DE GRUYTER BE J. Econ. Anal. Policy 2021; 21(2): 723–750

Research Article

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Local Labor Markets and Child Learning Outcomes in India

https://doi.org/10.1515/bejeap-2020-0281
Received August 26, 2020; accepted December 19, 2020

Abstract: This paper uses data from rural India to study the relationship between local labor market opportunities and child education outcomes. We construct a Bartik index as a measure of exogenous changes in district-level labor demand and find that an increase in predicted overall employment growth is associated with higher years of education and better test scores for both boys and girls of primary school age. The effects on test scores of older boys are smaller and less statistically significant. Older girls, however, do benefit from better labor market opportunities. We do not find evidence for changes in school quality or district-level investment. Instead, we find support for increases in household education spending, possibly because of overall higher wages, or re-allocation of resources.

Keywords: labor market conditions, test scores, India

JEL Codes: J20, I20, J1, O15

1 Introduction

Around the world, an extra year of schooling is associated with an average of 10% higher wages, with generally higher returns for low income countries with lower levels of education (Card 2001; Psacharopoulos and Patrinos 2004). In addition to better labor market outcomes, education has been associated with better nonmarket outcomes, including better health, lower crime, and higher social cohesion (Grossman 2006; Lochner 2011; Wolfe and Haveman 2002). Education may also have positive spillover effects on future generations by lowering fertility and improving child health (Breierova and Duflo 2004; Chou et al. 2010; Glewwe 1999; Osili and Long 2008).

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It is thus important to understand the determinants of schooling choices and skills. In this paper, we study how education outcomes of rural Indian children are affected by overall growth in labor market opportunities. Specifically, we use child-level data from the 2007 and 2009 ASER surveys and examine the effects of local labor market conditions on years of education and reading and math tests scores. To this end, we construct a measure of exogenous changes in district-level labor demand by calculating predicted employment growth rates based on variation in national industry-specific growth rates and baseline industry employment shares across districts (Bartik 1991; Blanchard and Katz 1992).

In the standard human capital model, children and parents are forward-looking and view schooling as an investment with financial returns. Resource constraints may lead to suboptimal levels of schooling but relaxing those constraints through better employment opportunities should lead to higher investments in human capital. And yet, when children engage in domestic or paid work, the effect of higher wages would depend on the substitutability between parental and child labor and the opportunity cost of time. In addition, while primary school enrollment in India is close to universal with more than 90% of children between the ages of 6 and 10 enrolled in school in 2007, secondary school enrollment rates are still lagging. The gross enrollment rate in secondary school in 2007 was only 57%.[1] This implies that the schooling of older children may also be more sensitive to changes in economic conditions. Therefore, we study the effect of local labor demand on children between the ages of 6 and 10 and older children ages 11 to 16, separately.

Investments in education may also be affected by context-specific parental and child preferences and aspirations, as well as the (perceived) returns to education. For example, in 1971, the net enrollment rate of boys in India was 25 percentage points higher than that of girls (73.6 vs 48.2%). By 2007, the gender gap in primary school enrollment was only 1.3%. However, given the historically large gaps in education attainment between girls and boys, we perform separate analyses by child gender. In addition, while our main results use a measure of overall labor demand, we also test the effects of gender-specific labor market opportunities.

Finally, despite the progress India has made in increasing years of schooling, in 2007, fewer than 60% of grade 5 students in rural India could read at the level of the grade 2 curriculum (ASER 2007). Thus, relaxing budget constraints may result in higher investments in education at the intensive margin as parents attempt to compensate for lack of quality education. Measures of cognitive ability and achievement are important predictors of economic outcomes independently of schooling

1 Education statistics from World Development Indicators: https://databank.worldbank.org/reports.aspx?source=world-development-indicators.

(Cawley, Heckman, and Vytlacil 2001; Glewwe 2002; Hanushek and Woessmann 2008; Heckman, Stixrud, and Urzua 2006). That is why we examine effects on math and reading test scores in addition to years of education and school attendance.

We find that a one percentage point increase in predicted overall employment growth between 2006 and 2008 is associated with an increase in reading scores of about a 3.4 (3.9)% of a standard deviation for boys (girls) between the ages of 6 and 10. The effects on math scores are similar for both genders – an increase of a 2.8% of a standard deviation. The effects on test scores of older children are smaller and not statistically significant for older boys. Older girls experience some significant improvements in their reading scores (2% of a standard deviation). The results are robust to including different sets of controls and using an alternative definition of growth in labor demand comparing districts with above and below median growth rates.

Overall, we find that increases in household-level education spending are a likely mechanism. We do not find evidence for changes in aspirations or perceptions of schooling returns affecting the results or any strong female bargaining power effects. We also do not find any changes in school quality or district-level investments.

Our paper extends the previous literature in several ways. First, we study a period of positive economic growth in India, whereas prior research has largely focused on identifying the effects of negative income shocks on household schooling decisions (Dhanaraj, Paul, and Gade 2019; Jacoby and Skoufias 1997). Second, we study the effect of overall growth in the labor market rather than the effects of a specific policy shock (Aggarwal 2018; Jensen 2012; Shah and Steinberg 2015). Third, we test several potential mechanisms, including higher spending on education by parents and districts, changes in education aspirations, and increases in female bargaining power. Next, we review the relevant literature on the relationship between labor markets and education outcomes in greater detail. In Section 3, we discuss the data used for the analysis. Sections 4 and 5 present the empirical methodology and discuss the results. Finally, Section 6 concludes.

2 Literature Review

Labor markets could affect education outcomes in several different ways. First, better employment opportunities may increase household income and thus household investment in education, increasing educational inputs and time spent in school. Yet, most of the previous research has focused on the effects of negative income shocks. For example, negative macroeconomic shocks have been shown to reduce enrollment and attendance rates (Ferreira and Schady 2009). In Brazil, Duryea, Lam, and Levison (2007) study the effect of the male household head becoming unemployed and show significant increases in the probability of dropping out of school and entering the labor force for children between the ages of 10 and 16. Jacoby and Skoufias (1997) find that school attendance in rural India fluctuates during periods of idiosyncratic income shocks. Björkman-Nyqvist (2013) shows that unexpected decreases in income in Uganda have significant negative impacts on girls' enrollment. She also finds that once school fees are abolished, negative income shocks do not affect enrollment but decrease girl test scores as parents reduce their school investments at the intensive margin or girls have to work and thus spend less time studying. Less is known about household response to positive income shocks. Our study extends this evidence by studying education outcomes in India during a period of strong economic growth.

