HIES (2005, 2010, 2016)	0.27	0	1	95,395

Table A.2 Post-matching Balance Statistics (15th Treatment Percentile)

Covariate balance summary

	Raw	Matched
Number of obs =	25,027	50,054
Treated obs =	12,414	25,027
Control obs =	12,613	25,027

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
lat	-.5916636	.1109662	.4018154	.5535451
lon	-.1533283	-.1200439	.5116452	.5049624
male	-.0284209	.0223618	1.000397	.9994042
age	.1011003	-.0187192	1.03346	.9952928
electricity	.641107	.0931547	2.05695	1.101942
internet	.141065	.0269438	11.40408	1.412025
mobile	.2932636	-.025295	1.267711	.9811363
year				
2010	.1142055	.1938456	1.153021	1.203079
2016	-.520997	-.2237352	1.171977	1.04301

Figure AI.1 Kernel Density Plot for Raw and Balanced Data (15th Percentile)

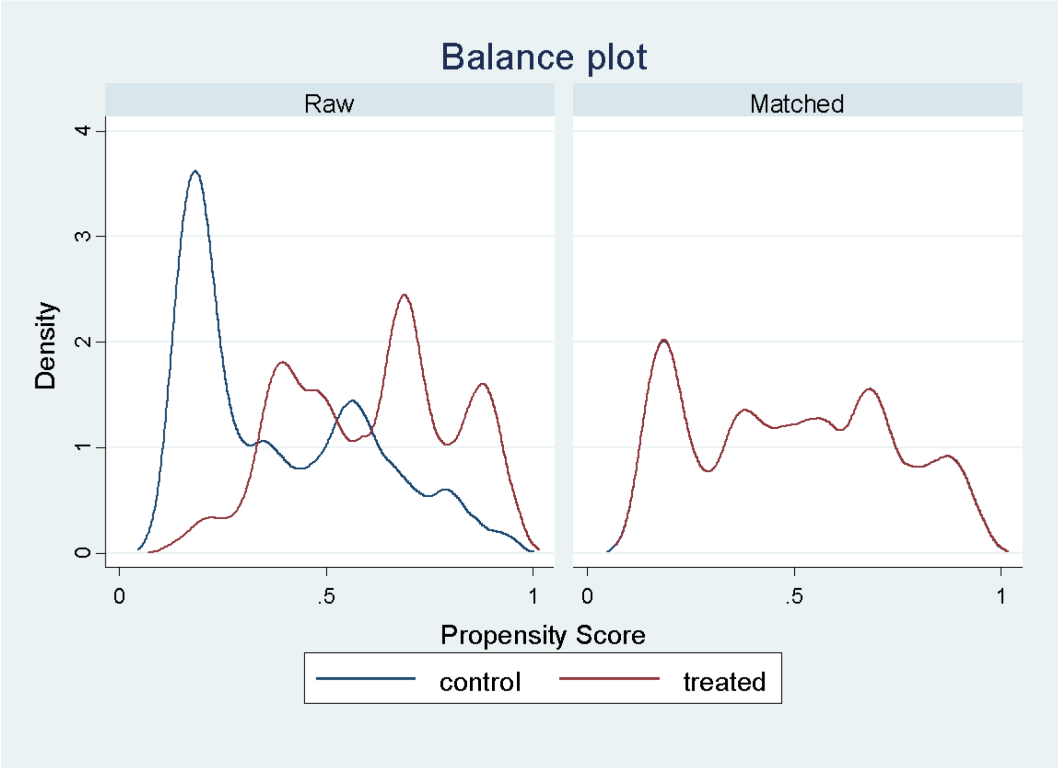
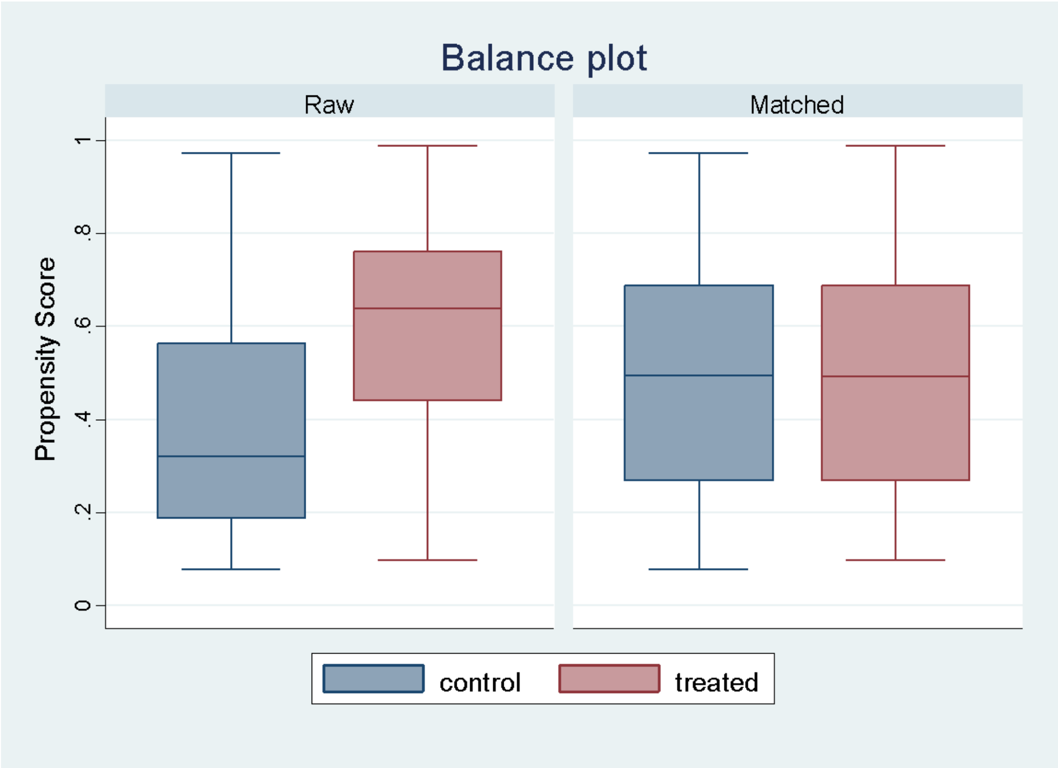
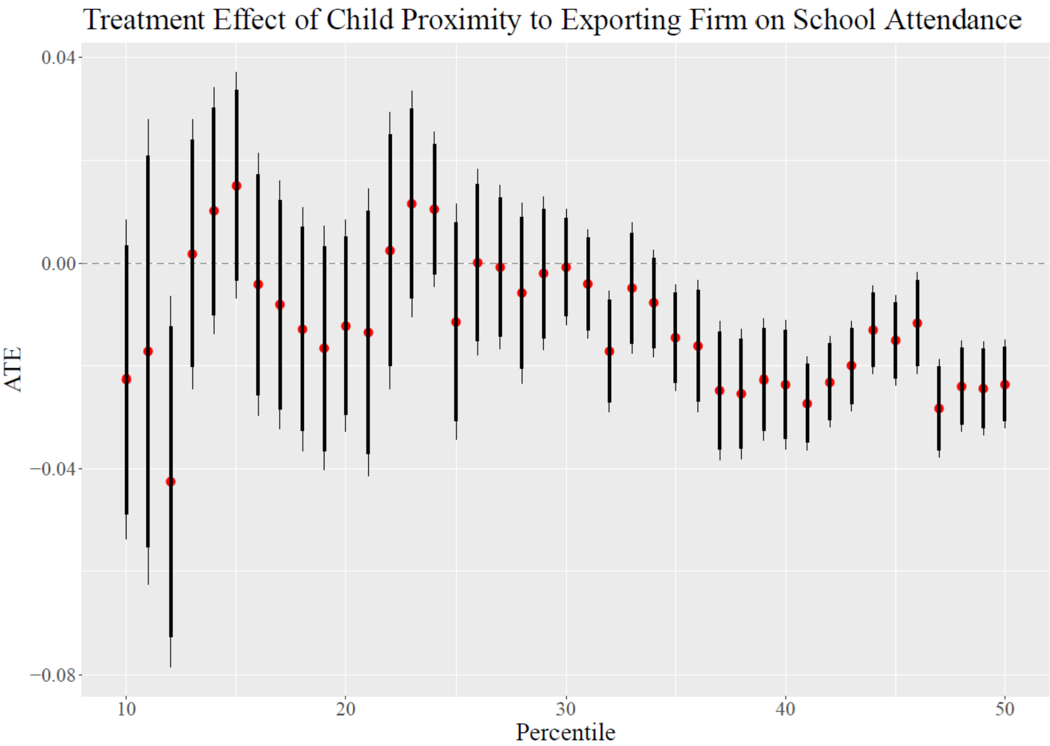


