The impact of parents' cognitive and noncognitive factors on their children's human capital development: Evidence from a unique dataset

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Abstract

While the previous literature considers parents as central in shaping their children's human capital, our understanding of the role parents' cognitive and noncognitive factors play in this process is limited. We conduct parent-child linked surveys in Pakistan and identify parental cognitive and noncognitive factors as well as children's cognitive ability. We append this information with the child's work and schooling outcomes obtained from surveys, school ledgers, and administrative data. Our results indicate that children's schooling and work outcomes are strongly affected by their parent's cognitive ability rather than their *own* ability. Moreover, noncognitive parental factors have an even stronger effect.

Key words: Child work, child schooling, education, human capital, cognitive ability, noncognitive factors.
O15, I25, J13, J22

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1 Introduction

According to theoretical work pioneered by Becker and Tomes (1979, 1986), human capital development is determined by a child's exogenous endowment (such as ability and parental human capital), parental investment in human capital, and government spending on education. More recently, this work has expanded in several directions allowing a child's endowment to be directly affected by parental decisions and for human capital to be multi-dimensional and therefore not limited simply to cognitive ability but including noncognitive factors (Cunha et al., 2005; Heckman, 2008).[1] However, there remain two essential gaps in this literature.

First, while the existing analysis demonstrates that both cognitive and noncognitive factors are important for one's *own* schooling and labor market outcomes (e.g., Herrnstein and Murray, 1994; Murnane et al., 1995; Heckman et al., 2006; Borghans et al., 2008; Kniesner and Ter Weel, 2008), it views parental human capital to be unidimensional. In particular, the effect of parents' noncognitive factors (in addition to cognitive factors) on their investment in their child's human capital is missing from the literature.[2] Second, the literature to date has concentrated on developed countries. However, human capital development is especially relevant for developing economies since it is directly related to economic growth (Schultz, 1961). Moreover, in developing countries, parental decisions are multi-dimensional due to the continued practice of routinely engaging children in paid or unpaid work (economic activity) in family enterprises or elsewhere and in household chores.[3] Parental decisions in developing countries therefore often encompass not only investment in their children through schooling but also divestment as a result of engaging their young children in various work activities that interferes with their children's human capital development.[4]

In this paper, we complement and contribute to the broad literature on human capital development by filling these essential gaps. In particular, we study how parental cognitive and noncognitive factors influence children's work and schooling outcomes in the context of developing countries.

A parent's cognitive ability may be important in child's schooling and work decisions because more able parents may better grasp the need to invest in their child's education relative to having

[1] This research establishes that children's social and economic outcomes are affected by their parental investments in human capital made at the early stage of their life cycle (Keane and Wolpin, 1997; Huggett et al., 2011), establishing that the variability in lifetime earnings is significantly determined by attributes developed in early life, where human capital is acquired during childhood investment (Heckman, 2008).

[2] See Lareau (2011); Doepke and Zilibotti (2017) for the importance of parenting skills and style for children's economic success.

[3] Putnick and Bornstein (2016) classifies children's work into a few major categories; however, some studies (Guarcello et al., 2005) currently aim to construct a fixed definition of child work, but this literature is nascent.

[4] In developing economies, the human capital development process is also impeded by various health issues that deprive children from full cognitive development. In general, Currie and Stabile (2003); Attanasio et al. (2015) discuss the importance of family background and health outcomes.

a child work early in life.[5] The decision to invest in education rather than having children work may also be influenced by noncognitive factors. To guide our data collection and empirical analysis for noncognitive factors, we invoke theories of child labor that routinely have intertemporal investment (i.e., time discounting) and parental altruism as common features (Baland and Robinson, 2000; Ranjan, 2001; Dessy and Knowles, 2008; Kumar, 2013), and models of human capital and wealth accumulation (Doepke and Zilibotti, 2008; Dohmen et al., 2015) that feature time discounting and risk aversion.[6] Our work therefore investigates how parents' decision to invest in education rather than having children work is influenced by cognitive and noncognitive factors, such as aversion toward risk (risk aversion), impatience (time discounting), and parents' selfless concern for their child's wellbeing (altruism).

We use novel and rich data that we collected by conducting surveys in Pakistan (in the rural-urban belt in Kasur) with children in grade 5 (median age of 12 years) and their parents.[7] We merge the data for each parent-child pair with school and administrative records. Geographically, we focus our attention on Pakistan because of its poor educational outcomes and the issue of persistent intergenerational social mobility, providing us with an environment that is especially relevant for our question and equally relevant for other developing economies that face similar issues.[8]

Specifically, we collect information on parents' and children's cognitive ability by conducting a standard Raven's test and colored Raven's test, respectively. The child's ability is also a crucial additional control because it is likely to influence their parents' decisions: parents may invest more in more able children to achieve greater returns to investment or invest more in less able children to achieve equity across their children, holding the parent's ability constant (Becker, 1981). This factor is important for our purposes since there is a genetic link between the parent's cognitive ability and the child's cognitive ability[9], so if one does not control for the child's cognitive ability, it is difficult to know if parents with high cognitive ability make investments in their children simply because the child has a high cognitive ability or because the parents better understand the need to invest in their children's future.

Parents' noncognitive characteristics are elicited using incentivized experiments for risk aversion, time discounting and altruism. Further, we collect numerous other important controls for children, including their age and gender; parents (responding and non-responding parents), in-

[5] The literature on cognitive ability and financial decisions finds that more able individuals are more likely to make optimal financial/investment decisions (Korniotis and Kumar, 2010; Agarwal and Mazumder, 2013).

[6] Parental altruism is also important in the seminal work of Becker and Tomes (1979) as well as Basu and Van (1998).

[7] We chose this group since, in Pakistan, all children in grade 5 take a national exam for which we can obtain their grades.

[8] Recent statistics show that roughly 25 million (of the total 75 million) children under the age of 16 in Pakistan are currently not attending school Alif Ailaan: Education Survey (2016).

[9] The role of the heritablity of skills has been the focus of study in the psychology literature, including Turkheimer et al. (2003); Tucker-Drob et al. (2009); Nisbett et al. (2012).

cluding their education and age; and household characteristics, including family size. We also collect rich information on a number of outcomes, including i) the child's economic activity and household work status, ii) the number of hours allocated to various types of work, studying and school and iii) absence from school and achievement scores on standardized central exams. The data we collect and use for our analysis are particularly suitable for estimating the importance of parental cognitive factors, but more importantly the significance of noncognitive characteristics, which are theoretically relevant but not elicited and empirically employed in this context.[10]

We find that both cognitive and noncognitive parental factors are important in determining a child's schooling and work outcomes. In particular, we find that parents' cognitive factors (while keeping all other factors constant at their original values) are negatively associated with the likelihood that their child misses school or engages in any form of work. In terms of noncognitive factors, altruistic, patient and risk-averse parents are less likely to have their children engage in work, drop out of school or be absent from school and are more likely to have their children spend more time on school-related activities and exhibit better school performance. We also find that parents whose child has a higher cognitive ability are less likely to engage their child in household chores, and the child is also less likely to miss school. While existing work highlights that the role of parental investment and families surpasses the importance of skill formation through formal schooling, our work shows that the (intergenerational) parent's noncognitive factors – more than parent's and child's cognitive ability – and the parent's cognitive factor – more than child's own cognitive ability – affect the child's human capital development. To the best of our knowledge, our paper is the first to consider and estimate these factors jointly.

Our findings have important implications for both the theoretical and empirical literature. First, the work broadens our understanding of the exogenous endowment, which is something of a black box in Becker and Tomes (1979) but plays an integral role in the parent's decision to invest in their children. In Becker and Tomes (1979) the authors state that "endowments depend on many characteristics of parents, grandparents, and other family members and may also be culturally influenced by other families." – Becker and Tomes (1979, page 1158). We contribute by showing the importance of both cognitive and noncognitive factors among these parental characteristics.

Second, the theoretical literature that includes a child's labor decision is often based on the idea that parents solve an optimization problem by trading off income from child's work against schooling. However, no previous study has considered the importance of the cognitive and noncognitive characteristics of parents in this context. Our finding that both cognitive and noncognitive factors are important for parents' decisions about their child's schooling and work complements the literature showing that cognitive (e.g., Korniotis and Kumar, 2010; Agarwal

[10]For work on the relationship between a child's cognitive ability and child labor and schooling outcomes, see Bacolod and Ranjan (2008) and Dendir (2014).

and Mazumder, 2013) and noncognitive (Kuhnen and Melzer, 2018) factors affect investment and financial decisions in financial markets. While time preferences and parental altruism play important roles in theoretical work (Baland and Robinson, 2000; Ranjan, 2001; Dessy and Knowles, 2008; Kumar, 2013) that incorporates the option of the child's work/schooling trade-off, our work finds that these aspects are also important in practice. Moreover, our finding that heterogeneity in cognitive ability and risk aversion are also potentially important aspects of the decision problem is novel.

Third, our results have implications for the empirical literature because they show the importance of commonly omitted variables. For example, studies showing a negative association between parental education and child labor (e.g., Strauss and Thomas, 1995; Kurosaki et al., 2006; Emerson and Souza, 2007) do not often contain a measure of cognitive factors. Since cognitive factors for parents and children are often omitted, the education variable captures the role of parents' cognitive ability and the child's cognitive ability, since both of these variables are correlated with parental education. Our data allow us to estimate these three effects separately and to show that all three factors can affect and play distinct roles in determining our outcomes of interest.

The remainder of this paper is organized as follows. In Section 2, we present the details of institutional background, our sampling and the data we collected. In Section 3, we present the variables that we collect and employ in this paper and then provide our econometric specifications. Section 4 presents our results on children's engagement in work activities and the allocation of hours and schooling outcomes, and we conclude in Section 5.

2 Background, sample and data

Our dataset includes 1416 parent-child pairs and contains detailed information about each child's engagement in work, their time spent working and in school, their schooling outcomes, and a broad range of both conventional and novel characteristics of the child, parent(s) and household, which we discuss in detail in Section 3. In this section, we provide a brief institutional background on public schools in Pakistan, describe the sample selection, and discuss the sources of the data we collect.

2.1 Institutional background

A few distinct features define the public school system in Pakistan. Despite the international perception of the prevalence of religious schools in Pakistan – "madrassahs" (religious schools) – public schools define the landscape of Pakistan's education system.[11] All children in the transi-

[11]In particular, Andrabi et al. (2005) show that the enrollment in these schools is less than 1 percent in the entire country, and no supporting evidence exists for a dramatic increase in the religious school system in recent years.

tioning phase from class 5 (primary school) to 6 (middle school) in these schools are required to take a centrally set exam. In public schools, the academic year runs from April to March, while in private schools, it runs from September to June. Therefore, the central exam occurs in March. Moreover, the majority of these schools are segregated by gender, and most children in these schools pursue primary and middle education at the same public school. All these features guide our access to parent-child pairs by sampling schools, which we describe next.

2.2 Sample selection

We acquired parents' contact information from school records. We restricted our sample of schools to public schools in which the transition of the currently enrolled students to an upper class (after the central exam) is possible. In particular, we choose schools that are categorized as middle (nursery to 8th grade) and high (nursery to 10th grade) schools. We further concentrated on peri-urban localities (often referred as rural/urban areas) of the Kasur district in Punjab.[12] This process left us with a pool of 45 schools from which we select the sample. The distribution of these 45 schools by gender is provided in Table A1. We select 32 schools, where the probability of a school being chosen for our sample increases with the number of students in grade 5. The distribution of schools (disaggregated by gender and level of school) is also presented in the same table.[13]

We then take all students enrolled in grade 5 (in February 2018) at these 32 schools. Our sampled students were due for transition to the next class (class 6) at the start of April 2018 after taking the national exam. In April, with the school's cooperation, we accessed the school records for the previous academic year and the current academic year and collected addresses for the parents of students enrolled in one of the sampled schools during the previous academic year (i.e., prior to the transition). We then collected information using parent-child pair surveys during the period from April to June 2018. The total number of observations collected is 1506, and 90 of these observations are parental variables collected from non-parental guardians of the child. We exclude such children and base our study on the sample of 1416 parent-child observations.

2.3 Data

The data come from two sources: administrative data collected from school and government records, and data from surveys conducted separately for parents and children.

Administrative data from schools and government records: We access each school's office records and class ledgers. Office records allow us to obtain the parents' residential addresses. Moreover, these records also facilitate the measurement of school dropouts by comparing the

[12] We provide more details on conducting this study in the district of Kasur in Appendix B.
[13] The location of each of the 32 schools can be found in Figure A1.

school records of a cohort enrolled in grade 5 in the previous academic year and in grade 6 in the current academic year. We minimize the potential issue of students switching schools, which could make following students from one school to another difficult. The most common reasons for a child switching schools are as follows: the school does not have the next grade level available; the child did not perform well enough to continue in the current school; or the household migrated to another geographic location. The first factor is minimized by our school choice of middle (nursery to 8th grade) and high (nursery to 10th grade) schools, while the second factor is accounted for by directly asking parents if the child was enrolled in a school different from that in our records, which we collected directly from schools. The last factor is not a great concern in most developing countries because the informal risk sharing and insurance possibilities that exist in family/friend networks make within-country migration especially rare (see Munshi and Rosenzweig, 2009).

The measure of school enrollment can be obtained via a one-time survey of the school. The official school records of enrollment closely replicate actual spot checking of enrollment and therefore avoids the potential measurement error of self-reported information obtained from household surveys (Baird and Özler, 2012). Using school ledgers, which contain information on each child's attendance in the previous year, provide a further measure of school participation.[14] For each of the grade 5 students in our sample, we also collect their central exam score by accessing the administrative data collected by the government of Punjab. This source provides us with independent data on each child's school performance. Tests that are the same across children are required to assess school performance (see, e.g., Gunnarsson et al., 2006; Baird et al., 2011; Dumas, 2012), so accessing scores from a uniform central exam is crucial for our study.

Parent-child linked survey data: Our surveys for each parent-child pair include two parts. The first part contains incentivized tests. For parents, this part includes a standard Raven's test to collect information on their cognitive ability and experiments designed to elicit three parental noncognitive factors: parental altruism, time discounting, and risk attitudes. For children, the first part includes only an incentivized colored Raven's test to measure their cognitive ability. The second part contains survey questions. The survey questions for parents aim to collect information on the standard control variables (such as parental education, age, household size, child's age and gender) and outcome variables pertaining to their child (such as the status of work, type of work, whether the child is in school, and whether the child has switched schools). The survey questions for the children aim to collect information about their allocation of hours in a typical day across school, work and leisure. We provide more detail in Section 3.