Labor markets could also affect child education if women, specifically, have better employment opportunities and this increases their household bargaining power.[2] Research has shown that women and men often have different preferences and higher bargaining power of women may improve child outcomes. For example, Duflo (2003) studies the South African Old Age Pension Program and finds that girls who live with grandmothers who receive a pension are heavier and taller than girls who live with a grandmother who is not age-eligible for the pension, while living with a man who is recipient of the pension has no effect on girl nutrition and health outcomes. Qian (2008) examines exogenous changes in sex-specific income in China and shows that increasing female income improves the survival rates of girls and the educational attainment of all children, while increasing male income reduces the education and survival rate of girls. In India, Afridi, Mukhopadhyay, and Sahoo (2016) find that a mother's participation in the labor force is associated with more time spent in school and better school progression for her children. In this paper, we are able to test whether higher female bargaining power is one of the key mechanisms explaining the positive relationship between local labor market opportunities and child education outcomes by examining separately the effects of male and female labor demand. In addition, by studying the effect of gender-specific labor demand on education outcomes separately for girls and boys of different age groups, we can examine the role of changing child aspirations and perceptions about return to schooling in response to better labor market opportunities.

Indeed, while education investments could be affected by changes in total household income and female-specific income, they could also vary in response to changes in perceptions about returns to education as labor market opportunities

2 Aizer (2010) finds that growth in female labor demand in the US reduces the gender wage gap and gender violence. In India, Heath and Saha (2018) show that an increase in women's job opportunities in the year of marriage is associated with higher quality of marriage while current job opportunities are also a strong determinant of women's household bargaining power.

for young people improve. For example, Jensen (2010) shows that the perceived returns to education in the Dominican Republic are low and providing information about the actual returns to secondary education increases years of education. In India, Jensen (2012) finds that providing job recruiting services for young women, and thus improving their labor market opportunities, increased younger girls' school enrollment. Similarly, in Bangladesh, Heath and Mobarak (2015) study the effects of growth in the garment sector and find that girls who live closer to garment factories have higher educational attainment.

On the other hand, an increase in low-skilled job opportunities may have a negative impact on education as children drop out of school to join the labor force or to substitute for parental labor in the household. For example, in Mexico, McKenzie and Rapoport (2010) find that areas with high historical migration rates have low education attainment as teenage boys drop out and migrate to find work, while girls drop out to engage in housework. In India, Shah and Steinberg (2015) show that the availability of a workfare program in a district is associated with lower enrollment rates and lower mathematics and reading test scores for older children as boys engage in market work while girls engage in unpaid household labor. Shah and Steinberg (2017) further show that a positive rainfall shock, leading to higher wages, is associated with lower probability of school enrollment and attendance and lower mathematics test scores. These findings are similar to the findings of research on road construction programs in India which shows an increase in school dropout rates for teenagers as they join the labor force (Aggarwal 2018).

In this paper, we use data from rural India and provide an empirical examination of the effect of overall local labor market conditions, as well as gender-specific labor market opportunities across all sectors of the economy during a period of strong economic growth. We overcome the problem of high informality rates and measurement error in wages or hours worked that many developing countries face by constructing a Bartik index to measure the exogenous changes in local labor demand. Next, we present the data used for the analysis and discuss our empirical methodology.

3 Data

3.1 Education Data

We use data from the Annual Status of Education Report (ASER) – a household-based survey from most rural districts in India.[3] This repeated cross-section survey

3 In 2007, there were 569 districts in the ASER data, compared to 581 rural districts in the National Sample Survey of 2007/8.

began in 2005 and collects information on reading and arithmetic skills for all school-aged children, irrespective of their schooling status. The survey takes place in the middle of the school year – between September and November. Reading comprehension tests taken during the survey show whether the child can read a letter, a word, a paragraph, or a story. The highest level of reading corresponds to grade 2 curriculum. Mathematics tests show whether the child can recognize numbers from 1 to 9, 10 to 99, can do subtraction, or do division, with the highest level of arithmetic corresponding to grade 3 or grade 4 curriculum, depending on the state. We examine each of these outcomes separately. Following Shah and Steinberg (2017), we also create a reading and math score ranging from 0 to 4, where a score of four shows the highest proficiency (reading a story or doing division) and a score of zero shows the lack of any skills (not being able to read a letter or not recognizing single-digit numbers for reading and math, respectively). Other outcomes we study include years of education, current school attendance status, and being 'on track'. The variable 'on track' is based on Shah and Steinberg (2017) and is a binary indicator of grade-for-age progression. It is coded as one if the difference between the child's age and their years of education is no greater than six (the school starting age).

We use data from the 2007 and 2009 surveys and a sample of children between the ages of 6 and 16 with non-missing education outcomes.[4] We match the child-level data to labor market data, as described below, and use rural districts with available education and labor information in every year for a total sample of 938,523 students across 533 districts.[5]

Table 1 presents summary statistics for the study sample. In 2007, there are few differences between girls and boys between the ages of 6 and 10. About 98% of both groups are currently in school and about 90% are in the correct grade for their age. Among the older children, about 92% of girls report attending school but only 69% are in the correct grade for age, suggesting a relatively high probability of grade repetition or temporary dropout among this group. The statistics for older boys are similar. The average reading score for all 6–10 year olds is about 2.2, while

4 In April 2010, the Indian Right to Education Act came into force, making primary education for children between 6 and 14 free and compulsory. Shah and Steinberg (2019) show that enrollments increase while test scores decrease after the implementation of the act. To avoid issues related to changes in sample composition or changes in school resources, we only use data before the reform took place. Data from 2005 to 2006 are not publicly available. Thus, we only use data from 2007 to 2009 that we are also able to match to labor market data.