Figure AI.2 Propensity Score Box Plot (15th Percentile)



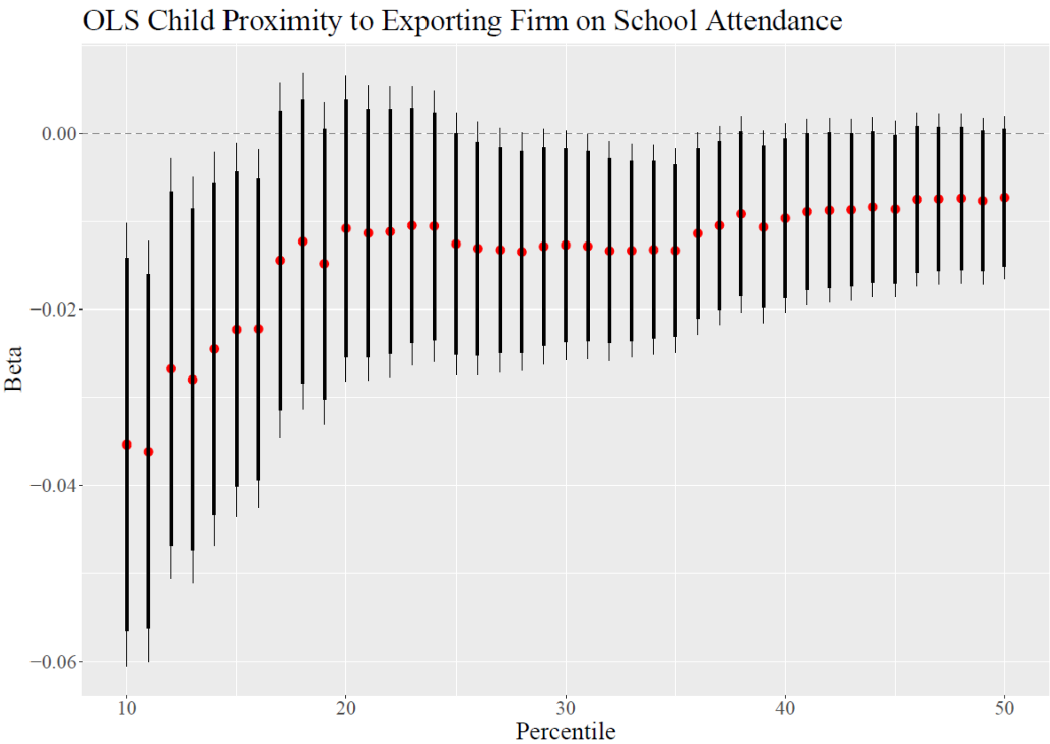
Appendix II: Robustness Checks

Figure AII.1: ATE of Firm Proximity on School Attendance (Exclude Cities)



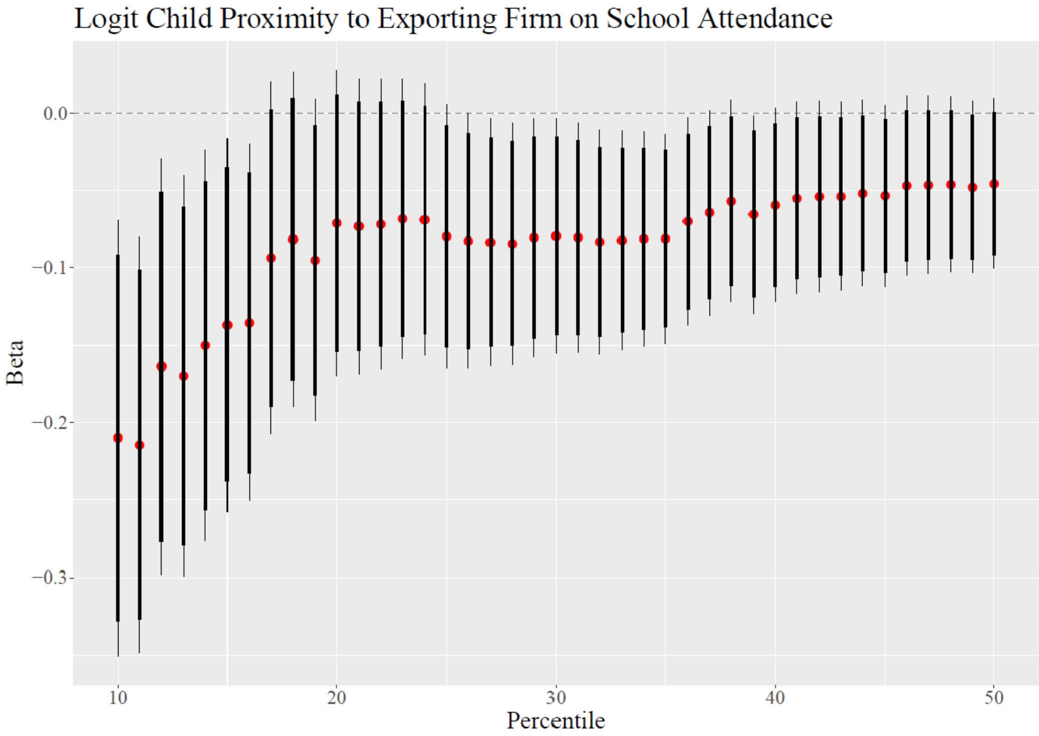
Average treatment effect given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.2: Firm Proximity on School Attendance (OLS)