In the Appendix, we further elaborate on the protocols we implement and cautions we take to ensure the quality of our collected data through surveys.The survey for parents took no more than an hour (30 minutes for the 60-question Raven's test and the rest for the remaining sur-

[14] School ledgers are also used by Baird and Özler (2012) for their benchmark measure of attendance.

vey), and the child survey took no more than 40 minutes (30 minutes for the 45-question colored Raven's test and 10 minutes for the remaining questions). Parents were paid on average $4.5 worth of mobile credit, while children were compensated with stickers and pencils worth $1.[15] The payment came in the form of a phone credit designed to be transferred directly to the parents' phone numbers. In Pakistan, phone credit is a valuable gift since the credit can be transferred to other people at no cost. Moreover, almost every person in Pakistan owns and regularly uses the phone service.[16] The payment for parents was similar to the hourly wage ($0.8 per hour) of a laborer in Pakistan.[17] For children, the wage calculation is challenging because many children are employed either in unpaid jobs or employed within their households, making it difficult to quantify their value addition or value from their engagement in economic activity. However, we tried to select gifts that were age appropriate and appealing to children.

3 Variables

We now describe the raw variables we collect and how we construct our main variables of interest. The key variables can be divided into three subgroups: standard control variables (Section 3.1), explanatory variables of interest (Section 3.2), and outcome variables (Section 3.3).

3.1 Standard control variables

The control variables are derived from our survey for parents. The selection of variables is motivated by previous literature that shows the importance of some characteristics in determining parental decisions about child work, the type of work child in which the child engages and the child's schooling outcomes (see references in Brown et al., 2002). These standard controls can be divided into three sets. The first set covers parental characteristics, such as education and age, the second set relates to the child's gender and age, and the last set covers household factors, such as income/assets and family size.

Theoretical models of child labor often treat all households as homogeneous. However, increasing empirical evidence suggests that parents with higher education are more likely to keep their children away from work activities (Strauss and Thomas, 1995). This fact suggests either that educated parents value child's education substantially more than parents with less education, or

[15] The payment for each respondents varied based on the decision made for altruism, the random draw of an option, the associated decision for each of the risk aversion and discounting games, and the number of correct answers on the Raven's test (see section 3.2.1 for more details on the Raven's test and section 3.2.2 for elicitation of non-cognitive factors). No variation in the total amount paid resulted from answering the other questions on the survey, which had a fixed payment for every respondent.

[16] From the survey perspective, this feature also provides the advantage of avoiding potential issues of theft due to enumerators carrying large sums of cash on the road.

[17] Based on the GDP per capita estimate for Pakistan in 2018, the average pay in Pakistan was roughly $1641 per year, which translates to $6 per-day.

that educated parents have higher income. The precise mechanism driving child work and parent's education is difficult to disentangle, and whether it is the father's or mother's education that matters most for a child's human capital decision is unclear. In the context of Brazil, Emerson and Souza (2007) report the father's education to be more important, while Kurosaki et al. (2006) report that the mother's education has a significant effect in rural India. Motivated by these empirical findings, we control for the responding and non-responding parent's education and age in our empirical specification.[18]

With regard to child's characteristics, empirical studies find both age and gender to be important in determining a child's work status, the type of work a child engages in and the number of hours a child works. For example, in the context of Colombia, Cartwright (1999) show that the probability of work increases by 8 percentage points for each year a child ages. Estimates of gender differences, however, are more sensitive to the type of activities considered, as numerous studies (see Levison and Moe, 1998 for Peru and Levison et al., 2001 for Mexico) note that omitting domestic work activities from child work can result in misleading conclusions in understanding the determinants of child labor. In developing economies, boys have higher participation rates in outside chores and market work than girls do. According to the estimates reported by Edmonds and Pavcnik (2005), girls are 18% more likely to be involved in domestic work and 30% less likely to engage in paid market work. In section 3.3, we discuss in more detail how we construct various types of work activities performed by children, but all our empirical analyses control for child's gender and age.

In our context, estimating gender has an associated trade-off: since public schools in Pakistan are segregated by gender, we can estimate either gender effects or school fixed effects. We further elaborate on this issue in section 3.4. School fixed effects can help to quell time-invariant concerns such as the availability of a school in the neighborhood (Duflo, 2001), the school's cost in terms of homogeneous travel time (Kondylis and Manacorda, 2012) and the school's quality (Chaudhury et al., 2006), all of which may influence parents' decisions regarding their child's work and schooling. These concerns are not significant for our sample since children in our sample were enrolled in one of the sampled schools in March 2017 and had access to schools in their neighborhood, as our survey shows that more than 90% of the students walked to a school in their neighborhood. Nevertheless, we show in an additional analysis that our results do not change when we include school fixed effects.

The last set of control variables is family size. The main motivation for including this factor is to account for household income; however, because of missing income data and endogeneity problems with income, studies often include indirect measures, such as household capital,

[18] The education level of parents in our sample ranges from 0 to 5, where 0 is no education (lowest level) and 5 is university education (highest level). As presented in Table A2, most of the fathers (66%) and mothers (85%) have not completed schooling. Therefore, we use the binary education variable for each parent, which takes the value of 1 if the parent has any level of education and 0 if the parent reported 0 level of education.

welfare, poverty status, total expenditures or expenditure on food, in lieu of household income. However, in our context, even indirect measures may be endogenous if children engage in work and contribute to household expenditure. Direct measures, however, frequently suffer from non-response and underreporting in surveys, which are especially common issues with income data (Moore et al., 2000). These issues are especially present in Pakistan where, even though income on a monthly basis is the most suitable time frame for formal labor, many economically active persons (especially in peri-urban regions) engage in informal employment. In addition, non-response and underreporting occurs due to tax concerns or cultural reasons – as we observe in many other cultures, people in Pakistan consider the discussion of money, expenditure, income or assets a strictly private business. Therefore, direct or indirect measures of household income are prone to missing data or measurement problems, as our collected information on household income commonly reports zero income. Despite having collected information on income, we consider variables such as both parents' education and age and household size as important determinants of household income, which relies on variables collected with limited measurement error. In particular, family size is interesting on its own since Hanushek (1992) finds a trade-off between educational attainment in the US and family size, and substantial evidence from both developed and developing economies suggests that children belonging to larger families have lower schooling levels, educational achievements and health outcomes (Patrinos and Psacharopoulos, 1997).

3.2 Explanatory variables of interest

3.2.1 Cognitive ability

Our first two explanatory variables of interest are measures of the cognitive abilities of a parent and their child. The cognitive ability of a child may be an important factor in the parents' decisions concerning the child's schooling and work. If parents have more than one child, they may think it is important to invest more heavily in the more gifted child for efficiency reasons or may invest more heavily in the less able child for equity reasons (Becker, 1981). Even if the family only has one child, the parents may feel that the return to education is higher the more gifted (in terms of cognitive ability) a child is. An extreme example of this phenomenon occurs in the Spence (1973) signaling model. Regardless, a child's cognitive ability should be accounted for to capture its role in determining the child's work and schooling related outcomes. Some studies have already examined this relationship between a child's cognitive ability and child's work and schooling (e.g., Bacolod and Ranjan, 2008; Dendir, 2014), but often previous studies do not consider the importance of a parent's cognitive ability. The parents' cognitive ability may be important because more able parents are better able to grasp the importance of investing in their children's education and reduce their time spent working. Indeed, the literature on cognitive ability and financial decision making shows that more able households make better investment decisions (e.g., Korniotis and Kumar, 2010; Agarwal and Mazumder, 2013).

To measure cognitive ability for each parent-child pair, we conduct the Raven's standard progressive test for parents and Raven's colored progressive test for children (Raven et al., 1938). Each test is a nonverbal test in which the participant completes a pattern. These tests are intended to be independent of any prior knowledge and capture the participant's capacity to reason and solve novel problems, a process called fluid intelligence (see Almlund et al., 2011 and references therein), and are often employed in the economics, psychology and, more generally, social sciences literature (Burks et al., 2009; Borghans et al., 2010).

The Raven's tests were incentivized such that each correct answer paid a rate of 1 PKR for parents and 1 sticker for children. We offered compensation to standardize subjects' motivation to do their best because, as Duckworth et al. (2011) illustrate, differences in test motivation can be a confounding factor in standardized intelligence tests. Both tests are restricted to a 30-minute time limit, with 60 questions for Raven's standard progressive test and 45 questions for the colored Raven's test for children. On the basis of the number of correct answers, we construct our Raven's scores for parents, denoted by $Raven(parent)$, and those for children, denoted by $Raven(child)$. Unlike previous studies this measure is observed in our study, and can also be an important determinant for our outcome variables, which we describe in Section 3.3. Moreover, the fluid intelligence of parents can also be indicative of parental income levels (or, more generally, their labor outcomes, as highlighted in Heckman et al., 2006).[19]

3.2.2 Noncognitive factors

The next three explanatory variables of interest are derived from incentivized tests (in field experiments) conducted with the parents. The three experiments are designed to elicit three parental preferences: parental altruism, time discounting, and risk attitudes.[20]

Parental altruism is a central assumption in most theories of skill formation (e.g., Becker and Tomes (1979); Aiyagari et al. (2002); Doepke and Zilibotti (2017)) and child labor (e.g., Basu and Van, 1998; Baland and Robinson, 2000; Ranjan, 2001; Dessy and Knowles, 2008; Kumar, 2013). In Basu and Van (1998), for example, parental altruism is the basis of the luxury axiom that states that parents will send children to work only if necessary for the economic survival of the household. Previous research on the relationship between parental altruism and child labor has relied on indirect evidence. Parsons and Goldin (1989), for example, use US household survey data from the late 19th century and interpret the positive asset holdings of parents whose children work

[19] The estimated effect of parents' cognitive ability on children's outcomes, therefore, may not independently identify the direct effect from fluid intelligence but instead also capture the indirect effects of such factors on parents' earning potential. However, the same argument also holds for variables pertaining to formal education.

[20] Additional details are provided in Appendix B.

as evidence against the idea that parents send their children to work only if necessary for subsistence. We take a more direct approach by eliciting parental altruism using an incentivized experiment.

Specifically, we elicit parental altruism using a modified dictator game based on Vyrastekova et al. (2014). The modified design changes the choice of the dictator regarding how much of an endowment to give to a stranger into a binary choice between the parent keeping money for themselves or providing a gift for their child. Specifically, to measure altruism towards the child instead of a general level of altruism (even though the two forms of altruism may be correlated), each parent is asked to make one decision: choosing 35 PKR for themselves or choosing a gift worth 50 PKR for their child. The value of the child's gift is set marginally higher due to liquidity differences between the options. If a parent chooses a gift for the child, we record that the parent is altruistic (coded as 1) towards their child; otherwise, we code the parent as non-altruistic.

Time discounting is also potentially important in child's work decisions. According to Baland and Robinson (2000), when making decision to engage their child in some form of work, parents are often assumed to weigh the present discounted value of the future income of an educated child against the foregone current income while the child is in school. Time discounting therefore generally plays an important role when parents make such intertemporal investment decisions (see also Ranjan, 2001; Raut and Tran, 2005; Dessy and Knowles, 2008; Kumar, 2013). Previous evidence on the importance of this intertemporal decision making in the context of child's work and schooling outcomes has been relevant. For example, Beegle et al. (2006), using a household panel survey from Tanzania, find that asset holdings offset the impact of transitory agricultural shocks on child labor, indicating that households internalize the importance of not interrupting a child's education as an investment in the future. However, no previous study has considered whether differences in parents' levels of patience affect their decisions about their child's work and schooling activity.

We elicit time discounting using a standard choice list experiment (e.g., Coller and Williams, 1999; Harrison et al., 2002; Tanaka et al., 2010) in which we ask parents to make 10 decisions based on two available choices (A and B) in 10 scenarios. Choice A is such that some amount of phone credit is transferred to the parent on the same day, while choice B provides a larger credit but the transfer is made 2 weeks later. The parent is asked to make 10 such choices, where the value of option A decreases from 95 PKR to 50 PKR and the value of option B is maintained at 100 PKR. The point at which the parent shifts to option B represents how much he/she values a present gain over a future gain. Specifically, a parent who has a higher switching point places higher value on the present and discounts the future. The switching point allows us to determine the range of weekly time discounting.[21] The higher the time discounting is, the more the parent

[21] The switching point is used in the following formula: $(ln(100) \quad ln(100 \quad 5 \quad Switched\ Option))/(2)$ to calculate the exponential discounting rate.

cares about the present.

Despite the importance of risk aversion in human capital accumulation (e.g., Shaw, 1996; Palacios-Huerta, 2003; Dohmen et al., 2015) in general and the risk aversion of parents in educational attainment (Wölfel and Heineck, 2012; Checchi et al., 2014) in particular, to the best of our knowledge, no previous study has assessed risk aversion in the context of child's enaggement in work. We fill this gap in the literature by considering a measure of risk attitudes. The incentivized experiment is based on the widely used Holt and Laury (2002) lottery choice list, contextualized such that the lotteries are framed in terms of betting on cricket teams scheduled to bat the following day at two different venues. We use this scenario because cricket is one of the most commonly followed games in Pakistan and, regardless of the gender of the respondent and the enumerator, the rules of cricket are widely understood by people of all socioeconomic backgrounds. This design ensures that the game and the associated risk are well understood.

The parents are asked to make 10 decisions based on two available lotteries (watch team A or team B bat) for each of the 10 scenarios in which team performance (captured by the number of runs) is associated with the amount of money the parent wins. These scenarios differ based on the probability of the choice of ball (tape or hard ball) used in the match. Team A is a low-risk team since it performs more consistently with either type of ball. However, team B is a high-risk team that performs better than team A if a tape ball is used but performs more poorly when a hard ball is used. For each subsequent lottery in the list, the expected value of the high-risk lottery (watch team B) falls relative to the low-risk lottery (watch team A). The middle scenario is where the two lotteries give the same expected payoff. Whether the parent switches from lottery B to lottery A before the middle scenario is coded with a range of positive numbers to depict increasing aversion to risk, while switching after the middle scenario is coded with a range of negative numbers to depict decreasing aversion to risk. The higher this measure is, the more the parent dislikes risk.

For both the risk aversion and time preference experiments, at the end of the entire survey, one scenario is selected at random, and the participant is paid based on their decision made for that scenario. The income from the modified dictator game is paid or the gifts are given to the child at the same time.