5 ASER data is representative and self-weighting at the district level (ASER 2013). Thus, we follow Spears and Lamba (2016) and present unweighted regression estimates. Estimates using household weights are similar.

Table 1: Descriptive statistics.

	2007				2009			
	6–10 year olds		11–16 year olds		6–10 year olds		11–16 year olds	
	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Age	8.19	8.19	13.14	13.19	8.21	8.24	13.32	13.36
Years of education	2.85	2.86	6.83	6.89	2.87	2.87	7.1	7.14
Currently in school	0.98	0.98	0.92	0.93	0.98	0.98	0.92	0.94
On track	0.9	0.9	0.69	0.68	0.9	0.9	0.71	0.7
Reading score	2.22	2.25	3.49	3.53	2.21	2.24	3.48	3.52
Can read a letter	0.89	0.9	0.97	0.97	0.9	0.9	0.97	0.98
Can read a word	0.67	0.67	0.93	0.94	0.66	0.67	0.93	0.94
Can read a paragraph	0.43	0.43	0.86	0.88	0.43	0.44	0.86	0.87
Can read a story	0.24	0.24	0.73	0.74	0.22	0.23	0.72	0.73
Math score	2.07	2.11	3.27	3.37	2.06	2.11	3.28	3.36
Can recognize numbers 1–9	0.89	0.89	0.97	0.97	0.9	0.9	0.97	0.98
Can recognize numbers 10–99	0.66	0.67	0.92	0.94	0.65	0.67	0.92	0.94
Can do subtraction	0.37	0.39	0.8	0.83	0.37	0.38	0.8	0.83
Can do division	0.15	0.16	0.58	0.62	0.14	0.15	0.58	0.61
Number of students	117,329	139,909	107,826	129,525	97,976	116,789	103,580	125,589

the average math score is 2.1. About 43% of them can read a paragraph and 37% can do subtraction. For the 11–16 year olds, the average reading score is 3.5, while the average math score – 3.3. We do not find big changes in outcomes between the two survey years.

3.2 Labor Market Data

For the main analysis, we use three rounds of the Employment and Unemployment survey module of the nationally representative National Sample Survey (NSS).[6] Specifically, we use Round 62 – from July 2005 to June 2006, Round 64 – from July 2007 to June 2008, and Round 66 – from July 2009 to June 2010 – to create an aggregate labor demand index. We then merge the district-level index to the ASER data by year and district. We are interested in capturing the effects of labor market conditions before the start of the school year. Thus, we merge the index calculated from NSS Round 62 to ASER data from 2007 and we merge the index from NSS Round 64 to ASER data from 2009. We use NSS Round 66 data for placebo tests (more details below).[7] All aggregate statistics from the NSS data are calculated using the NSS sampling weights.

The NSS data contain information on the employment status of all members of the household, as well as their industry of employment according to the National Industrial Classification (NIC). In order to explore the effects of local economic conditions and to allow variation in industry composition across districts at baseline, we create 11 broad industry categories based on the NIC-2004 industry code: Agriculture, Mining, Low-tech manufacturing, Other manufacturing, Utilities, Construction, Trade, Transportation, Public administration, Education and Health, Business activities, and services.[8]

Table 2 presents the national employment growth rate in each industry between NSS Rounds 62 and 64 and the average fraction of workers employed in each industry at baseline (Round 62). In our sample of rural districts, the largest employer is agriculture with an average of 59% of all workers in a district. It is followed by manufacturing (11%), trade (9%), and construction (7%). Between the two survey rounds, agricultural employment experienced a small growth rate of

6 Data publicly available at: http://microdata.gov.in/nada43/index.php/catalog/central/about.

7 The latest NSS round that is publicly available is Round 68 which took place in 2011/2012. This round, however, uses a different occupation code, NIC-2008, which is not easily matched to the NIC-2004 code used in previous survey waves, and is thus not used in this analysis.

8 Similarly, Gunes and Marchand (2018), Schaller (2016), and Regmi and Henderson (2019) use broad industry categories when studying the effect of local labor market conditions on education in Turkey, and fertility and education in the US, respectively.

Table 2: Industry composition and growth rates.

			Baseline share		
		Growth rate (%)	**All workers**	**Male workers**	**Females**
		(1)	(2)	(3)	(4)
Sector	**Name**				
1	Agriculture	1.52	58.87	54.04	66.28
2	Mining	−20.98	2.62	2.97	1.95
3	Low-tech manufacturing	−4.82	5.40	4.52	9.85
4	Other manufacturing	2.50	5.54	6.43	3.20
5	Utilities	−16.16	0.98	1.40	0.22
6	Construction	12.58	6.93	8.45	2.32
7	Trade	3.18	8.74	10.39	4.05
8	Transportation	4.81	3.95	5.15	0.27
9	Public administration	5.72	2.59	3.08	1.85
10	Education and health	7.04	3.53	3.22	7.15
11	Business activities and services	7.01	5.25	5.43	6.03
			All	Male	Female
	Overall growth rate (%)		2.64	2.89	1.97

[a]For ease of presentation, growth rate statistics are presented in percentage terms by multiplying by 100. All regression models use the raw growth rate number.

1.52%, while construction, trade and manufacturing other than low-tech manufacturing experienced growth of 12.58, 3.18, and 2.5%, respectively. Low-tech manufacturing experienced a decline of 4.82%. In columns 3 and 4, we further show the gender segregation in some sectors. For example, a higher percentage of men are employed in physically demanding industries, such as construction, mining, and transportation, compared to women.