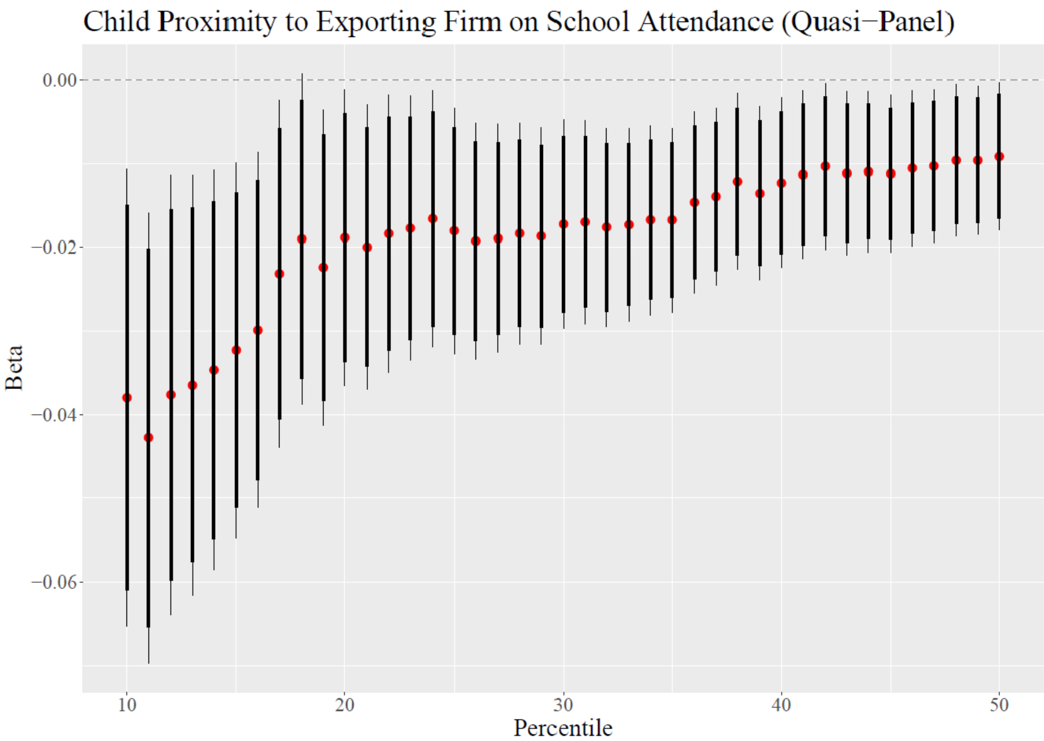
“Treatment” beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.3: Firm Proximity on School Attendance (Logit)



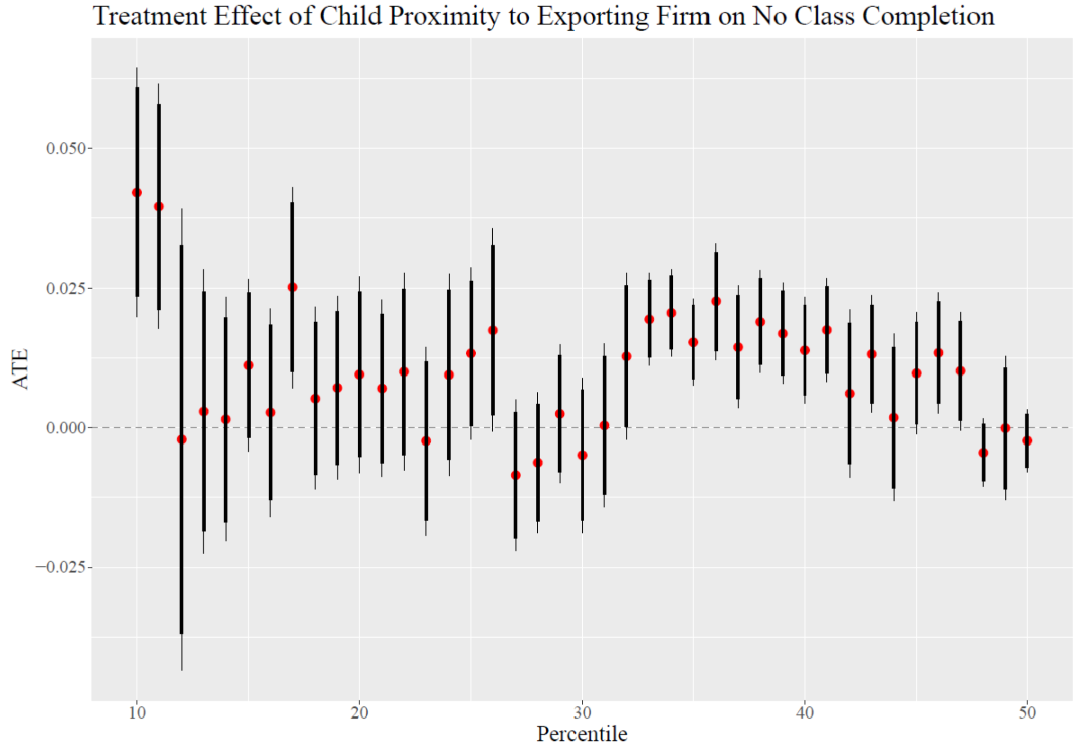
"Treatment" beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.4: Firm Proximity on School Attendance (Quasi-Panel)