We have two possibilities to construct a measure of time discounting and risk aversion: use continuous measures, as described above, or convert these measures into binary variables. We opt to use the latter strategy for two main reasons. First, given that altruism is already measured as a binary variable, using the same scale for the remaining noncognitive factors makes the estimated coefficient easy to interpret and comparable with other estimates for binary variables. In terms of the relative importance of the noncognitive variables, binary treatment of all variables circumvents the need to transform and homogenize the different scales and allows reasonable comparisons. Second, when we consider the distributions of these variables in our data (shown in the appendix Figure A2), much of the variation arises from the tails of the distribution, making the loss of variation, information and measurement error through conversion to binary measures minimal.

We construct the binary variable for time discounting ($Discounting$) by using the mean discounting in the sample as the threshold and coding the values of time discounting above the sample mean as 1, depicting a high discount rate for future periods. We code values below the mean as 0. For the risk aversion ($Risk\ Averse$) measure, we take the risk-neutral option in the game – option 5, where the two lotteries give the same expected payoff – as the threshold. All parents above this threshold – i.e., those having a positive value for the continuous measure – are coded 1 as highly risk averse, whereas parents below the threshold – i.e., those having a negative value for the continuous measure – are coded 0 as low risk averse.

3.3 Outcome variables

Our primary outcome variables can be divided into two groups: outcomes related to a child's work and outcomes related to a child's schooling. For the variables pertaining to the child's work, we consider various types of work. In particular, following the previous literature (Putnick and Bornstein, 2016), we break the concept of the child's engagement in work into two major categories: *economic activity*, where a child engages in paid or unpaid work outside the home or related to a family business; and *household chores*, where a child engages in noneconomic household work. Previous studies have focused primarily on paid work; however, based on a bibliometric analysis, Edmonds (2007) reports that a predominant fraction of the past literature focuses on formal wage work, while only a few studies consider informal work, such as unpaid work in a domestic enterprise (farm or business) or household chores. Household chores are especially ignored and missing from the literature. However, the majority of child work is concentrated in the informal categories of unpaid and household chores, especially for young children, whose labor often is unreported or missing from official surveys (Gibbons et al., 2005; Webbink et al., 2012). The danger of misleading conclusions about the displacement of other activities – especially schooling – due to household chores, for example, is highlighted in Levison and Moe, 1998 for Peru and Levison et al., 2001 for Mexico. Edmonds (2007) therefore suggests that a wide scope of activities should be considered as child labor, which is the approach we take in this paper by using a rich set of child work types. While we include paid and unpaid work as a single category, we allow for household chores, which we divide into chores conducted inside or outside of the house. We explain these variables in more detail below.

We derive our main child work variables using the parent survey. No consensus exists on whether it is better to ask parents or the child about the child's work activity. Moreover, while Dillon et al. (2012) find little difference between work reported by children and their guardians, both Dammert and Galdo (2013) and Janzan (2018) find the reports inconsistent in a significant number of cases. We take the following approach. For questions regarding types of work (extensive margin), we ask the child's guardian, as we believe they are well suited to answer what type of work their child does for them, whereas for the hours of work (intensive margin), we ask the children themselves, as we believe they are best suited to answer how they typically spend their days.

We use various types of child work measures, starting with any type of work a child engages in, which we denote by $All\ Work$. We then categorize the type of work as $Economic\ Activity$, which includes paid/unpaid work; household chores (HHC), which is denoted by $All\ HHC$, and chores inside the house and outside the house, denoted by $HHC \quad In$ and $HHC \quad Out$. All these variables are dummy variables that take a value of 1 if the parent reports that a child engages in a particular type of work; otherwise, if the child does not engage in that type of work, we code the variable as 0.

For the intensive margin of work, we categorize the time allocation of a child by activity. For this, we use the idea that there is a fixed number of hours in a day and that the child spends time on work (economic activity and household chores), leisure (playing, watching TV, and resting) and schooling (studying and attending school). The consideration of leisure hours in our study is primarily for completeness, and we only report the results in the Appendix for the following reason. In particular, if a variable of interest and the decision of a parent in allocating hours for work are positively associated and hours of schooling negatively associated (or vice verse), then these opposing associations will offset and appear as an insignificant association with leisure hours. Indeed, we do not find any significant relation between the cognitive and noncognitive factors of parents and their children's leisure hours.[22] While we do not present these results for brevity reasons, it is worth mentioning that despite the importance of leisure in children's development, as highlighted by Fuller, 1922; Pangburn, 1929, especially for young children, considerations of leisure hours are mostly missing – due to data limitations – from the recent literature.[23] However, our data do not face these limitations.

We construct the child's average time allocation across work, schooling and leisure activities by means of a survey module in which we directly ask the child to split a regular 24 hour weekday between these activities and other activities that are not covered. We construct the number of work hours as the hours reported by each child in the category of work if their parent reported that the child engages in any form of work, whereas the remaining children receive 0 hours for

[22] The allocation of a child's hours in a day can be presented as $24 = Hours\ work\ (h_w) + Hours\ schooling\ (h_s) + Hours\ leisure\ (h_l)$ and let the variable of interest be X. Then, this relation implies that $\delta(h_l)/\delta(X) = \quad \delta(h_w)/\delta(X) \quad \delta(h_s)/\delta(X)$. As a result an opposing effect of X on h_w and h_s implies off-setting effect of X on l.

[23] An exception to this gap is a recent study Ravallion and Wodon (2000) that shows that child labor can displace both schooling and leisure activities. Similarly to this recent work, we have a measure of leisure hours; however, unlike this work, we do not find significant effects on leisure hours.

$Work\ Hours$. [24]

Our second set of outcome variables is related to the child's school participation and performance. To construct the schooling outcomes, our work makes important contributions by merging school and administrative data with survey data. A common problem with using school data from developing countries is that the data are not computerized; however, we take important steps to codify the data for all the schools to utilize as much of the information about schooling outcomes as possible. Our set of outcome variables pertaining to schooling outcomes include (i) whether the child transitioned to the next class or not, $Dropout$; (ii) whether the child was present during the school days based on information acquired from school ledgers, $Absence$; (iii) whether the child passed the central exams, $Pass$; and (iv) the marks achieved on the central exams, $Marks$. For these variables, we restrict our sources to school and administrative data.

The first variable, which is based on school records for the 2017-2018 academic year, is coded as 1 if a student was enrolled in the last month (March 2018) of the academic year but not enrolled in the first month of the next academic year (April 2018). We confirm from parents whether the child repeated a grade or has switched schools. Therefore, the $Dropout$ variable receives a value of 1 if a student has re-enrolled and a value of zero otherwise. For the $Absence$ variable, we use daily attendance registers from each school for as many months as provided by the school. While two schools did not provide registers, the remaining schools provided ledgers for some months. We code each available month's attendance and then count the number of days a child missed school. We normalize the total number of absent days by the number of available months of data to obtain absence per month. We then use the normalized absent days to construct a dummy variable that takes a value of 1 if a child missed at least one day of school and a value of 0 otherwise. This variable is missing for children who were enrolled in two schools that did not provide the registers, and therefore, those observations are not included in our analysis for the absence outcome. For our last variable, $Marks$, we use the official administrative data on central exams for grade 5 and match each student in our sample by the student's name, father's name and the name of the school. The total score is out of 500. The advantage of using the central exam as a measure of school performance is that all students in our sample took the same exam. Therefore, differences in exams or standards for passing in different schools do not affect any of our results.[25]

Our second variable – hours spent on school-related activities, denoted as $School\ Hours$ – is obtained from a question on the number of hours spent on schooling and self-study (such as homework). We construct this outcome variable by directly using the information we gathered

[24] We use this process as a guiding rule for cases in which we observe any inconsistency. For example, if a parent reports their child not engaging in any form of work but their child notes positive hours of work, we use the parent's information as the guiding rule and set the child's work hours for such cases to be zero.

[25] Collecting and integrating these data are an important component of our work, as (Hilson, 2012) notes the perils of interpreting the effects of school-based attainment tests that may follow different standards for advancement.

from the child. To construct the portion of school hours that considers only the time spent on self-study at home, we can separately determine those hours on the basis of the information provided in the variable school hours. To construct the variable for self-study, we first note that the reported school hours do not account for the absence from school; therefore, we construct an effective school hours measure based entirely on the absence data collected directly from school registers. However, the base time for our absence data is days per month, so we construct the school hours as follows. We begin with the knowledge that public schools in Pakistan have 24 hours of school per week, which is 4.8 hours per-day, with each month having 22 school days.[26] We then remove 4.8 hours for each missed school day and construct the per-day effective school hours for a child. Using these school hours, we separately calculate the hours a child spends on school-related activities at home, such as homework or self-study, and denote this value as $Self\ Study$. We calculate this value by subtracting the effective hours from the total $School\ Hours$ variable.[27] We present the summary statistics for our outcome variables in Table A3.

3.4 Statistical model

We model a number of outcomes (described above) for child i who attends school s, allowing each outcome to depend on the characteristics of the child, his/her parents and household, in addition to the cognitive and noncognitive characteristics of the child's guardian (who is the responding parent). Our full specification is as follows:

$$Y_{is} = \beta_0 + \beta_c^{0} X_{is}^{c} + \beta_{cog}^{0} X_{is}^{cog} + \beta_{ncog}^{0} X_{is}^{ncog} + \epsilon_s + \mu_{is} \qquad (1)$$

where Y_{is} denotes the outcome for child i attending school s. We consider the following outcomes: (1) variables pertaining to the child's work – these variables are binary variables for whether a child engages in any type of work [All Work, Economic Activity, All Household (HHC), HHC-In, HHC-Out] and continuous variables for allocation of hours on work [Work Hours]; and (2) variables pertaining to the child's schooling outcomes, these variables are binary for whether the child is currently in school or not, has missed school or not and has passed the central exams or

[26]Regular public schools in Pakistan operate from 8:00 am to 1:00 pm on all weekdays except Friday. On Friday, the school day is from 8:00 am to 12:00 pm. In total, there are 24 hours of school in a week, or 4.8 hours of schooling per-day.

[27]Note that because absence data are missing for two schools, this variable is also constructed only for observations in which school hours and absence data were available. Additionally, we construct a variable for $Leisure\ Hours$, which is based on the questions asked directly to the child about leisure activities. We sum the hours spent on the following categories to construct the variable for leisure hours: playing with friends, games, toys, watching TV, using a phone, sleeping and any $Other\ activities$ that do not classify as work or schooling. For brevity, we present only the results for the association between our explanatory variables and leisure hours in Appendix Table A4 since we do not find any significant results for that category.

not [Dropout, Absence, Pass] and continuous for marks and allocation of time for school-related activities [Marks, School Hours, Self Study].

For our independent variables, we define X_{is}^{c} as a vector of control variables [that includes Edu(Father), Edu(Mother), Age(Father), Age(Mother), Family size, Age(child), Female], X_{is}^{cog} as a vector of cognitive factors [that includes Raven(child), Raven(parent)], and X_{is}^{ncog} as a vector of noncognitive factors of the parent [that includes Risk Averse, Discounting, Altruism]. The definition and construction of these dependent and independent variables are provided in Section 3.

In Equation 1, we separated the error term into a school effect and an idiosyncratic effect. One possibility in the estimation would be to use fixed effects to capture the school effects. This approach would avoid the problem that each school has its own quality, institution or culture, which can be correlated both with our outcomes and our new independent variables of interest. In most studies, the use of school fixed effects would sacrifice some efficiency but would insure against bias from school peer effects. However, in our case, the trade-off is different because our schools are segregated by gender; hence, using fixed effects precludes measuring gender effects, which is a strong argument for not using fixed effects alone. However, if the peer effects issue is important, we will identify gender effects at the cost of the biased estimation of all coefficients.

To shed light on this issue, we first include a gender dummy and estimate a random effects version of Equation 1. Next, we estimate a fixed effect specification, as presented in Equation 1 for all outcomes. We present results from a random effects specification in the paper and a fixed effects specification in the Appendix. We show that the conclusions do not differ for our variables of interest, regardless of the specification employed for the structure of the error term.

Additionally, there is the question of whether we need to adjust the standard errors for correlation across students at the same school. Previously, based on the work of Moulton (1986, 1990), we would have allowed for this correlation in calculating the standard errors, perhaps letting it be very flexible. However, recent work by Abadie et al. (2017) demonstrates that such clustering is not always necessary and that using it unnecessarily leads to overly conservative standard errors and confidence intervals.[28]

In Abadie et al.'s setup, one first chooses clusters from a population of clusters and then samples individuals from each cluster. Denote the fraction of all clusters sampled by f_c; thus, if there are one hundred possible clusters and we sample fifty, $f_c = 0.5$. Denote the fraction of individuals sampled in each cluster by f_n; thus, if there are one hundred individuals in each cluster and we sample thirty of the individuals in each cluster, $f_n = 0.3$. Then, the product of f_c and f_n is what matters, and the closer $f_c \quad f_n$ is to zero, the more important it is to allow for correlations across students at the same school. It follows that the closer f_c and f_n are to zero, the more

[28]Note that their study does not offer guidance on how to allow for the clustering, i.e., random effects versus arbitrary correlations.

important it is to allow for these correlations. In our case, we sample 32 schools from a population of 45 schools in the rural urban belt of Kasur and then choose all the students transitioning from grade 5 to grade 6 from each school. Thus, in our case, $f_c \quad f_n = 0.71 \quad 1 = 0.71$. Therefore, the case for making an adjustment to standard errors is relatively weak, and as a practical matter, we focus primarily on the standard errors from random effects estimation since they offer the efficiency of generalized least squares (GLS) estimators.

4 Results

In this section, we study the effects of the cognitive and noncognitive measures on the child work and schooling outcome variables. Table 1 and Table 2 show the results of the random effects regression model (1).[29] Table 1 presents all the outcome variables related to child work – All Work, Economic Activity, Household Chores (All HHC), Chores inside (HHC-In) and outside (HHC-Out) the house, and Work Hours – regressed on relevant controls and the variables of interest, i.e., the child's cognitive ability (Raven(child)), the parent's cognitive ability (Raven(parents)), and the parent's altruism (Altruism), impatience (Discounting), and aversion to risk (Risk Averse). Table 2 presents our schooling outcomes – Dropouts, Absence, Pass, Marks, School Hours and Self Study – regressed on the same set of explanatory variables outlined above.