4 Empirical Strategy

In order to estimate the effects of local economic conditions on child learning outcomes, we use the following empirical specification:

$$Y_{i,d,t} = \alpha + \delta EC_{d,t} + Age_{i,d,t}\beta + Z_{d,t}\gamma + \alpha_t + \eta_d + \eta_{s,t} + \epsilon_{i,d,t} \tag{1}$$

where $Y_{i,d,t}$ is the education outcome of child i living in district d at time t and $EC_{d,t}$ is a measure of local economic conditions. We control for child age fixed effects, $Age_{i,d,t}$, to account for cohort-specific effects, and year of interview fixed effects, α_t, to account for common trends in education. The term η_d represents the district fixed effect which controls for any time-invariant district characteristics. We also include state-specific linear time trends, $\eta_{s,t}$, to control for unobservable factors correlated with education that vary linearly over time within states. These are defined as the interaction between state dummies and the continuous ASER survey year. Finally, we control for trends in district demographics $(Z_{d,t})$ that may be correlated with both economic conditions and education, including proportion of rural, ST, SC, and illiterate population in the district, average years of education, proportion of population under the poverty line, and female and male labor force participation rate. These are defined as the interaction between district characteristics before the study period (using data from NSS Round 61) and the continuous ASER survey year.

While aggregate local economic conditions are commonly measured by unemployment rates, there are concerns about using this measure in identifying the effects. For example, unemployment rates may increase during an economic upturn if more people enter the labor market in hopes of finding a job. Changes in labor supply could thus confound the relationship between local economic conditions and education. In addition, developing countries often have a large share of employment in agriculture and the informal sector and official unemployment statistics may thus not be representative of the true economic conditions. Other measures such as hours worked or mean wage may also be subject to measurement error and attenuation bias.[9] In order to overcome these concerns, previous research in India has studied the effects of rainfall shocks (e.g. Shah and Steinberg 2017) or policy shocks (e.g. Aggarwal 2018; Shah and Steinberg 2015). In our paper, we use a more general measure of economic conditions that is not driven by a specific policy or event and is thus potentially relevant for a broader section of the population.[10] We are also able to differentiate between the effects of overall labor market conditions and the effects of gender-specific opportunities which allows us to explore different potential mechanisms that may explain the relationship between economic conditions and educational outcomes. In particular, we construct an index of predicted employment growth rates based on Bartik (1991), Blanchard and Katz (1992), and Katz and Murphy (1992). We define an overall Bartik index for each district, d , as the sum of the changes in the national employment rate in

9 In Table 1 of the Online Appendix, we show results of analysis using these alternative measures. We find no statistically significant effect of the unemployment rate on any of the education outcomes, as well as no significant effect of mean hours worked for employees. We also find no significant effect on young boys or young girls when using mean wage for an employee although we do find some statistically significant effects on school attendance and math scores for older boys and girls.

10 While rainfall shocks may be a good indicator of changes in economic conditions for agricultural households, Table 2 shows that about 40% of workers in our sample of rural districts are engaged in non-agricultural work.

industry k between year $t2$ and year $t1$, weighted by the district-level proportion of workers employed in industry k at baseline, year $t1$:

$$Bartik_d = \sum_k \frac{\left[\log\left(Natl\,E_{k,-d,t2}\right) - \log\left(Natl\,E_{k,-d,t1}\right)\right] * Employees_{k,d,t1}}{Employees_{d,t1}} \tag{2}$$

Following previous research, we exclude each district's employment in industry k when calculating the growth in national employment to account for potential bias due to employment concentration in an industry in a specific district.[11] We avoid any district-specific changes in labor supply by using national-level changes in employment and identify the effect of changes in local labor demand based on baseline differences in employment shares across districts. Controlling for time trends in district-level demographics, which could be associated both with employment shares in a given industry and education outcomes, accounts for possible endogeneity in the baseline employment shares (Goldsmith-Pinkham, Sorkin, and Swift 2020).

We further use a placebo test following Goldsmith-Pinkham, Sorkin, and Swift (2020) to examine whether future values of employment growth can predict current outcomes of interest. In particular, we regress the future predicted employment growth (i.e. a labor demand index computed for employment growth between NSS Rounds 64 and 66) on the current predicted employment growth (from NSS Rounds 62 and 64) controlling for all of the control variables included in the main estimation. Using this regression, we compute the residuals, i.e. the 'residualised future demand index'. We then regress our education outcomes of interests on the residualised future demand index to test whether future predicted employment growth is significantly associated with changes in education after accounting for the correlation in demand indices across time. This analysis tests whether our main results could be biased by lack of parallel pre-trends (Goldsmith-Pinkham, Sorkin, and Swift 2020).

While we estimate the effects of overall economic conditions on education, we also examine gender-specific labor demand. If preferences for education vary within the household, children may be affected differently depending on whether economic conditions affect men or women. Similarly, if child aspirations, potentially affected by better job opportunities, or parental perception of the returns to education matter, then gender-specific labor demand may affect learning outcomes of girls and boys differently. We follow Schaller (2016) to construct gender-specific labor demand indices and disentangle the effects:

11 The growth in national employment used in the calculation of the Bartik index is thus slightly different for each district.

$$Bartik_{d,g} = \sum_k \frac{\left[\log\left(Natl\,E_{k,-d,t2}\right) - \log\left(Natl\,E_{k,-d,t1}\right)\right] * Employees_{k,d,g,t1}}{Employees_{d,g,t1}} \quad (3)$$

where g represents gender.

Overall, we find that the average predicted district employment growth between Round 62 and Round 64 is 2.64% across all workers, 2.89% for male workers, and 1.97% for female workers (Table 2) with substantial variation across districts, as shown in Appendix Figure 1.[12] In Appendix Table 1, we show there is a positive association between our measure of predicted employment growth and the overall probability of working as well as wages in the NSS data for the working age population of 15–60 year olds. An increase of one percentage point in the Bartik index is associated with an increase of 0.2 percentage points increase in the probability of working, mostly driven by a large increase of 0.36 percentage points in the probability of women working (vs a small change of 0.078 percentage points in the probability of men working). This corresponds to a 1.5% increase in the probability of working for women given a baseline proportion of working women of 23.88%. Increase in labor demand is also associated with an average increase in weekly wages of about 13 rupees (or 21 rupees for women). Given a mean predicted growth in labor demand of 2.64%, our findings suggest that a worker in the average district could expect an additional Rs. 142 per month (=2.64*Rs. 13*4 weeks) on average. Since the average monthly consumption per capita for rural households during this time period was estimated to be about Rs. 559 (MoSPI 2006), this increase corresponds to about 25% of the monthly consumption per capita. Using clustered standard errors in these regression models increases the standard errors and reduces the statistical significance of our estimates but the magnitude of the effects remains large. All subsequent regression models for education outcomes cluster standard errors at the district level to allow for correlation of the error term within a district.