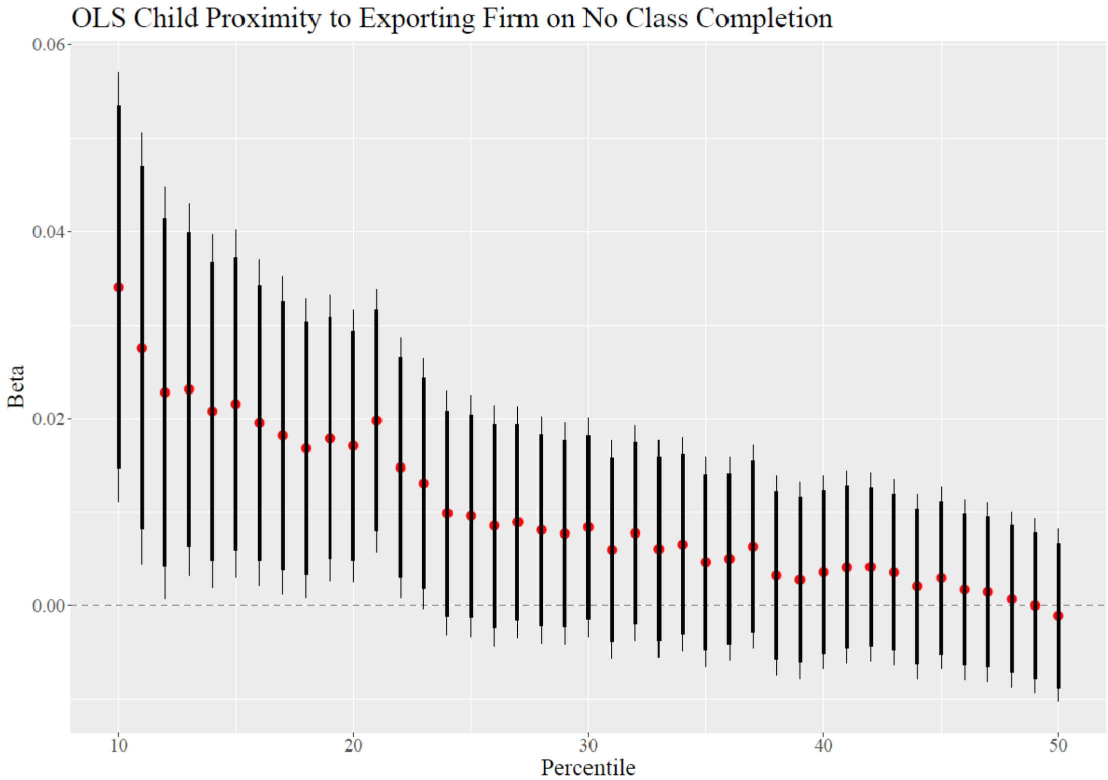
"Treatment" beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis

Figure AII.5: ATE of Firm Proximity on No Class Completion (Excluding Cities)



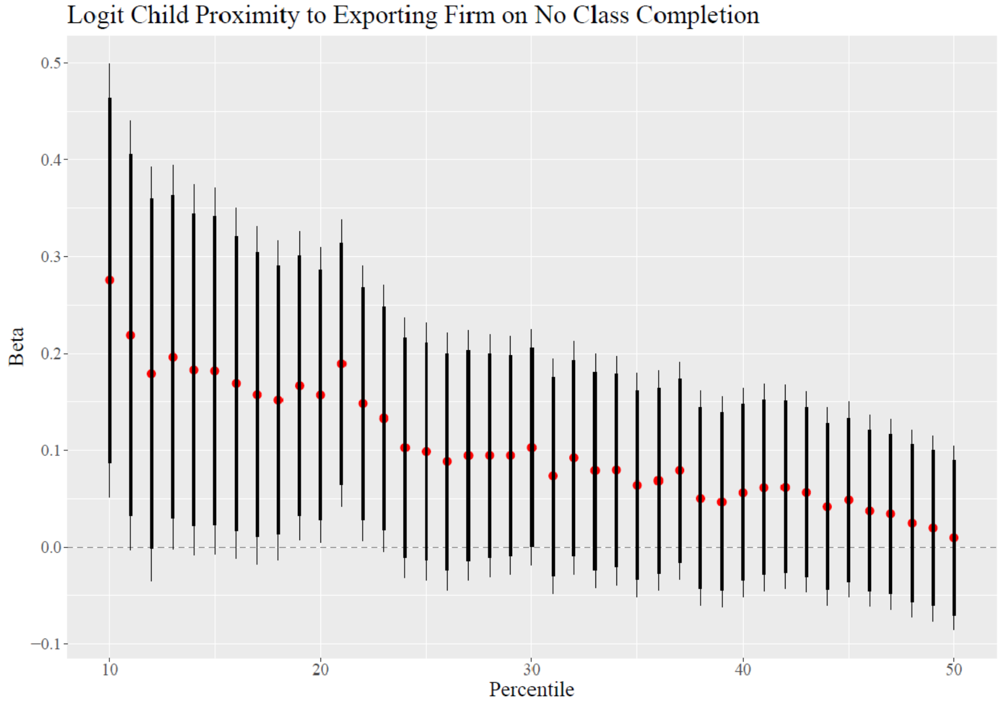
Average treatment effect given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.6: Beta of Firm Proximity on No Class Completion (OLS)