4.1 The impact of standard control variables

Before we assess the role of the cognitive ability of the parent and child in Section 4.2 and the noncognitive characteristics of parents (altruism, impatience, and risk aversion) in Section 4.3, we note the role of some important standard control variables. In Table 1, for children's work outcomes, consistent with previous findings (e.g., Edmonds and Pavcnik, 2005), we see that the child's gender is important, with a female child being significantly more likely to engage in chores inside the house (probability 30% higher than that of a male child). A female child is 25% less likely than a male child to be engaged in chores outside the house. Since these two effects, while of similar magnitude, are opposite to each other, the effect of gender on all household chores (which is the sum of chores inside and outside the house) is insignificant. We also find that the age of a child increases the probability of engaging in any type of work by 2.6%, driven primarily by household chores, with an additional 5 minutes of time spent on work. Since a child who is a year older may be physically more able to work, age is a relevant factor and this effect is also consistent with the past literature (see e.g., Cartwright, 1999).

We also see in Table 1 that the mother's age appears to be important for children's work-related outcomes, with the probability that a child engages in any form of work increasing with

[29] We also present the school fixed effects regression model 1 in Table A5-A6.

Table 1: Baseline Regression – Work Outcomes

	All Work (Y/N)	Economic Activity (Y/N)	All HHC (Y/N)	HHC-In (Y/N)	HHC-Out (Y/N)	Work Hours (Hours)
	(1)	(2)	(3)	(4)	(5)	(6)
Edu(Father)	-0.11	0.092	-0.097	-0.048	-0.071	-0.055
	(0.091)	(0.099)	(0.092)	(0.088)	(0.083)	(0.083)
	[-0.030]	[0.021]	[-0.026]	[-0.015]	[-0.024]	
Edu(Mother)	0.054	0.082	-0.0055	-0.16	0.20	-0.043
	(0.12)	(0.13)	(0.12)	(0.12)	(0.11)	(0.11)
	[0.014]	[0.019]	[-0.0015]	[-0.051]	[0.069]	
Age(Father)	-0.0092	-0.0042	-0.0079	-0.022	-0.0091	0.0045
	(0.013)	(0.013)	(0.013)	(0.012)	(0.011)	(0.011)
	[-0.0024]	[-0.00094]	[-0.0021]	[-0.0069]	[-0.0031]	
Age(Mother)	0.031	-0.0057	0.033	0.049	0.019	0.015
	(0.013)	(0.014)	(0.014)	(0.013)	(0.012)	(0.012)
	[0.0083]	[-0.0013]	[0.0087]	[0.015]	[0.0066]	
Family-size	-0.0020	0.0015	-0.0076	-0.028	0.0043	-0.016
	(0.031)	(0.034)	(0.032)	(0.030)	(0.028)	(0.029)
	[-0.00052]	[0.00034]	[-0.0020]	[-0.0087]	[0.0015]	
Age(child)	0.10	-0.054	0.099	0.067	0.012	0.087
	(0.049)	(0.052)	(0.049)	(0.045)	(0.043)	(0.044)
	[0.026]	[-0.012]	[0.027]	[0.021]	[0.0040]	
Female	-0.074	-0.15	-0.044	0.89	-0.69	-0.17
	(0.19)	(0.22)	(0.21)	(0.14)	(0.17)	(0.19)
	[-0.019]	[-0.033]	[-0.012]	[0.30]	[-0.25]	
Raven(child)	-0.014	-0.000046	-0.016	-0.0036	-0.0090	-0.0070
	(0.0079)	(0.0084)	(0.0080)	(0.0076)	(0.0073)	(0.0076)
	[-0.0036]	[-0.000010]	[-0.0044]	[-0.0011]	[-0.0031]	
Raven(parent)	-0.023	-0.044	-0.023	-0.016	-0.013	-0.012
	(0.0050)	(0.0056)	(0.0050)	(0.0045)	(0.0043)	(0.0044)
	[-0.0060]	[-0.0099]	[-0.0060]	[-0.0051]	[-0.0044]	
Altruism	-0.20	-0.24	-0.18	-0.17	-0.11	-0.14
	(0.094)	(0.099)	(0.095)	(0.087)	(0.083)	(0.084)
	[-0.051]	[-0.055]	[-0.047]	[-0.053]	[-0.039]	
Discounting	0.22	-0.026	0.26	0.16	0.025	0.18
	(0.087)	(0.092)	(0.088)	(0.081)	(0.077)	(0.080)
	[0.059]	[-0.0059]	[0.070]	[0.051]	[0.0087]	
Risk Aversion	0.29	-0.094	0.33	0.26	0.012	0.25
	(0.095)	(0.099)	(0.095)	(0.085)	(0.083)	(0.084)
	[0.075]	[-0.021]	[0.087]	[0.082]	[0.0040]	
N	1298	1325	1270	1307	1325	1154

Note: This table provides the estimates based on the random effects specification presented in Equation (1). We estimate a probit model for binary outcomes reported in columns (1)-(5), and an OLS model for continuous outcome in column (6). Robust standard errors are provided in parentheses and corresponding margins are reported in brackets.

mother's age. This result is driven by household chores, specifically, chores inside the house. A mother who is one year older has a 0.87% higher probability of engaging her child in any type of chores, primarily due to an increase of 1.5% in the probability that the child engages in chores inside the house. Since in our sample, the average mother is middle-aged, this result is not surprising, given that older mothers may require more help with chores within the house.

Table 2 describes the schooling outcomes. It shows that whether the parent is educated or not is important for their child's schooling outcomes. A child whose father is educated has a 2.3% higher probability of passing the central exam and achieves, on average, an additional 13.9 points on the exam (where the total points are 500). A child with an educated mother scores 14.3 points higher on average. Moreover, a child of an educated mother spends an additional 4 minutes per-day[30] in self-study at home – which translates to 20 minutes per week or 12 hours per year, and since the construction of self-study (as described in Section 3.3) is correlated with attendance, one can also interpret this effect as 2.5 fewer days of absence from school. However, there is no effect on the total school hours. Our results are consistent with previous evidence (e.g., Strauss and Thomas, 1995; Kurosaki et al., 2006; Emerson and Souza, 2007); however, it must be noted that unlike most of the past work, our specification includes not only variables pertaining to parental education but also the cognitive ability variable (which we discuss in Section 4.2). Moreover, the age of the child itself is significantly associated with a 1.2% increase in the probability of dropping out of school, reducing school hours by 5.5 minutes per-day; most of the reduction comes from self-study, which is school activities conducted at home.

We now turn to our primary variables of interest: the cognitive abilities of the child and parent (Section 4.2) and the noncognitive characteristics of the parents (Section 4.3).

4.2 The impact of cognitive ability

Table 1 shows that the parent's cognitive ability is significantly negatively associated with the child's work. A parent with a one standard-deviation higher Raven's test score (i.e., 9.15 correct responses) has a 5.5%[31] lower probability of engaging a child in any form of work. This lower probability of all forms of labor is driven by both a 9% lower probability of engaging children in economic activity and a 5.5% lower probability of children doing any type of household chores. Household chores are driven primarily by inside household chores. A parent with a one standard-deviation higher test score also reduces the work hours of a child by 6.6 minutes per-day. These estimates indicate a small effect of cognitive ability on the intensive margin of work hours relative to the large predictive probabilities estimated for the extensive margin of work.

Table 2 shows that a parent with a one standard-deviation higher test score has a 2.3% lower probability of a child being absent from school in any given month. Therefore, while the association of a parent's cognitive ability with school outcomes is not as wide-reaching as the association with child's work outcomes, we see evidence that children of more able parents have better schooling outcomes in terms of less absence from school. We find no effect of parent's cognitive ability on school hours or self study where school-related activities are conducted at home. However, it must be noted that in our results, the child's schooling outcomes, especially performance, can mostly be attributed to both the father and the mother's education rather than the cognitive ability of the parent.[32]

[30] The additional minutes are calculated by converting the estimate – which gives an hourly effect – to minutes as $= 0.068 \quad 60$.

[31] To interpret the estimates of cognitive factors, we use a one standard-deviation change in the Raven's score, where the standard-deviation is 9.15 correct responses and the estimated effect is for one additional correct response. As a result, a standard-deviation change translates to a $= 0.0060 \quad 9.15$.

[32] One may expect that both parental variables of education and cognitive ability affect the child's schooling out-

Table 2: Baseline Regression – Schooling Outcomes

	Dropout (Y/N)	Absence (Y/N)	Pass (Y/N)	Marks (Points)	School Hours (Hours)	Self Study (Hours)
	(1)	(2)	(3)	(4)	(5)	(6)
Edu(Father)	0.016	-0.058	0.35	13.9	0.040	0.016
	(0.16)	(0.12)	(0.18)	(4.52)	(0.053)	(0.052)
	[0.0011]	[-0.0100]	[0.023]			
Edu(Mother)	-0.42	-0.013	0.48	14.3	0.091	0.15
	(0.26)	(0.15)	(0.26)	(6.14)	(0.070)	(0.068)
	[-0.022]	[-0.0022]	[0.028]			
Age(Father)	-0.0044	-0.025	0.0053	-0.030	0.0074	0.0044
	(0.022)	(0.016)	(0.023)	(0.60)	(0.0071)	(0.0070)
	[-0.00031]	[-0.0043]	[0.00037]			
Age(Mother)	-0.011	0.023	-0.0088	-0.16	-0.0086	-0.0047
	(0.023)	(0.017)	(0.025)	(0.63)	(0.0075)	(0.0073)
	[-0.00079]	[0.0039]	[-0.00062]			
Family-size	0.093	0.043	-0.038	-0.61	0.0098	0.016
	(0.056)	(0.042)	(0.062)	(1.55)	(0.018)	(0.018)
	[0.0065]	[0.0073]	[-0.0027]			
Age(child)	0.17	0.082	0.083	-1.59	-0.092	-0.065
	(0.081)	(0.063)	(0.089)	(2.38)	(0.028)	(0.027)
	[0.012]	[0.014]	[0.0058]			
Female	-0.070	0.31	0.67	44.6	0.24	0.26
	(0.17)	(0.45)	(0.49)	(15.8)	(0.17)	(0.21)
	[-0.0049]	[0.053]	[0.045]			
Raven(child)	-0.0099	-0.019	0.024	0.69	-0.0041	-0.0043
	(0.014)	(0.011)	(0.015)	(0.40)	(0.0047)	(0.0046)
	[-0.00070]	[-0.0033]	[0.0017]			
Raven(parent)	0.013	-0.015	-0.0091	-0.17	0.00043	-0.00048
	(0.0080)	(0.0063)	(0.0089)	(0.24)	(0.0028)	(0.0027)
	[0.00088]	[-0.0026]	[-0.00064]			
Altruism	-0.046	-0.24	0.29	5.68	0.092	0.10
	(0.15)	(0.13)	(0.17)	(4.65)	(0.054)	(0.054)
	[-0.0033]	[-0.041]	[0.021]			
Discounting	0.28	-0.081	-0.36	-6.85	-0.041	-0.033
	(0.15)	(0.12)	(0.17)	(4.29)	(0.050)	(0.050)
	[0.019]	[-0.014]	[-0.025]			
Risk Aversion	0.044	0.22	-0.096	-0.60	0.026	0.034
	(0.15)	(0.12)	(0.18)	(4.67)	(0.054)	(0.053)
	[0.0031]	[0.038]	[-0.0068]			
N	1324	1246	1160	1173	1285	1209

Note: This table provides the estimates based on a random effects specification presented in Equation (1). We estimate a probit model for binary outcomes reported in columns (1)-(3), and an OLS model for continuous outcomes in columns (4)-(6). Robust standard errors are provided in parentheses and corresponding margins are reported in brackets.

The previous literature on cognitive ability and financial decision making (e.g., Korniotis and Kumar, 2010; Agarwal and Mazumder, 2013) has found that more able individuals make better financial decisions. The ability of parents to adequately grasp the importance of investing in their child's human capital can be viewed in a similar light. Faced with a trade-off between having the child work for gain today rather than participate in school for future rewards, a parent with a higher cognitive score may be better able to appreciate the importance of human capital investment. Our result that parents' cognitive ability is associated with a lower probability of child labor and a somewhat higher probability of school attendance is consistent with this idea.

come and are correlated, so our results could reflect multicollinearity. In the Appendix Tables A7-A8 where we include parent's education, cognitive ability and non-cognitive factors separately in each regression, we see that the estimated effects are similar to the results provided in Table 1-2.

While Cunha et al. (2006) find that maternal ability measured using the Armed Forces Qualifying Test (AFQT) is positively associated with children's skill outcomes, our results, which are based on the guardian's cognitive ability, show a negative association with child's work but not with school performance. Our results that the cognitive ability of the parent plays a more substantial role in child's work outcomes compared to schooling outcomes are especially relevant for human capital accumulation in developing countries. This highlights that the investment decision for parents in these economies involves the additional dimension of employing children when young for economic and non-economic activity, a dimension which is not prevalent in developed economies.

Table 1 and Table 2 show that the effect of the child's cognitive ability on work and schooling is somewhat weaker than that of the parent. A child with a one standard-deviation (i.e., 5.36 correct responses) higher test score has a 2.0% lower probability of working in any form of work, driven primarily by a reduction in chores of 2.3%. In terms of schooling, a one standard-deviation higher cognitive score is associated with an increase in this score on the central exam, but the estimate is no more than 3.7 additional marks (out of 500, which translates to a 0.74% increase). A one standard-deviation increase in the child's cognitive performance is also related to a 1.8% lower probability of absence. These reported estimated effects, especially that for a one standard-deviation increase in the cognitive score of the parent, holds more importance for the child's work than the child's own cognitive score, further underscoring the inherent agency problem whereby parents make important decisions for their children's human capital development. Additionally, as argued by Becker (1981), if parents have more than one child, they may believe that it is important to invest more heavily in the more gifted child for efficiency reasons; however, they could also invest more heavily in the less able child for equity reasons. While we observe only one child per parent in our data, the effects we find of the more able child being associated with lower child labor and better schooling outcomes are consistent with parents' willingness to invest more time in a gifted child in schooling rather than having them work, which is also found by Bacolod and Ranjan (2008) and Dendir (2014). However, the effect is weak, which could be due to concerns about equity across children, indicating that parental motivation to invest in a child goes beyond their child's cognitive ability.

4.3 The impact of noncognitive factors

Table 1 indicates that all three noncognitive characteristics play an important role in child's work outcomes. A parent who is altruistic has a 5% lower probability of engaging their child in any type of work, driven by a decrease in probability of 5.5% for economic activity and 4.7% for chores (whereby chores are driven by chores conducted inside the household, which have a decrease in probability of 5.3%). We see similar associations with child's work outcomes and the parent's patience. An impatient parent's child has a 5.9% higher probability of engaging in work, driven by an increase in the probability of chores of 7.0% (again driven by household chores). Moreover, an impatient parent's child spends, on average, 11 minutes more per-day working. Table 1 also shows that a risk-averse parent's child has a 7.5% higher probability of engaging in work, which is driven by a higher probability of doing chores 8.7% (primarily chores conducted inside the household). In terms of the additional time spent on work by a risk-averse parent's child (relative to a risk-seeking parent's child), our estimates show that such a child spends an additional 15 minutes per-day working. In summary, altruism is associated with a reduction in child's work, whereas impatience and risk aversion are associated with an increase in child's engagement in work.