5 Results

5.1 Main Analysis

Table 3 presents the results of the main analysis.[13] We present regression estimates separately for boys and girls and also separately for children of primary school age

12 While the time period we study, the second half of the 2000s, is largely a period of strong economic growth in India, with real GDP growing at an average rate of 9% for the five years between 2003/4 and 2007/8 (Nagaraj 2013), employment growth was low. This has been largely attributed to a fall in female agricultural employment (Thomas 2012).

13 The results are robust to the inclusion of household-level controls for mother's age, an indicator for the mother having gone to school, and number of children in the household.

Table 3: Main results.

	Years of education	Currently in school	On track	Reading: Reading score	Reading: Letter	Reading: Word	Reading: Paragraph	Reading: Story	Math: Math score	Math: Numbers 1–9	Math: Numbers 10–99	Math: Subtraction	Math: Division
Panel A: Boys 6–10													
Labor demand	2.3961**	−0.0018	0.5398**	4.4590**	0.8495**	1.6951**	1.3234**	0.591	3.4555**	0.6587**	1.4106**	1.0454**	0.3408
index	(0.8188)	(0.0840)	(0.2135)	(1.2094)	(0.2540)	(0.3857)	(0.4291)	(0.3740)	(1.0896)	(0.2643)	(0.3841)	(0.3727)	(0.2970)
Panel B: Boys 11–16													
Labor demand	1.2087	0.0468	0.3297	1.1862	0.0749	0.3279*	0.3658	0.4176	0.5508	0.0725	0.0735	0.2368	0.1681
index	(1.5000)	(0.1909)	(0.3612)	(0.8681)	(0.1037)	(0.1695)	(0.2951)	(0.4581)	(1.0495)	(0.1246)	(0.2478)	(0.3818)	(0.4796)
Panel C: Girls 6–10													
Labor demand	2.6509**	0.139	0.5003**	5.1692**	0.9671**	1.7893**	1.6763**	0.7366**	3.4437**	0.7633**	1.2828**	1.1821**	0.2155
index	(0.9128)	(0.1065)	(0.2114)	(1.3209)	(0.3067)	(0.4540)	(0.4256)	(0.3618)	(1.2472)	(0.3131)	(0.4486)	(0.4135)	(0.3096)
Panel D: Girls 11–16													
Labor demand	3.4183**	0.1609	0.5227	2.5525**	0.3136**	0.6391**	0.8930**	0.7067	1.7292	0.2954*	0.4336	0.6383	0.3618
index	(1.4786)	(0.2082)	(0.3187)	(0.9994)	(0.1512)	(0.2167)	(0.3105)	(0.4636)	(1.1803)	(0.1772)	(0.2959)	(0.3969)	(0.5049)

[a]Each regression model controls for age, year of interview and district fixed effects, as well linear state trends, and trends in baseline district characteristics (proportion of rural, ST, SC, and illiterate population in the district, average years of education, proportion of population under the poverty line, and female and male labor force participation rate). [b]Standard errors in parentheses, clustered at the district level. Total number of clusters = 533. [c] * denotes 10% significance level; ** denotes 5% significance level. [d]Panel A has 256,698 observations. Panel B has 255,114 observations. Panel C has 215,305 observations. Panel D has 211,406 observations.

(6–10) and older children, as they might respond differently to changes in economic conditions. Overall, we find no significant effect of predicted employment growth on the probability of currently being in school for either one of our samples but we do find small significant effects on total years of education for all groups but the older boys. An increase of one percentage point in the predicted employment growth is associated with an increase of 0.024 (0.027) years of education for boys (girls) between 6 and 10 years of age, and an increase of 0.034 for older girls.[14] With primary-school children spending about 200 days in school each year, this average increase of about four days is negligible. We also find that 6–10 year old boys and girls are more likely to be on track. Specifically, an increase of one percentage point in the predicted employment growth increases the probability that boys (girls) are on track by 0.54 (0.5) percentage points, suggesting school start for younger children is less likely to be delayed.

For younger children, higher predicted employment growth is also associated with better reading and math outcomes for both boys and girls although the effects for girls are slightly larger. An increase of one percentage point in predicted employment growth is associated with an increase of about 1.32 (1.68) percentage points higher probability of reading a paragraph for boys (girls), or about 3% (4%) increase relative to baseline. Young girls also experience a significant increase in the probability of reading a story of about 0.74 percentage points, or about 3%. Their overall reading score increases by 0.052 points, which is an effect size of about 3.9% of a standard deviation.[15] Young girls (boys) are also 1.18 (1.05) percentage points, or 3.2% (2.7%), more likely to know how to do subtraction when exposed to better labor market opportunities. The average effect on math test scores for both boys and girls is an increase of about 0.034 points, or about 3.4% of a standard deviation. This suggests that for the average growth in labor demand of 2.64%, the increase in reading (math) scores is about 10.3 (9.0)% of a standard deviation.

We do not find any strong effects on either reading or math skills for older boys. While the tests correspond to grade 2 reading curriculum and grade 3 or 4 math curriculum, Table 1 shows that at baseline only about 74% of older boys can read a story and 62% can do division, showing there is indeed room for improvement. Yet, it appears to be difficult for older boys to catch up on missed

14 In all regression models, predicted employment growth is distributed between –0.069 and 0.073. In other words, a 1 unit change in the labor demand index denotes a 100% change. Thus, we divide the coefficient by 100 to get the effect associated with a 1% change.

15 The standard deviation for reading scores of 6–10 (11–16) years olds in 2007 is 1.32 (1.0) for girls and 1.31 (0.94) for boys. The standard deviation for math scores of 6–10 (11–16) years olds in 2007 is 1.22 (1.05) for girls and 1.22 (0.99) for boys.

material from earlier grades. We do find that older girls have better reading outcomes associated with better labor market opportunities. Math outcomes are not statistically significantly increased possibly because of the higher cost of learning math at school than practicing reading at home.