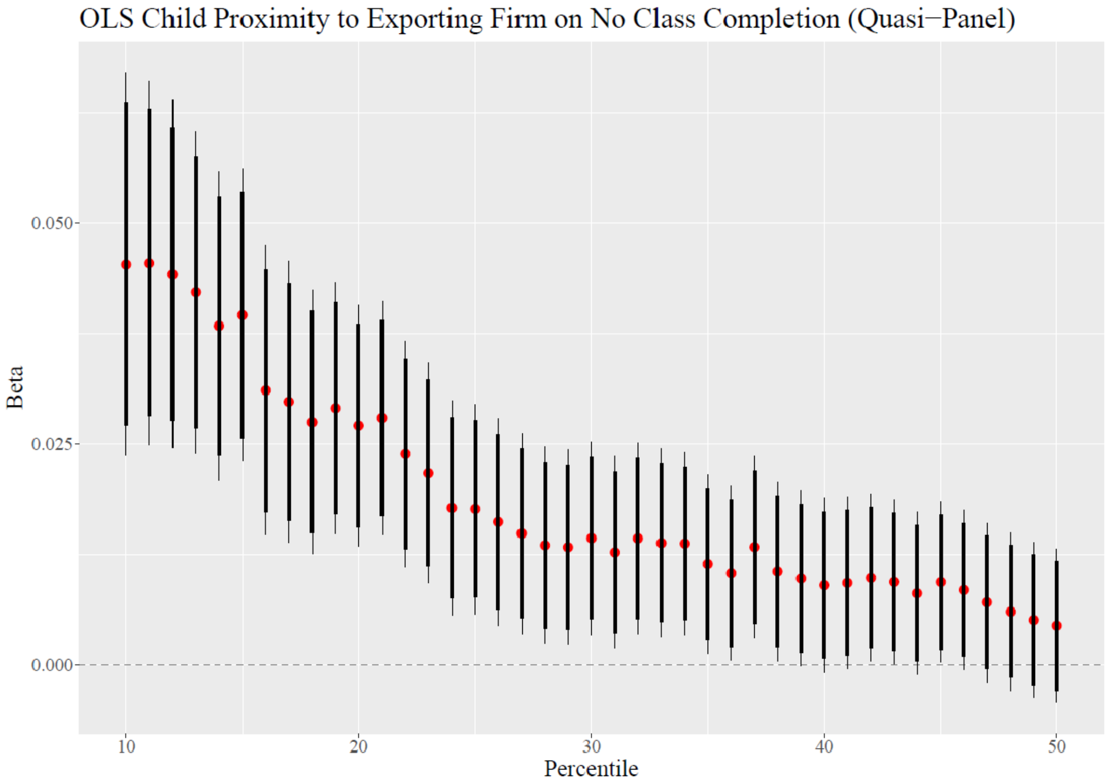
“Treatment” beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.7: Beta of Firm Proximity on Never Attending School (Logit)



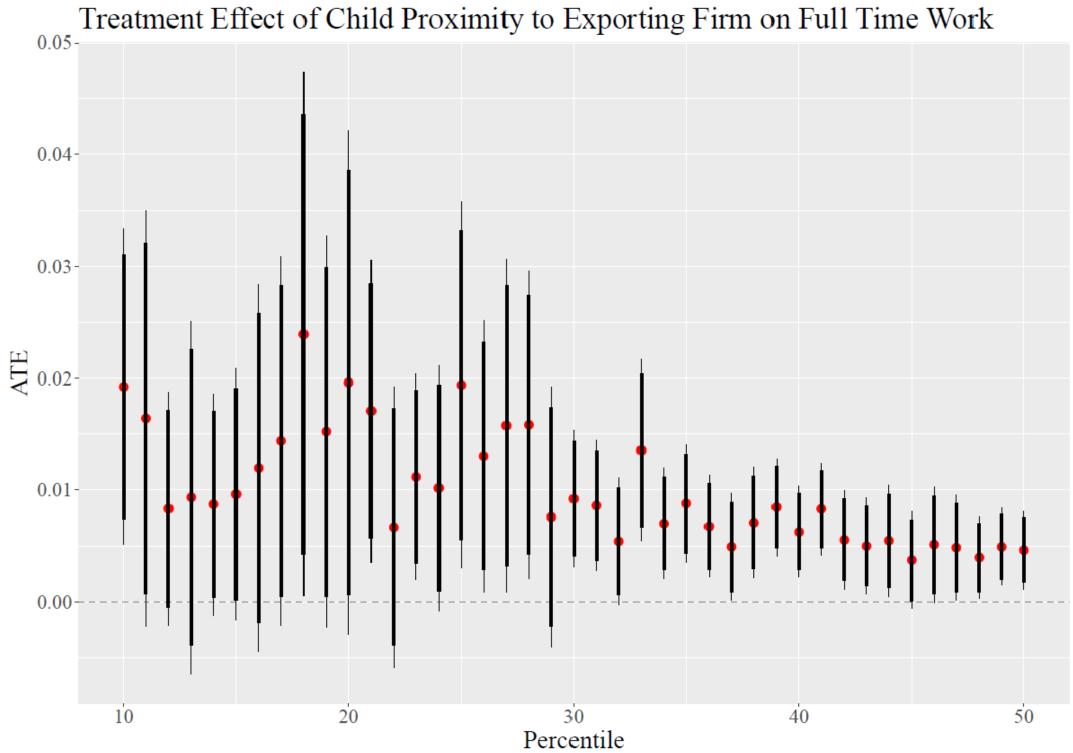
"Treatment" beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.8: Beta of Firm Proximity on Never Attending School (Quasi-Panel)