Table 2 shows that an altruistic parent's child has a 4.1% lower likelihood of being absent from school, spends 6 more minutes per-day in school; this effect is primarily driven by 6 additional minutes of self study, which translates to approximately 4 fewer days of absence from school each year or 20 additional hours per year on self study. An impatient parent's child has a 2% higher probability of dropping out of school and a 2.5% lower probability of passing the central exam. A risk-averse parent's child has a 3.8% higher probability of being absent from school at least once during a month. These results show that noncognitive factors play important roles in parent's decisions about their children's schooling outcomes since altruism is associated with better school outcomes in terms of participation and time spent on schooling, impatience is associated with worse schooling outcomes in terms of participation and performance, and risk aversion is associated with worse outcomes in terms of participation.

The effects of altruism and impatience are in line with what one would expect, given the common theories of child labor. In the seminal work of Baland and Robinson, 2000, for example, parents solve a trade-off between having their child work for income today and having their child in school so that they will earn higher income in the future. Altruism towards the child is essential for parents to invest in their children's education; otherwise, the parents would do best by having the child simply work for their current income. Impatience is likewise important because education provides a payoff in the future, and more impatient parents are less likely to invest to achieve future gains. Like the parent's cognitive ability, risk aversion has, to the best of our knowledge, not previously been considered as a driver of engaging children in work. Previous literature on risk aversion and schooling (Wölfel and Heineck, 2012; Checchi et al., 2014) indicates that more risk-averse parents will invest in less schooling for their children. Our results for risk aversion is consistent with the idea that parents view the schooling decision to be made under uncertainty, which is the main contribution of Altonji (1993). Our finding that risk aversion is associated with worse schooling outcomes is in line with the previous literature, but our finding that risk aversion increases child's work is new.

5 Conclusion

We conducted a novel survey of a large sample of parents and their children in Kasur, Pakistan, to provide new insights into whether parent's cognitive and noncognitive factors impact decisions about their child's work and schooling. In contrast to previous literature, we focus on the parent's cognitive ability and noncognitive characteristics in a context of developing countries where children working in economic and informal work is prevalent. In part, the limited research on these factors, especially in relation to child's work and schooling in developing economies, is due to the unobserved nature of the variables of interest. We circumvent this issue by collecting this information through parent-child linked surveys and merging it with administrative and school ledger data. The combination of these data provides a rich source of information on outcomes, control variables and explanatory variables of interest.

Consistent with the idea that parents trade off the contemporaneous gain from having a child work against the future gain produced by investing in education, we find that children whose parent has a higher cognitive ability work less and have better schooling outcomes. Moreover, we find that altruism is associated with less child work and better school outcomes and that impatience and risk aversion are associated with more child work and worse school outcomes. We also find that a child with a higher cognitive ability is less likely to work and has better schooling outcomes. Interestingly, the parent's cognitive ability is quantitatively more important than the child's own ability and parent's noncognitive factors play even more significant role in their child's work and schooling outcomes.

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Appendix A: Summary and Robustness

Figure A1: Spatial Distribution of Schools in Kasur

Table A1: School Sample

Gender	Total Schools level			Our Sample level		
	High	Middle	Total	High	Middle	Total
Female	11	10	21	11	4	15
Male	8	16	24	5	12	17
Total	19	26	45	16	16	32

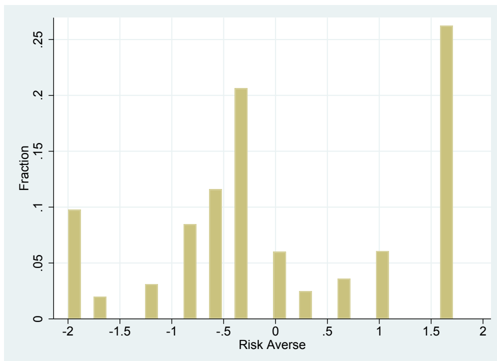
Note: This table provides the distribution of schools by school levels and gender.

Table A2: Summary Statistics - Independent Variables

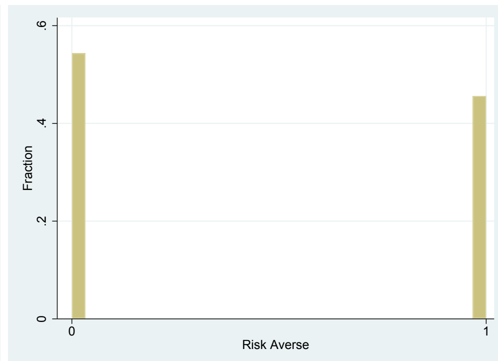
	All Sample
	(1)
Control–Parents	
Edu(Father)	0.34
	(0.47)
Edu(Mother)	0.15
	(0.35)
Age(Father)	43.43
	(6.65)
Age(Mother)	38.92
	(6.20)
Family-size	6.97
	(1.39)
Control–Child	
Age(child)	12.35
	(0.90)
Female	0.46
	(0.50)
Cognitive–Child	
Raven(child)	17.24
	(5.36)
Cognitive–Parent	
Raven(parent)	21.92
	(9.15)
Noncognitive–Parent	
Risk Aversion	0.46
	(0.50)
Discounting	0.55
	(0.50)
Altruism	0.57
	(0.49)
N	1416

Note: This table provides mean and standard errors (in parenthesis) for the control variables, cognitive factors and the noncognitive factors.

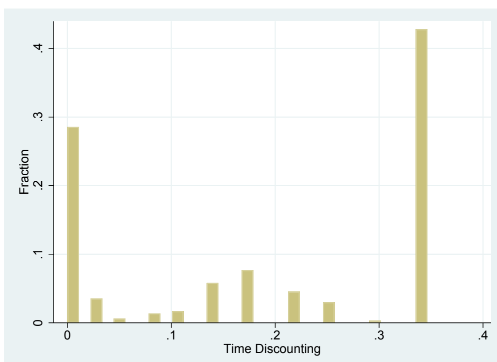
Figure A2: Noncognitive Variables



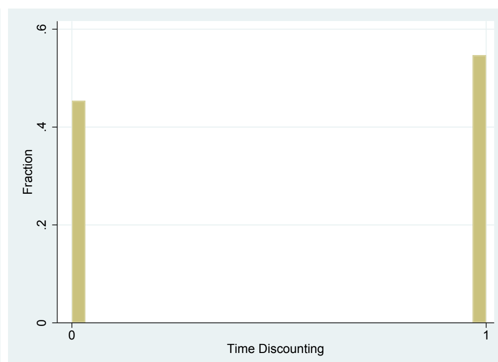
A2.1: Risk Aversion



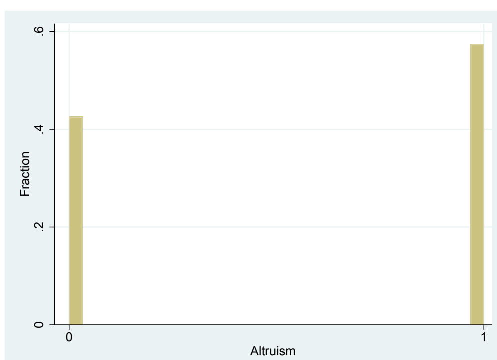
A2.2: Risk Aversion Dummy



A2.3: Time Discounting



A2.4: Time Discounting Dummy



A2.5: Altruism Dummy

Table A3: Summary Statistics - Dependent Variables

	All Sample	**Females**	**Males**
	(1)	(2)	(3)
All Work	0.75	0.73	0.77
	(0.43)	(0.44)	(0.42)
Economic Activity	0.19	0.18	0.19
	(0.39)	(0.39)	(0.39)
All HHC	0.74	0.72	0.76
	(0.44)	(0.45)	(0.43)
HHC-In	0.35	0.50	0.21
	(0.48)	(0.50)	(0.41)
HHC-Out	0.45	0.32	0.57
	(0.50)	(0.47)	(0.50)
Work Hours	1.89	1.79	1.98
	(1.37)	(1.38)	(1.36)
School Hours	8.29	8.50	8.10
	(1.06)	(0.92)	(1.14)
Self Study	3.65	3.90	3.44
	(1.00)	(0.87)	(1.06)
Dropout	0.03	0.03	0.04
	(0.18)	(0.17)	(0.19)
Marks	286.45	318.23	259.22
	(92.45)	(71.55)	(99.43)
Absence/month	0.83	0.89	0.79
	(0.37)	(0.31)	(0.41)
N	1416	655	761

Note: This table provides mean and standard errors (in parenthesis) for the dependent variables. All Work, Economic Activity, Household chores, Inside, Outside, Dropout and Absence are binary variables while remaining variables are continuous.

Table A4: Robustness Regression – Leisure Hours

	Baseline Random Effect	Robustness Random Effect			Baseline Fixed Effect	Robustness Fixed Effect		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Edu(Father)	-0.084	-0.094	-0.092	-0.086	-0.077	-0.088	-0.084	-0.080
	(0.064)	(0.063)	(0.064)	(0.063)	(0.064)	(0.063)	(0.063)	(0.063)
Edu(Mother)	0.016	0.019	0.021	0.015	0.013	0.017	0.018	0.013
	(0.084)	(0.083)	(0.084)	(0.083)	(0.084)	(0.083)	(0.083)	(0.083)
Age(Father)	-0.013	-0.013	-0.014	-0.012	-0.011	-0.012	-0.012	-0.011
	(0.0086)	(0.0085)	(0.0085)	(0.0085)	(0.0086)	(0.0085)	(0.0085)	(0.0085)
Age(Mother)	0.0096	0.010	0.010	0.0093	0.0094	0.010	0.010	0.0091
	(0.0090)	(0.0089)	(0.0090)	(0.0089)	(0.0090)	(0.0089)	(0.0089)	(0.0089)
Family-size	-0.0054	-0.0052	-0.0064	-0.0042	-0.0093	-0.0089	-0.011	-0.0078
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Age(child)	0.094	0.098	0.096	0.096	0.098	0.10	0.10	0.099
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Female	0.15	0.15	0.15	0.15				
	(0.22)	(0.21)	(0.20)	(0.22)				
Raven(child)	0.022	0.021	0.022	0.022	0.022	0.021	0.021	0.021
	(0.0056)	(0.0056)	(0.0056)	(0.0056)	(0.0057)	(0.0056)	(0.0056)	(0.0056)
Raven(parent)	-0.0012		-0.0015		-0.0019		-0.0022	
	(0.0033)		(0.0033)		(0.0034)		(0.0033)	
Altruism	-0.10			-0.10	-0.11			-0.10
	(0.065)			(0.065)	(0.066)			(0.065)
Discounting	0.0050			0.0082	0.014			0.017
	(0.060)			(0.060)	(0.060)			(0.060)
Risk Aversion	-0.056			-0.063	-0.050			-0.060
	(0.065)			(0.063)	(0.065)			(0.064)
N	1285	1289	1285	1289	1285	1289	1285	1289

Note: This table provides the estimates for leisure hours for a random effects and a fixed effects version of specification (1). Column (1) and (5) use the same explanatory variables as used in the baseline regressions presented in Table 1-2. Note that because schools are segregated by gender, a coefficient for "Female" dummy cannot be estimated under the school fixed effect specification. For each of the baseline results, in columns (2)-(4) and (6)-(8), respectively we present estimates when parental variables for education, cognitive and noncognitive factors are added separately in each regression. Robust standard errors are provided in parentheses.

Table A5: School Fixed-Effect Regression – Work Outcomes

	All Work (Y/N)	Economic Activity (Y/N)	All HHC (Y/N)	HHC-In (Y/N)	HHC-Out (Y/N)	Work Hours (Hours)
	(1)	(2)	(3)	(4)	(5)	(6)
Edu(Father)	-0.13	0.094	-0.11	-0.038	-0.087	-0.061
	(0.093)	(0.10)	(0.094)	(0.090)	(0.085)	(0.083)
	[-0.034]	[0.023]	[-0.029]	[-0.011]	[-0.029]	
Edu(Mother)	0.064	0.079	0.0017	-0.16	0.21	-0.016
	(0.12)	(0.13)	(0.12)	(0.12)	(0.11)	(0.11)
	[0.017]	[0.019]	[0.00045]	[-0.049]	[0.073]	
Age(Father)	-0.0087	-0.0022	-0.0073	-0.019	-0.0099	0.0035
	(0.013)	(0.014)	(0.013)	(0.012)	(0.011)	(0.011)
	[-0.0023]	[-0.00054]	[-0.0020]	[-0.0057]	[-0.0034]	
Age(Mother)	0.031	-0.0065	0.032	0.046	0.021	0.013
	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)	(0.012)
	[0.0082]	[-0.0016]	[0.0086]	[0.014]	[0.0070]	
Family-size	0.0029	-0.0022	-0.0021	-0.027	0.0083	-0.011
	(0.032)	(0.035)	(0.032)	(0.030)	(0.029)	(0.029)
	[0.00077]	[-0.00053]	[-0.00056]	[-0.0082]	[0.0028]	
Age(child)	0.11	-0.062	0.11	0.065	0.012	0.084
	(0.050)	(0.054)	(0.050)	(0.046)	(0.044)	(0.044)
	[0.029]	[-0.015]	[0.029]	[0.020]	[0.0041]	
Raven(child)	-0.012	-0.0022	-0.015	-0.0018	-0.0094	-0.0075
	(0.0081)	(0.0086)	(0.0082)	(0.0079)	(0.0074)	(0.0076)
	[-0.0033]	[-0.00052]	[-0.0040]	[-0.00055]	[-0.0032]	
Raven(parent)	-0.027	-0.045	-0.026	-0.018	-0.015	-0.012
	(0.0051)	(0.0057)	(0.0051)	(0.0047)	(0.0044)	(0.0044)
	[-0.0071]	[-0.011]	[-0.0072]	[-0.0055]	[-0.0050]	
Altruism	-0.22	-0.29	-0.20	-0.22	-0.13	-0.17
	(0.098)	(0.10)	(0.098)	(0.091)	(0.086)	(0.086)
	[-0.060]	[-0.070]	[-0.054]	[-0.068]	[-0.043]	
Discounting	0.24	-0.015	0.28	0.17	0.025	0.16
	(0.090)	(0.095)	(0.091)	(0.084)	(0.079)	(0.080)
	[0.066]	[-0.0037]	[0.078]	[0.052]	[0.0086]	
Risk Aversion	0.34	-0.028	0.38	0.27	0.056	0.26
	(0.098)	(0.10)	(0.098)	(0.089)	(0.085)	(0.086)
	[0.091]	[-0.0067]	[0.10]	[0.083]	[0.019]	
N	1298	1223	1270	1307	1325	1154

Note: This table provides the estimates based on a fixed effects specification presented in Equation (1). We estimate a probit model for binary outcomes reported in columns (1)-(5), and an OLS model for continuous outcome in column (6). Note that because schools are segregated by gender, a coefficient for "Female" dummy cannot be estimated under the school fixed effect specification. Robust standard errors are provided in parentheses and corresponding margins are reported in brackets.