One reason for the increase in the reading scores of older girls could be the marginal increase in years of education they experience as a result of the growth in labor demand. Yet, in Table 2 of the Online Appendix, we show that the test score results for all age and gender groups are robust to controlling for years of education in the regression model. Thus, older girls likely experience an increase in their reading abilities possibly because of other time or money investments that they didn't have access to before. The reason older boys do not see those benefits could be because of son preference where parents were already investing in the boys even in the absence of growth in labor opportunities, while investment in older girls could be considered a luxury good.[16] The reason the average effects on older children are generally muted could also be that while some may benefit from parental investment, others may face greater pressure to start working either outside of the house (especially for boys) or helping with chores at home (for girls).[17, 18]

Overall, while the effects of local labor market conditions on children past primary school age are not as strong, the effects on young children are substantial. In our sample of students with ages between 6 and 10, we find that an additional year of education is associated with about 0.49 (0.44) points higher reading (math) test score. While the estimated effect of education on test scores is not a causal estimate, it suggests that the increase in reading (math) test scores associated with

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16 We discuss some evidence of that when examining education investments later on in Table 5. Azam and Kingdon (2013) find evidence of differential spending on sons and daughters in India in the primary and middle school age groups, as well as differences in enrollment rates between girls and boys in secondary school. India has traditionally had high son preference, resulting in skewed sex ratios, lower investments and worse health and education outcomes for girls (Azam and Kingdon 2013; Barcellos, Carvalho, and Lleras-muney 2014; Pande and Astone 2007).

17 We examine the NSS data for the effect of the predicted growth in labor demand on children's primary activity and we find that while local labor demand does not have a statistically significant effect on the probability of older boys working, older girls are significantly more likely to work when labor market conditions are better. Any additional investment for girls must thus be outweighing the negative effects of working.

18 In Table 3 of the Online Appendix, we test for heterogeneity in the effect of labor demand on child education outcomes by number of school-aged girls and boys in the household. We find some evidence that younger children benefit more from an increase in local labor market opportunities when there are more children of the same gender in the household. Older girls also tend to benefit more when there are more girls in the household.

the average growth in local labor demand of 2.64% would be equivalent to the effect of about two months of extra schooling.

Next, we present results from robustnesss and analysis of potential mechanisms. For the sake of conciseness, we focus our discussion on the effects on the aggregate reading and math test scores, and not on individual test components.

5.2 Robustness

In Appendix Table 2, we test whether our main results could be biased by lack of parallel pre-trends. To this end, we use a placebo test following Goldsmith-Pinkham, Sorkin, and Swift (2020) to examine whether future values of employment growth can predict current outcomes of interest. The estimated effects of the residualised future demand index on all education outcomes are not statistically significantly different from zero, yielding support to our identification strategy.

In Table 4 of the Online Appendix, we present results using an alternative specification with a binary measure of local labor demand instead of the continuous index. Specifically, we define the treatment indicator as one if the district had above median (2.52%) local labor demand, and zero otherwise. Thus, we estimate the difference in outcomes for children living in high growth districts versus children in lower growth districts. All results are qualitatively similar to the main results presented in Table 3 with strong effects among the young children and no effects among older boys.

5.3 Mechanisms

In Table 5 of the Online Appendix, we examine if our results could be explained by changes in the availability of public works projects during this time. Specifically, we use district-level data on the National Rural Employment Guarantee Scheme (NREGS) to control for number of NREGS person-days used in the year prior to the two ASER surveys.[19] We find that our results are unaffected by this additional control, suggesting that our measure of local labor demand is capturing other labor market developments.

Next, we examine whether the effects differ when using gender-specific indices. Increase in female labor demand may increase girls' aspirations for their

19 Data on NREGS intensity is from 'DMU reports' available at <http://mnregaweb4.nic.in>. We match 2006 (2008) intensity data to ASER survey from 2007 (2009). Districts that had delayed implementation of the program and were missing information in 2006 are included and assigned zero person-days.

future as they face better job market opportunities. This could result in girls staying longer in school or doing better in school. Increase in female labor demand may also increase mothers' bargaining power and allow them to invest more in the education of their girls as well as boys. In Table 4, we test these potential mechanisms by regressing education outcomes on predicted employment growth for female and male workers in the district. We find that controlling for male labor demand, female labor demand has a relatively small, statistically insignificant effect on education outcomes. Male labor demand is a significant predictor of years of education, on track status, and reading and math skills for young children, as well as years of education and reading skills for older girls. This suggests that most of the effects we observe for overall labor demand could be explained by changes in male labor demand and improvement in economic conditions. This is consistent with the lower growth rate in employment among women during the study period. Indeed, Thomas (2012) shows that during the second half of the 2000s female agricultural employment fell and women moved back to housework as better income-earning opportunities for male members of the household were created. In addition, Thomas (2012) shows that most of the workers who lost manufacturing jobs during this time period were women, while construction, a largely male-dominated field, accounted for almost all of the new jobs created in rural areas in the second half of the 2000s.

In Appendix Table 3 we further examine the possibility of female bargaining effects by testing for heterogeneity in the treatment effect by mother's education. More educated mothers may have higher bargaining power and may thus be better able to direct any additional household income towards education spending. Dasgupta and Kar (2018) further show that while labor force participation fell among the least educated women, it increased for educated women.[20] For all age and gender groups, we find that children of mothers who have completed eight or more years of education tend to benefit more from increased labor market opportunities in the district, although the additional benefit is small. Interestingly, even older boys, the group previously found to be largely unaffected, tend to benefit from local labor demand if their mothers are more educated. Overall, while we cannot reject the hypothesis of female bargaining power mediating the effect of labor demand on education outcomes, we do not find any strong support for it.

Next, we examine if there was an increase in investment in education. While the ASER data does not allow a direct test of the investment hypothesis because we do not have information on time allocation or household spending, we use

20 However, we do not find any evidence in the NSS employment survey data that our measure of local labor demand has a different effect on the probability of employment for women who have completed middle school versus those who have not.

Table 4: Results by growth in gender-specific labor demand.