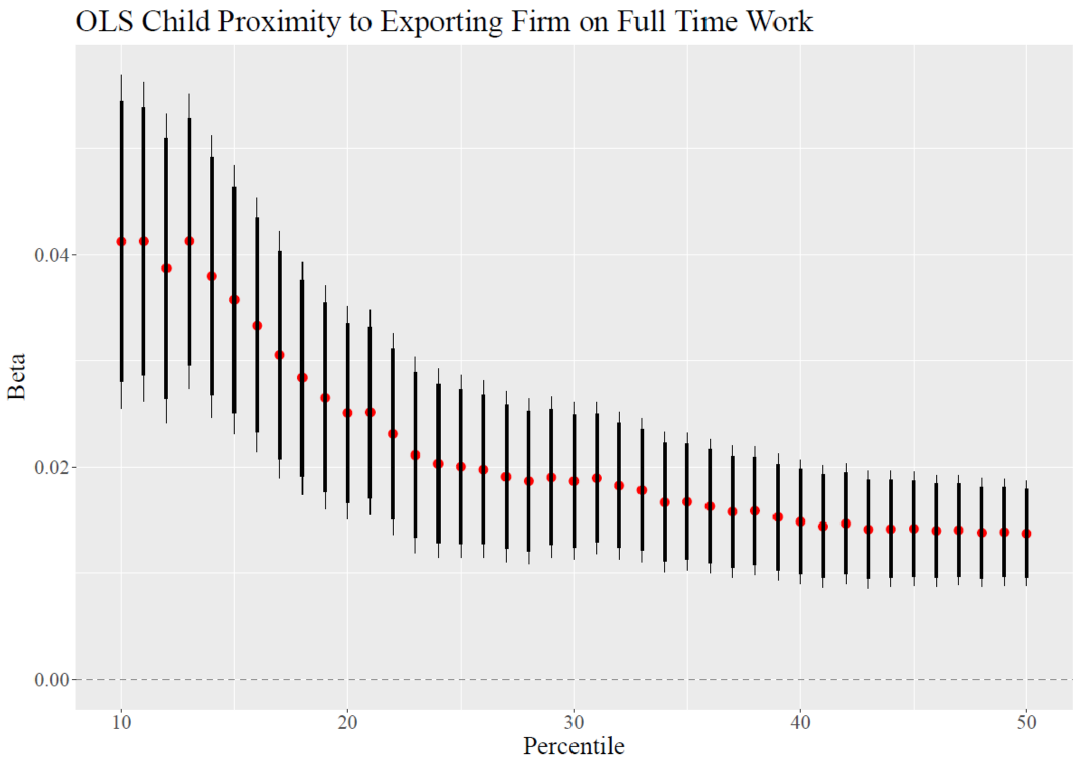
"Treatment" beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.9: ATE of Firm Proximity on Full Time Work (Exclude Cities)