Table A6: School Fixed-Effect Regression – Schooling Outcomes

	Dropout (Y/N)	Absence (Y/N)	Pass (Y/N)	Marks (Points)	School Hours (Hours)	Self Study (Hours)
	(1)	(2)	(3)	(4)	(5)	(6)
Edu(Father)	0.036	-0.049	0.36	13.5	0.037	0.015
	(0.17)	(0.12)	(0.19)	(4.50)	(0.053)	(0.052)
	[0.0033]	[-0.0082]	[0.057]			
Edu(Mother)	-0.46	0.0032	0.51	14.6	0.082	0.14
	(0.27)	(0.16)	(0.27)	(6.10)	(0.070)	(0.068)
	[-0.031]	[0.00054]	[0.073]			
Age(Father)	-0.0017	-0.026	0.0063	-0.048	0.0072	0.0043
	(0.026)	(0.017)	(0.024)	(0.60)	(0.0072)	(0.0070)
	[-0.00015]	[-0.0043]	[0.0010]			
Age(Mother)	-0.013	0.023	-0.014	-0.23	-0.0083	-0.0046
	(0.027)	(0.017)	(0.027)	(0.63)	(0.0075)	(0.0073)
	[-0.0012]	[0.0039]	[-0.0023]			
Family-size	0.099	0.048	-0.034	-0.52	0.010	0.017
	(0.061)	(0.043)	(0.066)	(1.54)	(0.018)	(0.018)
	[0.0088]	[0.0081]	[-0.0058]			
Age(child)	0.15	0.086	0.083	-1.94	-0.092	-0.066
	(0.090)	(0.065)	(0.094)	(2.38)	(0.028)	(0.027)
	[0.013]	[0.015]	[0.014]			
Raven(child)	-0.012	-0.022	0.030	0.74	-0.0027	-0.0035
	(0.016)	(0.011)	(0.016)	(0.40)	(0.0047)	(0.0047)
	[-0.0011]	[-0.0038]	[0.0051]			
Raven(parent)	0.014	-0.016	-0.011	-0.19	0.00032	-0.00055
	(0.0090)	(0.0065)	(0.0092)	(0.24)	(0.0028)	(0.0028)
	[0.0013]	[-0.0027]	[-0.0018]			
Altruism	0.097	-0.27	0.29	5.66	0.10	0.11
	(0.18)	(0.13)	(0.18)	(4.67)	(0.055)	(0.054)
	[0.0086]	[-0.045]	[0.049]			
Discounting	0.33	-0.098	-0.38	-6.43	-0.037	-0.032
	(0.17)	(0.12)	(0.18)	(4.28)	(0.051)	(0.050)
	[0.028]	[-0.016]	[-0.062]			
Risk Aversion	0.028	0.24	-0.098	-0.45	0.025	0.034
	(0.17)	(0.13)	(0.19)	(4.69)	(0.054)	(0.054)
	[0.0025]	[0.040]	[-0.017]			
N	969	1080	546	1173	1285	1209

Note: This table provides the estimates based on a fixed effects specification presented in Equation (1). We estimate a probit model for binary outcomes reported in columns (1)-(3), and an OLS model for continuous outcomes in columns (4)-(6). Note that because schools are segregated by gender, a coefficient for "Female" dummy cannot be estimated under the school fixed effect specification. Robust standard errors are provided in parentheses and corresponding margins are reported in brackets.

Table A7: Robustness Regression – Labor Outcomes

	All Work (Y/N)			Economic Activity (Y/N)			All HHC (Y/N)			HHC-In (Y/N)			HHC-Out (Y/N)			Work Hours (Hours)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Edu(Father)	-0.14	-0.12	-0.13	0.0054	0.073	0.029	-0.13	-0.11	-0.12	-0.078	-0.056	-0.071	-0.091	-0.078	-0.083	-0.075	-0.062	-0.070
	(0.089)	(0.090)	(0.090)	(0.095)	(0.098)	(0.096)	(0.090)	(0.091)	(0.090)	(0.086)	(0.087)	(0.087)	(0.082)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
	[-0.040]	[-0.033]	[-0.036]	[0.0013]	[0.017]	[0.0070]	[-0.037]	[-0.030]	[-0.033]	[-0.025]	[-0.018]	[-0.022]	[-0.032]	[-0.027]	[-0.029]			
Edu(Mother)	0.11	0.096	0.071	0.095	0.086	0.10	0.053	0.042	0.014	-0.12	-0.13	-0.16	0.21	0.21	0.20	-0.0040	-0.0083	-0.036
	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
	[0.029]	[0.025]	[0.019]	[0.023]	[0.020]	[0.025]	[0.015]	[0.011]	[0.0037]	[-0.038]	[-0.039]	[-0.049]	[0.072]	[0.073]	[0.069]			
Age(Father)	-0.0038	-0.0074	-0.0041	-0.0041	-0.0056	-0.0015	-0.0024	-0.0056	-0.0031	-0.018	-0.020	-0.020	-0.0081	-0.0095	-0.0072	0.0072	0.0057	0.0068
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
	[-0.0010]	[-0.0020]	[-0.0011]	[-0.00098]	[-0.0013]	[-0.00035]	[-0.00068]	[-0.0015]	[-0.00086]	[-0.0058]	[-0.0062]	[-0.0063]	[-0.0028]	[-0.0033]	[-0.0025]			
Age(Mother)	0.025	0.029	0.026	-0.0051	-0.0040	-0.0080	0.026	0.030	0.027	0.044	0.046	0.047	0.018	0.020	0.017	0.011	0.012	0.012
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
	[0.0071]	[0.0080]	[0.0070]	[-0.0012]	[-0.00091]	[-0.0019]	[0.0075]	[0.0083]	[0.0075]	[0.014]	[0.015]	[0.015]	[0.0063]	[0.0067]	[0.0060]			
Family-size	0.0085	0.0042	0.0033	0.029	-0.0020	0.031	0.0027	-0.00075	-0.0033	-0.020	-0.024	-0.023	0.012	0.0035	0.012	-0.0050	-0.0098	-0.011
	(0.031)	(0.031)	(0.031)	(0.033)	(0.034)	(0.033)	(0.031)	(0.031)	(0.031)	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)
	[0.0024]	[0.0011]	[0.00091]	[0.0068]	[-0.00046]	[0.0073]	[0.00077]	[-0.00021]	[-0.00090]	[-0.0063]	[-0.0076]	[-0.0073]	[0.0041]	[0.0012]	[0.0043]			
Age(child)	0.097	0.10	0.093	-0.063	-0.050	-0.067	0.095	0.10	0.091	0.068	0.076	0.059	0.012	0.015	0.0085	0.090	0.094	0.084
	(0.047)	(0.048)	(0.048)	(0.051)	(0.052)	(0.051)	(0.048)	(0.048)	(0.048)	(0.044)	(0.045)	(0.044)	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)	(0.044)
	[0.027]	[0.028]	[0.025]	[-0.015]	[-0.011]	[-0.016]	[0.027]	[0.028]	[0.025]	[0.022]	[0.024]	[0.019]	[0.0041]	[0.0053]	[0.0030]			
Female	-0.034	-0.055	-0.038	-0.12	-0.14	-0.10	-0.0068	-0.028	-0.0082	0.91	0.90	0.91	-0.68	-0.69	-0.69	-0.15	-0.16	-0.15
	(0.17)	(0.18)	(0.17)	(0.22)	(0.22)	(0.21)	(0.18)	(0.19)	(0.19)	(0.13)	(0.14)	(0.13)	(0.17)	(0.17)	(0.17)	(0.19)	(0.19)	(0.19)
	[-0.0094]	[-0.015]	[-0.010]	[-0.029]	[-0.032]	[-0.024]	[-0.0019]	[-0.0078]	[-0.0023]	[0.31]	[0.30]	[0.31]	[-0.24]	[-0.24]	[-0.24]			
Raven(child)	-0.014	-0.015	-0.013	-0.00014	-0.0012	0.00065	-0.017	-0.018	-0.016	-0.0039	-0.0054	-0.0022	-0.010	-0.0096	-0.0095	-0.0085	-0.0085	-0.0071
	(0.0077)	(0.0079)	(0.0078)	(0.0082)	(0.0084)	(0.0082)	(0.0078)	(0.0079)	(0.0079)	(0.0075)	(0.0076)	(0.0075)	(0.0072)	(0.0072)	(0.0072)	(0.0076)	(0.0076)	(0.0076)
	[-0.0040]	[-0.0042]	[-0.0035]	[-0.000033]	[-0.00026]	[0.00015]	[-0.0049]	[-0.0050]	[-0.0044]	[-0.0012]	[-0.0017]	[-0.00069]	[-0.0035]	[-0.0033]	[-0.0033]			
Raven(parent)		-0.020			-0.044			-0.019			-0.014			-0.013			-0.011	
		(0.0048)			(0.0055)			(0.0048)			(0.0044)			(0.0042)			(0.0043)	
		[-0.0054]			[-0.010]			[-0.0053]			[-0.0046]			[-0.0044]				
Altruism			-0.17			-0.23			-0.15			-0.15			-0.11			-0.13
			(0.092)			(0.096)			(0.093)			(0.086)			(0.082)			(0.084)
			[-0.045]			[-0.055]			[-0.042]			[-0.049]			[-0.037]			
Discounting			0.23			0.0012			0.26			0.18			0.039			0.20
			(0.085)			(0.089)			(0.086)			(0.081)			(0.077)			(0.080)
			[0.064]			[0.00028]			[0.074]			[0.057]			[0.014]			
Risk Aversion			0.18			-0.24			0.22			0.20			-0.035			0.20
			(0.090)			(0.094)			(0.091)			(0.083)			(0.081)			(0.083)
			[0.049]			[-0.057]			[0.060]			[0.064]			[-0.012]			
N	1303	1298	1303	1330	1325	1330	1275	1270	1275	1312	1307	1312	1330	1325	1330	1158	1154	1158

Note: This table provides the estimates based on a random effects specification presented in Equation (1). We estimate a probit model for binary outcomes reported in columns (1)-(15), and an OLS model for continuous outcome in columns (16)-(18). Robust standard errors are provided in parentheses and corresponding margins are reported in brackets.

Table A8: Robustness Regression – Schooling Outcomes

	Dropout (Y/N)			Absence (Y/N)			Pass (Y/N)			Marks (Points)			School Hours (Hours)			Self Study (Hours)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Edu(Father)	0.020	0.013	0.027	-0.059	-0.070	-0.048	0.37	0.36	0.36	13.9	14.3	13.5	0.047	0.047	0.040	0.021	0.023	0.015
	(0.15)	(0.15)	(0.15)	(0.12)	(0.12)	(0.12)	(0.18)	(0.18)	(0.18)	(4.49)	(4.52)	(4.50)	(0.053)	(0.053)	(0.053)	(0.052)	(0.052)	(0.052)
	[0.0014]	[0.00090]	[0.0019]	[-0.010]	[-0.012]	[-0.0083]	[0.025]	[0.024]	[0.024]									
Edu(Mother)	-0.38	-0.40	-0.40	-0.0044	0.021	-0.036	0.40	0.40	0.48	13.5	13.4	14.5	0.088	0.084	0.094	0.14	0.14	0.15
	(0.25)	(0.26)	(0.25)	(0.15)	(0.15)	(0.15)	(0.25)	(0.25)	(0.26)	(6.08)	(6.11)	(6.11)	(0.070)	(0.070)	(0.070)	(0.068)	(0.068)	(0.068)
	[-0.021]	[-0.022]	[-0.022]	[-0.00077]	[0.0037]	[-0.0063]	[0.025]	[0.024]	[0.028]									
Age(Father)	-0.0074	-0.0055	-0.0069	-0.023	-0.025	-0.023	0.010	0.0094	0.0063	0.051	0.0093	0.017	0.0081	0.0082	0.0073	0.0052	0.0051	0.0045
	(0.021)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)	(0.022)	(0.022)	(0.023)	(0.60)	(0.60)	(0.60)	(0.0071)	(0.0071)	(0.0071)	(0.0070)	(0.0070)	(0.0070)
	[-0.00052]	[-0.00039]	[-0.00048]	[-0.0041]	[-0.0043]	[-0.0040]	[0.00073]	[0.00067]	[0.00044]									
Age(Mother)	-0.0078	-0.0098	-0.0088	0.020	0.022	0.020	-0.016	-0.016	-0.0096	-0.24	-0.21	-0.19	-0.0094	-0.0094	-0.0086	-0.0056	-0.0055	-0.0049
	(0.022)	(0.023)	(0.023)	(0.016)	(0.017)	(0.017)	(0.024)	(0.024)	(0.025)	(0.63)	(0.63)	(0.63)	(0.0075)	(0.0075)	(0.0075)	(0.0073)	(0.0073)	(0.0073)
	[-0.00056]	[-0.00069]	[-0.00062]	[0.0036]	[0.0038]	[0.0035]	[-0.0012]	[-0.0011]	[-0.00067]									
Family-size	0.086	0.093	0.087	0.038	0.037	0.045	-0.037	-0.041	-0.034	-0.66	-0.73	-0.54	0.0096	0.0100	0.0096	0.016	0.016	0.015
	(0.054)	(0.055)	(0.055)	(0.041)	(0.041)	(0.041)	(0.061)	(0.061)	(0.062)	(1.54)	(1.55)	(1.54)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
	[0.0061]	[0.0066]	[0.0061]	[0.0067]	[0.0064]	[0.0077]	[-0.0027]	[-0.0029]	[-0.0024]									
Age(child)	0.18	0.18	0.17	0.084	0.087	0.080	0.059	0.064	0.078	-1.73	-1.78	-1.54	-0.096	-0.095	-0.093	-0.068	-0.068	-0.066
	(0.080)	(0.080)	(0.081)	(0.061)	(0.062)	(0.062)	(0.088)	(0.088)	(0.089)	(2.37)	(2.38)	(2.37)	(0.028)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
	[0.013]	[0.013]	[0.012]	[0.015]	[0.015]	[0.014]	[0.0042]	[0.0046]	[0.0055]									
Female	-0.11	-0.095	-0.099	0.36	0.36	0.32	0.70	0.70	0.68	45.1	44.9	44.9	0.25	0.25	0.24	0.26	0.26	0.26
	(0.17)	(0.17)	(0.17)	(0.44)	(0.44)	(0.45)	(0.49)	(0.49)	(0.49)	(15.5)	(15.6)	(15.6)	(0.16)	(0.16)	(0.17)	(0.19)	(0.20)	(0.21)
	[-0.0080]	[-0.0067]	[-0.0069]	[0.062]	[0.061]	[0.054]	[0.048]	[0.047]	[0.045]									
Raven(child)	-0.012	-0.011	-0.010	-0.019	-0.019	-0.019	0.026	0.026	0.024	0.73	0.74	0.67	-0.0038	-0.0038	-0.0041	-0.0038	-0.0039	-0.0042
	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)	(0.011)	(0.015)	(0.015)	(0.015)	(0.40)	(0.40)	(0.40)	(0.0047)	(0.0047)	(0.0047)	(0.0046)	(0.0046)	(0.0046)
	[-0.00083]	[-0.00081]	[-0.00072]	[-0.0033]	[-0.0034]	[-0.0033]	[0.0019]	[0.0019]	[0.0017]									
Raven(parent)		0.011			-0.013			-0.0095			-0.17			0.00063			-0.00027	
		(0.0077)			(0.0062)			(0.0087)			(0.23)			(0.0028)			(0.0027)	
		[0.00078]			[-0.0022]			[-0.00068]										
Altruism			-0.050			-0.23			0.29			5.97			0.093			0.10
			(0.15)			(0.13)			(0.17)			(4.63)			(0.054)			(0.053)
			[-0.0036]			[-0.039]			[0.021]									
Discounting			0.25			-0.075			-0.36			-6.70			-0.040			-0.033
			(0.15)			(0.12)			(0.17)			(4.27)			(0.050)			(0.050)
			[0.017]			[-0.013]			[-0.025]									
Risk Aversion			0.075			0.19			-0.13			-1.34			0.026			0.031
			(0.15)			(0.12)			(0.18)			(4.58)			(0.053)			(0.053)
			[0.0053]			[0.032]			[-0.0089]									
N	1329	1324	1329	1251	1246	1251	1165	1160	1165	1178	1173	1178	1289	1285	1289	1213	1209	1213