	Years of education	Currently in school	On track	Reading score	Math score
Panel A: Boys 6–10					
Female labor	−0.6414	−0.0761	−0.1556	1.3365*	1.1936
demand	(0.5466)	(0.0584)	(0.1401)	(0.7661)	(0.8003)
Male labor demand	2.4469**	0.03	0.5540**	2.7115**	1.9615**
	(0.7290)	(0.0742)	(0.1992)	(1.1184)	(0.9495)
Panel B: Boys 11–16					
Female labor	−0.0075	−0.164	−0.04	0.5969	0.035
demand	(0.9654)	(0.1316)	(0.2549)	(0.5256)	(0.6703)
Male labor demand	0.4665	0.0751	0.1658	0.3731	0.2266
	(1.3772)	(0.1693)	(0.3273)	(0.8398)	(0.9725)
Panel C: Girls 6–10					
Female labor	−0.3052	−0.0446	−0.0538	0.7603	0.8205
demand	(0.5733)	(0.0628)	(0.1511)	(0.8420)	(0.8228)
Male labor demand	2.5374**	0.1605	0.4769**	3.9786**	2.3835**
	(0.7859)	(0.1005)	(0.2059)	(1.1366)	(1.0992)
Panel D: Girls 11–16					
Female labor	−0.1086	−0.2292	−0.1385	0.0019	−0.2573
demand	(1.1530)	(0.1545)	(0.2500)	(0.7544)	(0.9277)
Male labor demand	2.4836*	0.2242	0.46	2.0956**	1.6567
	(1.4128)	(0.2050)	(0.3158)	(0.9470)	(1.1176)

[a]Each regression model controls for age, year of interview and district fixed effects, as well linear state trends, and trends in baseline district characteristics (proportion of rural, ST, SC, and illiterate population in the district, average years of education, proportion of population under the poverty line, and female and male labor force participation rate). [b]Standard errors in parentheses, clustered at the district level. Total number of clusters = 533. [c] * denotes 10% significance level; ** denotes 5% significance level. [d]Panel A has 256,698 observations. Panel B has 255,114 observations. Panel C has 215,305 observations. Panel D has 211,406 observations.

household expenditure data from the NSS surveys Rounds 61 and 64 to examine the effect of predicted employment growth during this time period on education spending in the past year (i.e. re-calculating the Bartik index using data for Rounds 61–64).[21] In Table 5, we find that better labor market opportunities in the district are associated with higher spending on tuition, as well as higher overall education spending. A one percentage point increase in local labor demand is associated with an additional 165 Rupees spent on tuition, or 191 Rupees spent on overall education expenses, which is roughly 0.5% of total annual household

21 The expenditure data from Round 62 is missing.

expenditure.[22] Interestingly, there is heterogeneity in the effect of labor demand on household spending by the gender of the children in the household. Households with larger number of girls tend to increase their education spending slightly more, while having a larger number of boys has a smaller and statistically insignificant effect on tuition and overall education spending. Households with more boys, however, do spend more on private tutors. This is consistent with the hypothesis that investment in the education of older girls may be considered a luxury good and only when economic conditions are good do girls see higher investments in their education. Son preference leads to no significant changes in overall education expenditures although the signs of the effects are positive. In addition, there is a small but statistically significant increase in spending on private tutors, suggesting that boys may have access to higher quality teaching. We find small and statistically insignificant effects of labor demand on per capita expenditure during the last month. This suggests that increases in education spending could result from reallocation of resources within the household or that any additional income in the household is potentially saved and allocated to annual education expenses. Another important component of parental investment in children is time investments which could complement education spending. Unfortunately, we do not have information on time allocation of parents and children to further test this hypothesis.

An alternative explanation for our results could be that increases in local labor demand are associated with increases in education spending by the district, not the parents. In panel A of Table 6, we further test this hypothesis using administrative data from the District Information System for Education (DISE), which collects information on various school characteristics.[23] We find that the Bartik index has a small and statistically insignificant effect on a variety of measures of school resources including number of students per school, number of students per teacher, number of schools which received the school development grant (SDG) and Teacher Learning Material (TLM) grant, and proportion of students with books and uniforms. Similarly, in Panel B, we use school-level data from the ASER surveys from our study period[24] and find no significant effects of growth in local labor demand on changes in school quality indicators such as the availability of a black

22 In 2004/5, the average monthly consumption per capita for rural households was estimated to be Rs. 559 (MoSPI 2006). In our sample of rural households with school-aged children, the average household size is 5.91, suggesting total household annual spending of about Rs. 39,700.

23 The results from the DISE surveys of schools are aggregated at the district-level. Data for the district report cards available at <udise.in/drc.htm>.

24 In 2005, 2007, and every year since 2009, ASER collected information on school characteristics of one government primary school in each sampled village. We aggregate this information at the district level.

Table 5: Household-level investments using NSS data.

	Tuition and other fees		Private tutor/coaching center		Total education expenditures		Monthly per capita expenditure	
Labor demand index	16521.6**	16127.6**	1114.7	998.2	19125.3**	18419.6*	1455.5	1198.1
	(7478.9)	(7490.9)	(2286.0)	(2287.3)	(9423.1)	(9431.2)	(957.6)	(952.2)
Labor demand index*Number of female children		116.9**		22.2		181.4**		73.9**
		(49.1)		(17.1)		(71.5)		(10.1)
Labor demand index*Number of male children		62.4		35.4**		110.1		59.8**
		(55.2)		(17.1)		(85.5)		(8.3)
Number of observations	80,694	80,694	80,694	80,694	80,694	80,694	80,694	80,694
Number of districts	533	533	533	533	533	533	533	533

[a]Total education expenditures include annual spending on books, newspapers, library charges, stationary, tuition, private tutor, and other. [b]Each regression model controls for age, year of interview and district fixed effects, as well linear state trends, and trends in baseline district characteristics (proportion of rural, ST, SC, and illiterate population in the district, average years of education, proportion of population under the poverty line, and female and male labor force participation rate), as well as household size. [c]Standard errors, in parentheses, clustered at the district level. [d] * denotes 10% significance level; ** denotes 5% significance level.