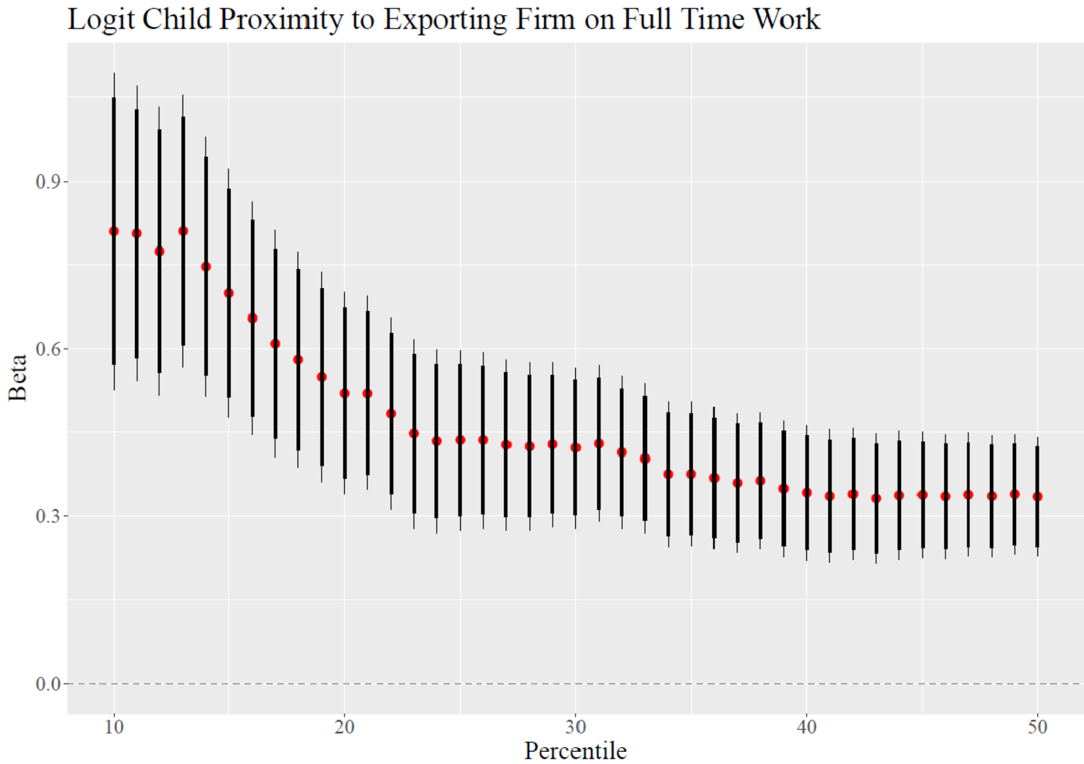
Average treatment effect given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.10: Beta of Firm Proximity on Full Time Work (OLS)



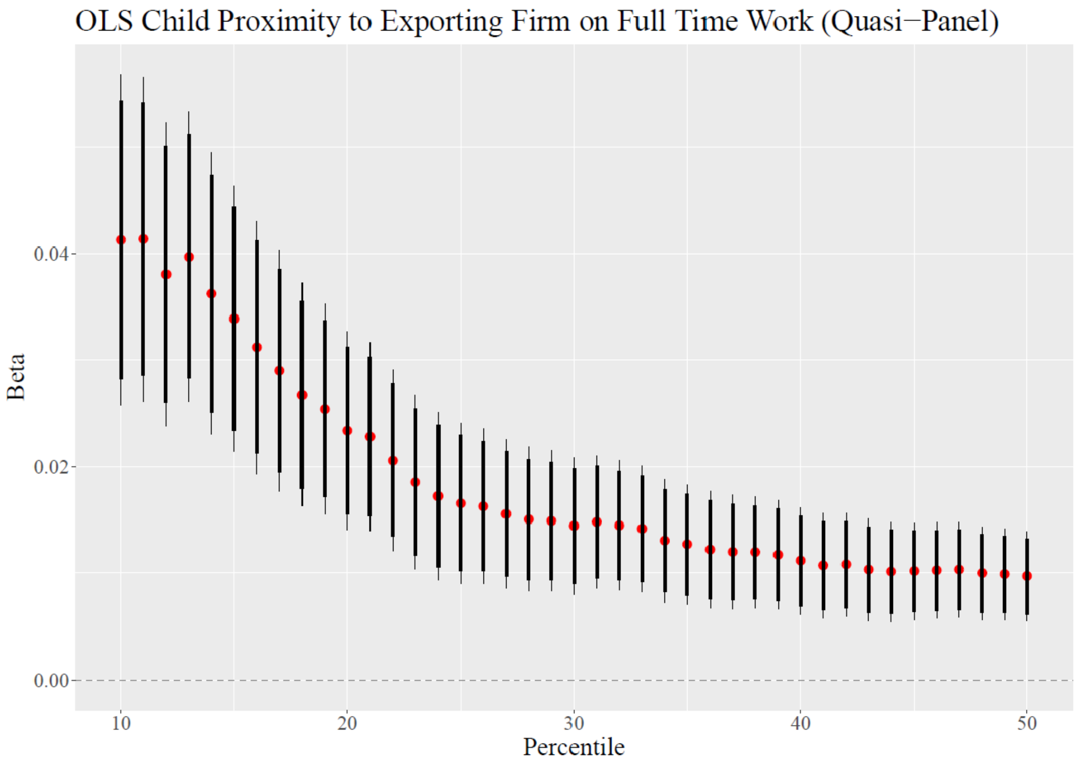
“Treatment” beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.11: Beta of Firm Proximity on Full Time Work (Logit)



"Treatment" beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Figure AII.12 Beta of Firm Proximity on Full Time Work (Quasi-Panel)



"Treatment" beta given by red dot with 90% (thick) and 95% (thin) confidence intervals. Distance percentile for treatment assignment on x-axis.

Table AII.1: Treatment Percentiles and Distance to Firms (Excluding Cities)

Percentile	Distance Treated (N)	Distance Control (N)
10/90	<1.53 km (8,168)	>36.62 km (8,153)
15/85	<3.75 km (12,258)	>31.14 km (12,245)
25/75	<7.13 km (20,441)	>24.20 km (20,395)
50/50	<14.75 km (40,840)	>14.75 km (40,800)

Number of observations given in parentheses