Note: This table provides the estimates based on a random effects specification presented in Equation (1). We estimate a probit model for binary outcomes reported in columns (1)-(9), and an OLS model for continuous outcomes in columns (10)-(18). Robust standard errors are provided in parentheses and corresponding margins are reported in brackets.

Appendix B: Online

Province/District Selection

We select Punjab province for the following reasons. While out of the four provinces of Pakistan, Punjab is the most populous and contributes the largest share of GDP to the national economy,[33], but similar to other provinces also suffers from alarmingly low rates of school enrollments.[34] Additionally, the government of Punjab has recently made an effort to collect education-related statistics (which are not always available for other provinces), and the crucial feature this study is based on are the scores on the central exam, which is designed exclusively for the province of Punjab and is not currently implemented in other provinces.

Geographically, we choose the district of Kasur in Punjab[35] because the average level of various development indicators (such as school drop-out rates, monthly income of employed, population involved in agriculture, youth labor market participation and crime rate) in Punjab are closest to those observed in Kasur; therefore, Kasur is representative of Punjab in many important factors.[36] The economy of Kasur is characterized by a mix of agricultural and industrial economic activity, where industrial output often utilizes inputs from the agriculture sector.[37] Our analysis aims to include a mix of rural/urban areas. Since collecting data from urban and rural areas would require us to treat the two samples separately, thus affecting the power of the analysis, we concentrate on areas that, according to the urbanization index, are classified as rural/urban areas. Geographically, these areas lie between urban and rural areas. While urban areas provide a variety of opportunities for manual work in various industrial units and small businesses, rural areas offer rich opportunities for agricultural work. Rural/urban areas, therefore, offer both types of opportunities for work, potentially making this sample of the population most exposed to the problem of children's participation in some form of economic activity.

[33]Punjab is home to more than 52% of the population of Pakistan (Census 2017, Pakistan) and contributes more than 57% of Pakistan's GDP

[34]Recently published statistics (Alif Ailaan: Education Survey, 2016) highlight that of the estimated 26 million children in Punjab between the ages of 5 and 16 years, 11.4 million are out of school. Moreover, 5.1 million children are enrolled in government primary schools, but only 3.4 million are enrolled in middle and secondary schools.

[35]Kasur is neighbored by Lahore to the east, Nankana Sahib to the north, Faisalabad to the west and Okara and India to the south.

[36]See, Online Appendix B Figures B1-B7, which are based on the author's calculations using the data from Alif Ailaan: Education Survey (2016).

[37]Kasur produces agriculture products, such as sugar cane, rice, wheat and cotton, and has number of industries, such as sugar, textiles, flour and vegetable oil mills.

Figure B1: Dropout

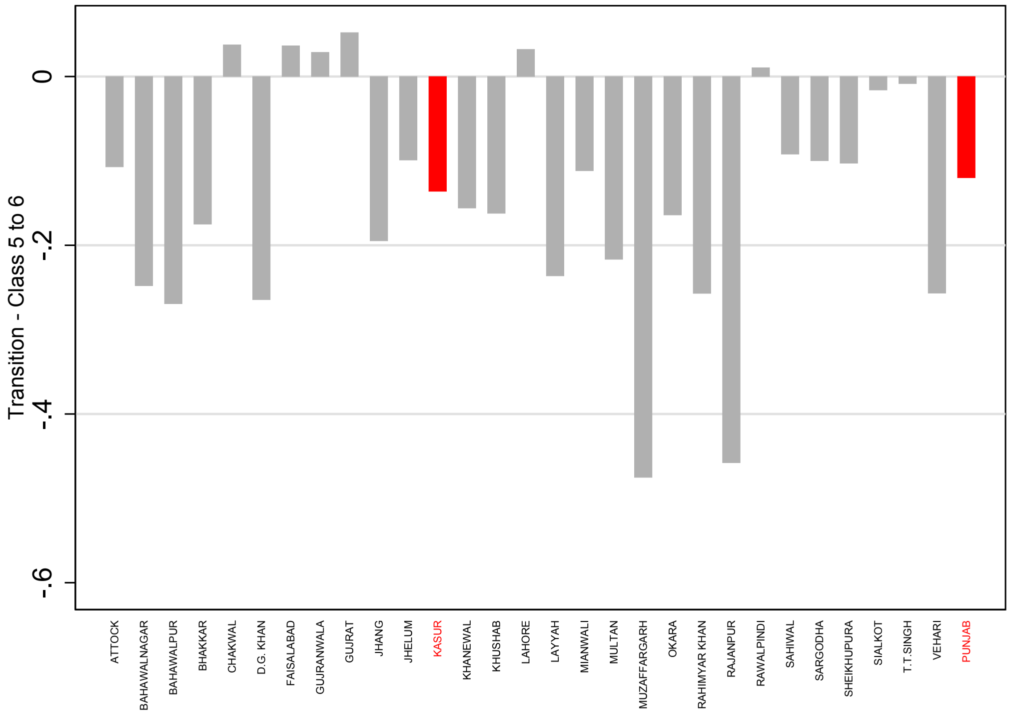


Figure B2: Real Wage 2011

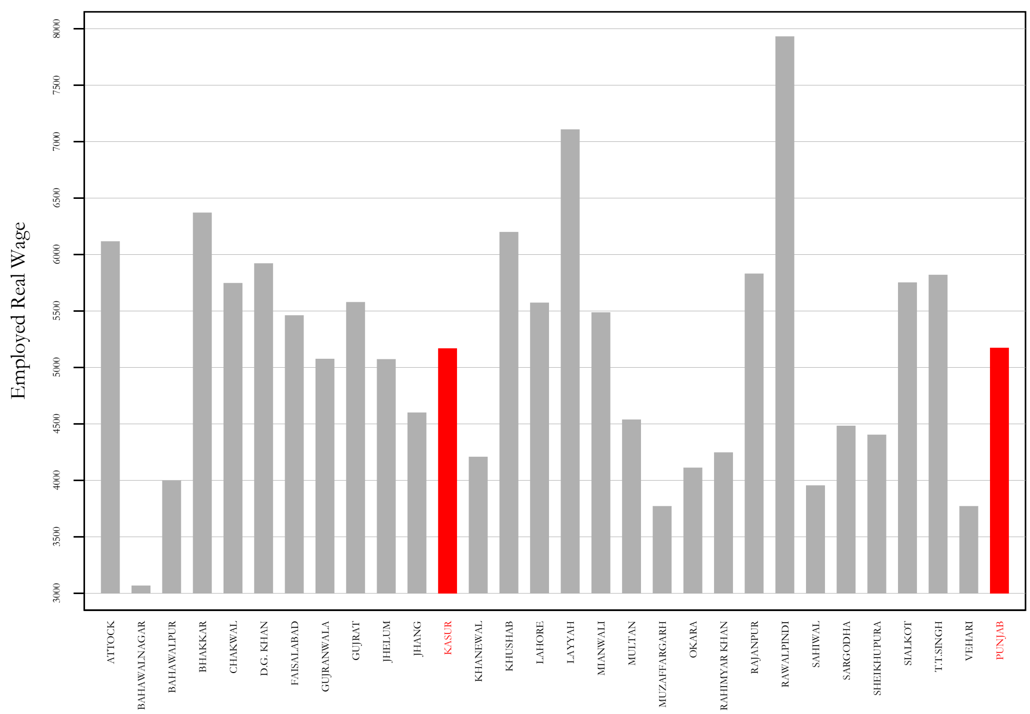


Figure B3: Employment 2011

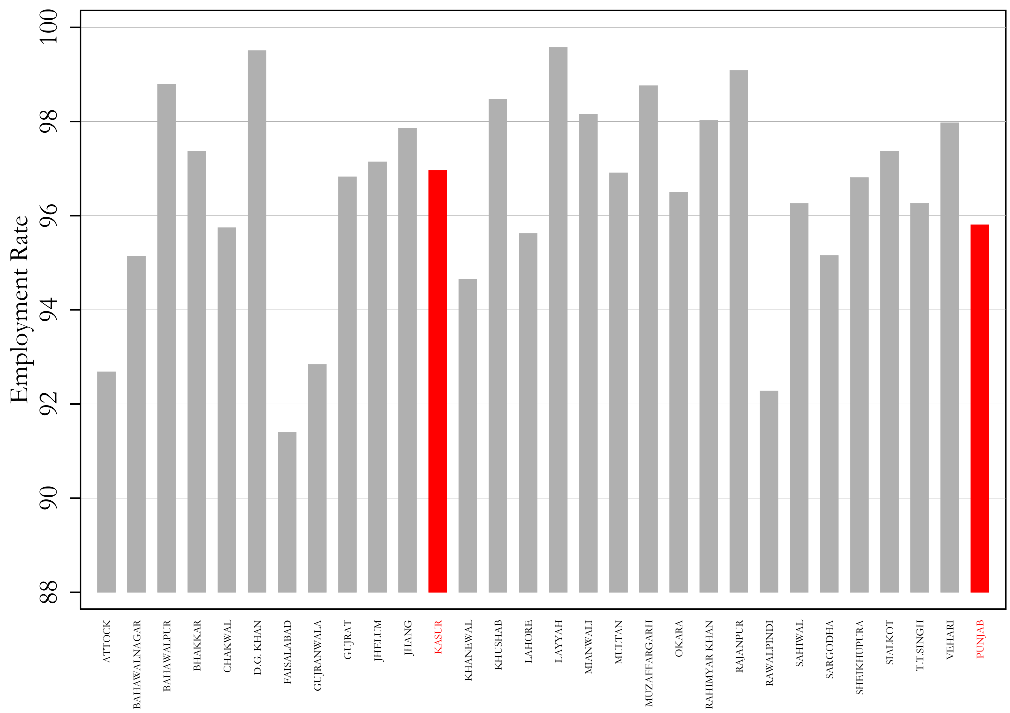


Figure B4: Employed Population in Cultivation 2011

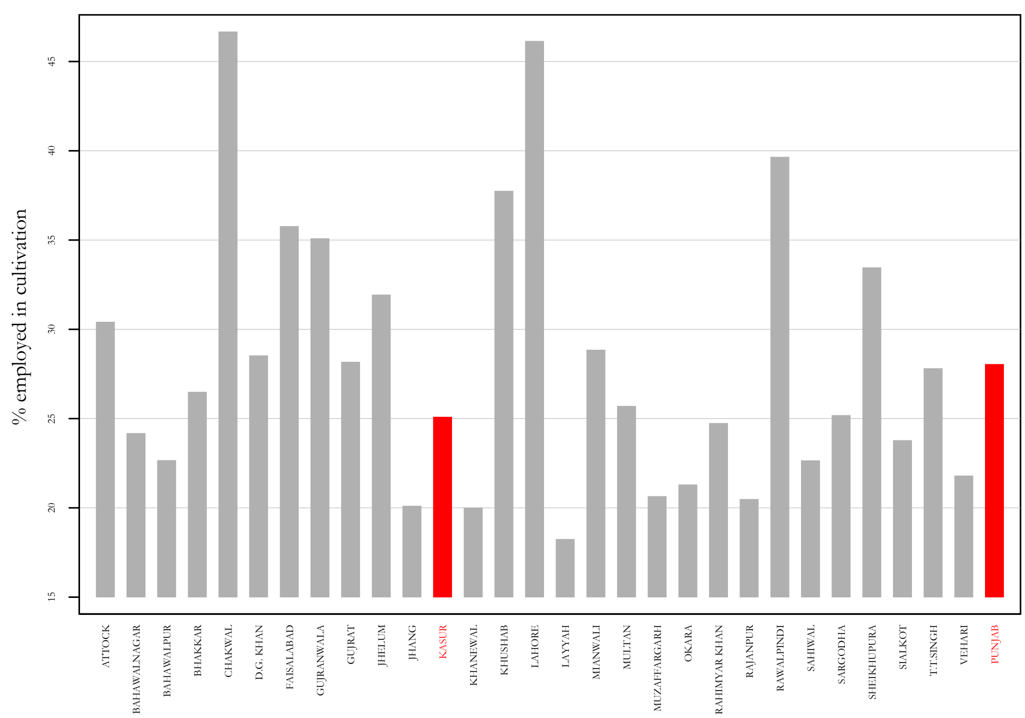


Figure B5: Female Youth Population Employed 2011

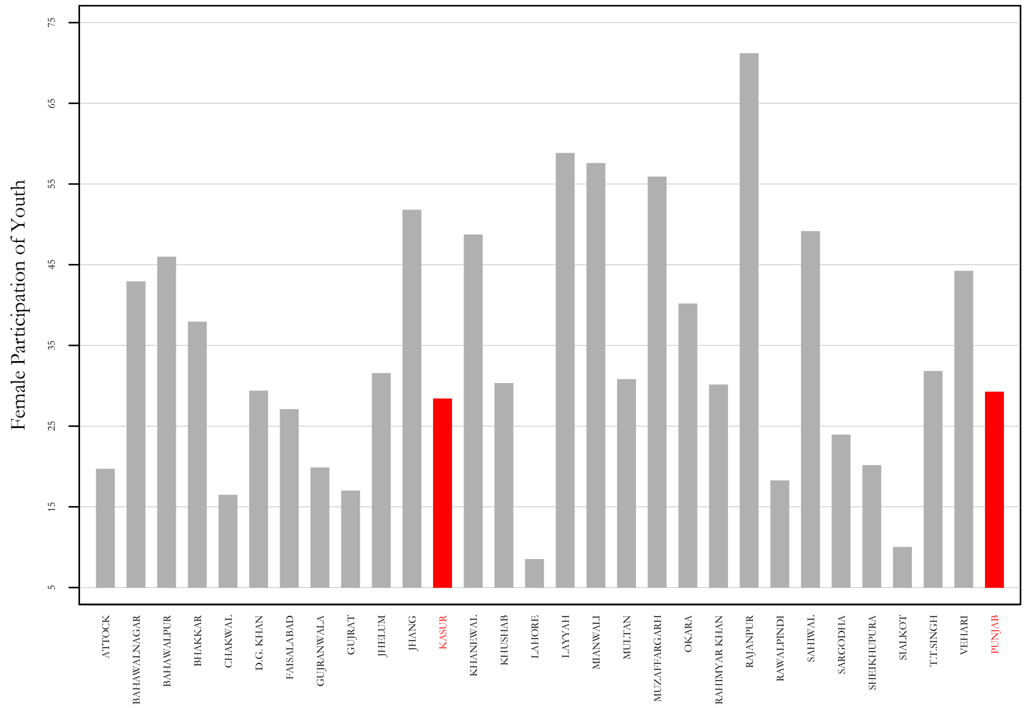


Figure B6: Male Youth Population Employed 2011

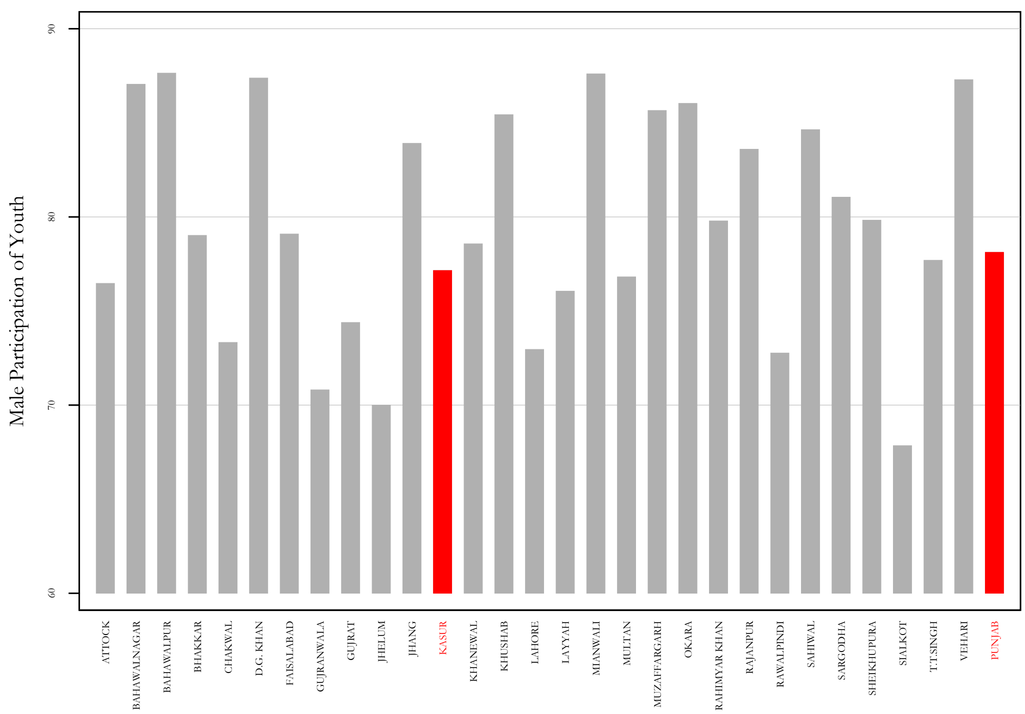
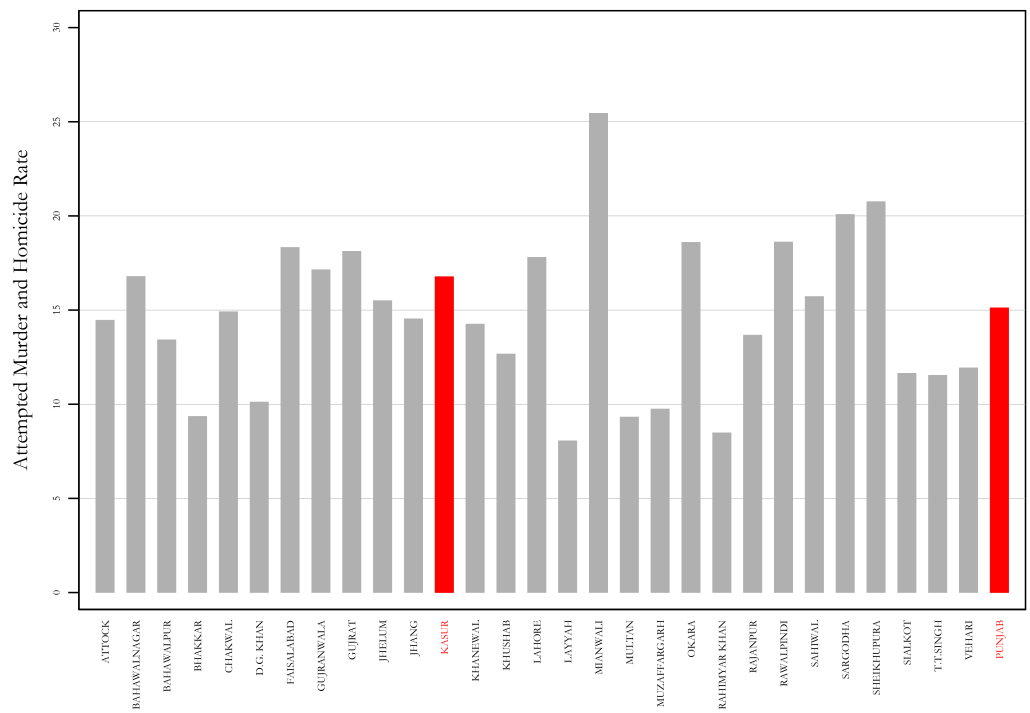


Figure B7: Crime rate 2011



Protocol

Since this study involves human subjects (parents and children), the project was reviewed and approved by the institutional review board (IRB). Moreover, we paid special attention to various concerns that could impact the quality of the survey data. First, we hired and trained 25 enumerators from January to March 2018. The enumerators were provided with digitized surveys on iPads. The digitization of the surveys allowed us to add additional checks to minimize mistakes or incoherent answers. Where possible, we added conditional statements and restricted the survey from proceeding to the next question if, for example, the answer was missing or numerals were added by mistake. In addition, digitization enabled direct codification of the data, which further helped us to prevent potential human errors (especially those associated with paper-based surveys).

The enumerators were trained to ensure that they could navigate the digital survey and were encouraged to ask questions if there was any confusion during training. Issues pertaining to enumerators self-filling surveys was minimized by employing enumerators who have conducted surveys in the past and highlighting the fact that their future employment for other projects could be hampered. We additionally required each enumerator to record (using voice recorders) their interactions with subjects, and in each locality, an assigned manager conducted random spot checks.

To minimize potential issues that could arise because of subjects speaking about the survey with any other potential subject (in our sample), we covered all the households in a neighborhood (within walking distance) within one day. Given that the responder could be a woman, we recruited both men and women as enumerators so that the responder would be at ease and to substantially reduce non-response.

Finally, the most important protocol in conducting surveys with children is compliance with the additional requirements of the IRB. We fully complied with those protocols by acquiring a parent's consent to survey the child. Parents were also asked to be present during the Raven's test and when the child was asked additional questions. We, however, provided special instructions to the enumerator and parents to minimize any interference by the parent during the child survey. We also recorded these interactions.

Behavioral Games

In this section, we present the behavioral games we use in the field to elicit parent's altruism, risk aversion and time discounting.

Altruism

Please choose one of the two options below:

Table B1: Altruism

o Child Consumption Good (PKR 50)	o Mobile Credit (PKR 35)

You will be asked to play two different types of games in this section [Game 1 (Risk Aversion) and 2 (Time Discounting)]. Two games are independent and give a payoff. With each game, we will explain the payoff structure that will be applied to determine your payoff, but you will know only at the end of the visit what payoff you received from Game 1 and Game 2. No game will give you negative payoff.

To determine what payments you receive from Game 1 and Game 2, we will ask you at the end of the survey to take a slip out of a hat containing slips numbered from 1 to 10. The number on the slip will represent the decision and the corresponding payment method you will receive. You should try to answer the questions as best as you can. There are no right or wrong answers. Do you understand the instructions? Please ask questions if you do not understand anything.

Risk Aversion

Tomorrow there are two cricket matches in two different venues. One cricket match has team A batting while the other match has team B batting. You are asked to make a decision to attend one of the two matches (match with team A or match with team B). Both matches have a free cost of entry and you will receive 1 PKR per 10 runs made by the team for the match you decide to attend. You cannot attend both matches as they are in different locations. You know that team A and team B have different performance in terms of batting if they play with a tape ball versus a hard ball. Team A gets 200 runs with a tape ball but only 160 runs with a hard ball. Team B, on the other hand, gets 385 runs with the tape ball but 10 runs with the hard ball. Both of tomorrow's matches use the same type of ball, but the chance that each ball (tape or hard) is used is not known. Below you will make 10 choices to watch either team A or team B under different chances of the type of ball used. If you select to watch team A, then you get 20 PKR if a tape ball is used and 16 PKR if a hard ball is used. On the other hand, if you select to watch team B and a tape ball is used, then you get 38.5 PKR, while if a hard ball is used, then you get only 1 PKR. Therefore, for your return, team B performs very well with a tape ball but extremely bad with a hard ball, while team A performs consistently with the two types of balls but marginally better with the tape ball. See the payoff table to understand the game:

Table B2

If	Tape	Hard
Watch Team A	20 PKR	16 PKR
Watch Team B	38.5 PKR	1 PKR

Please select (A) or (B) for each of the 10 decisions below. For payment, you will be asked at the end of the survey to select a slip from a hat containing numbers from 1 to 10. The slip you chose will determine which decision will be used for your payment. For example, if you pick a slip with number 7, then Decision 7 will be selected. Decision 7 is as follows: Decision 7 70% chance of using a tape ball, 30% chance of using a hard ball

Then, the final payment will be determined based on the probability attached to Decision 7 for a tape ball (70%) and hard ball (30%) and your chosen option (A) or (B). Imagine that there are 100 balls in a basket and you cannot see the type of balls. Decision 7 states that of the 100 balls, there are 70 TAPE balls and 30 HARD balls. If you chose to watch TEAM (A) and then you pick out a ball without looking and it is a TAPE ball (which has a higher chance of happening) then you will get 20 PKR, but if you chose to watch TEAM (B) then you will get 38.5 PKR. What will you get when a HARD ball is selected and you chose to watch Team A?

Do you understand the payment method? Please ask questions if you do not understand anything about the game. Again, the payment will be made through mobile credit today.

Table B3: Risk Aversion

Decision	Watch A	Tape Ball Chances	Watch B	Hard Ball Chances
1	o	10% chance of using a tape ball	o	90% chance of using a hard ball
2	o	20% chance of using a tape ball	o	80% chance of using a hard ball
3	o	30% chance of using a tape ball	o	70% chance of using a hard ball
4	o	40% chance of using a tape ball	o	60% chance of using a hard ball
5	o	50% chance of using a tape ball	o	50% chance of using a hard ball
6	o	60% chance of using a tape ball	o	40% chance of using a hard ball
7	o	70% chance of using a tape ball	o	30% chance of using a hard ball
8	o	80% chance of using a tape ball	o	20% chance of using a hard ball
9	o	90% chance of using a tape ball	o	10% chance of using a hard ball
10	o	100% chance of using a tape ball	o	0% chance of using a hard ball

Time Discounting

Pick one option (A or B) for each of the 10 decisions below. Each decision asks you to pick (A) some amount of PKR today vs. (B) another amount 2 weeks from now. You can give only one answer per decision.

For the payment, you will be asked to draw a slip from a hat containing slips numbered from 1 to 10. The number on the slip will determine which decision [from 1 to 10] will be used for your payment, and your answer for that decision will determine your payoff. For example, if you draw slip number 7, Decision 7 is selected for payment. Decision 7 is as follows:
Decision (7): (A) PKR 65 guaranteed today - (B) PKR 100 guaranteed in 2 weeks

If for that decision you chose (B), then you will get payment for PKR 100 as a mobile credit, which you will receive two weeks from now. However, if you chose option (A) for Decision 7, then the mobile credit will be transferred by the end of today. Do you understand the game and the payment method?

Please ask questions if you do not understand anything.

Table B4: Time Discounting

Decision	Option A	TODAY	Option B	2 WEEKS
1	o	(A) PKR 95 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
2	o	(A) PKR 90 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
3	o	(A) PKR 85 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
4	o	(A) PKR 80 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
5	o	(A) PKR 75 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
6	o	(A) PKR 70 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
7	o	(A) PKR 65 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
8	o	(A) PKR 60 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
9	o	(A) PKR 55 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks
10	o	(A) PKR 50 guaranteed today	o	(B) PKR 100 guaranteed in 2 weeks