Table 6: District-level investment.

Panel A: District-level investments using DISE data

	Students per school	Students per teacher	Proportion of schools received SDG grant	Proportion of schools received TLM grant	Proportion of students who have books	Proportion of students who have uniforms
Labor demand index	−23.9816	−22.0712	−0.6964	−0.9728	0.7478	−0.0899
	(73.2248)	(17.0194)	(0.5456)	(0.6263)	(1.2223)	(0.3285)
Number of districts	531	531	531	531	531	510

Panel B: District-level investments using school-level ASER data

	Blackboard in classroom grade 2	Blackboard in classroom grade 4	Supplementary learning materials in grade 2	Supplementary learning materials in grade 4	Midday meal program in school	Tap water in school
Labor demand index	0.017	0.0861	−0.3884	0.6659	−0.7665	−0.3474
	(0.2231)	(0.2839)	(0.6840)	(0.8046)	(0.5624)	(0.3700)
Number of schools	27,033	23,371	26,442	23,255	27,340	27,045
Number of districts	526	526	526	526	526	526

[a]Each regression model controls for year and district fixed effects, as well linear state trends, and trends in baseline district characteristics (proportion of rural, ST, SC, and illiterate population in the district, average years of education, proportion of population under the poverty line, and female and male labor force participation rate). [b]Standard errors, in parentheses, clustered at the district level. [c] * denotes 10% significance level; ** denotes 5% significance level.

board in classrooms, availability of learning materials, access to the midday meal program and access to usable tap water in school.

6 Conclusion

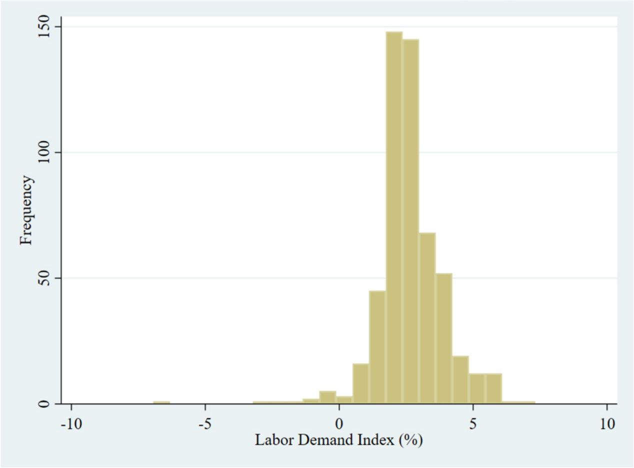
This paper constructs a district-level measure of exogenous changes in labor demand and studies the effect of predicted employment growth on education outcomes of children between the ages of 6 and 16 in India. We find that for young children, higher predicted employment growth is associated with more schooling and better reading and math test scores. Among 6–10 year olds, the effects are similar in size and significance for boys and girls alike with girls having slightly larger impacts. We find no strong significant effects on test scores of older boys between the ages of 11 and 16 but we do find that older girls tend to benefit from better labor market opportunities in terms of increased schooling and better reading scores, possibly because education of older girls may be a luxury good and parents invest in girls only when the economic conditions are good.

We use measures of gender-specific labor demand to test if some of the effects could be explained by changes in perceived returns to education for girls or by higher bargaining power of mothers. Female labor demand does not have a strong significant impact on older girls, suggesting a limited role for changing aspirations. It does have a small effect on young children, and especially boys, however, which could be due to higher bargaining power of women and son preference, although the effect is small.

Next, we examine changes in investments at the intensive margin. We find that better labor market opportunities are associated with higher education spending, and households with more girls experience a greater increase. We find no effects on investments at the school-level and no changes in school quality. Overall, our analysis suggests that better labor market opportunities could have a beneficial effect on young children, as well as older girls, from rural areas as parents respond by investing in the human capital of their children.

Research Funding: None.
Competing interests: None.

Appendix



Appendix Figure 1: Distribution of the labor demand index across districts.

Appendix Table 1: Labor demand index and labor market outcomes in NSS data

	All		Males		Females	
	Worked	Weekly wage	Worked	Weekly wage	Worked	Weekly wage
Panel A: Model without clustering standard errors						
Labor demand	0.1981*	1346.8211**	0.078	1142.4296	0.3634**	2154.2650*
index	(0.1057)	(609.1941)	(0.1236)	(700.6789)	(0.1606)	(1212.5163)
Panel B: Model with clustered standard errors						
Labor demand	0.1981	1346.8211	0.078	1142.4296	0.3634	2154.265
index	(0.2827)	(997.5360)	(0.1861)	(1028.3955)	(0.4795)	(1492.8721)
Observations	545,629	130,260	275,298	101,087	270,331	29,173

[a]Each regression model controls for age, year of interview and district fixed effects, as well linear state trends, and trends in baseline district characteristics (proportion of rural, ST, SC, and illiterate population in the district, average years of education, proportion of population under the poverty line, and female and male labor force participation rate). [b]Standard errors in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level. [c]The variable weekly wage is defined for employed people with non-missing wage.

Appendix Table 2: Placebo test using residualised future demand index.

	Years of education	Currently in school	On track	Reading: Reading score	Reading: Letter	Reading: Word	Reading: Paragraph	Reading: Story	Math: Math score	Math: Numbers 1–9	Math: Numbers 10–99	Math: Subtraction	Math: Division
Panel A: Boys 6–10													
Labor demand	−0.1257	−0.0087	0.0278	0.0491	0.015	−0.0026	0.0004	0.0363	0.1445	0.0213	0.1114	0.0446	−0.0328
index t+1	(0.3240)	(0.0558)	(0.0928)	(0.4992)	(0.0996)	(0.1545)	(0.1683)	(0.1412)	(0.4689)	(0.0989)	(0.1580)	(0.1620)	(0.1216)
Panel B: Boys 11–16													
Labor demand	−0.4156	−0.0281	−0.089	0.188	−0.0015	0.0595	0.0625	0.0676	0.2297	−0.0211	0.0434	0.1169	0.0905
index t+1	(0.5544)	(0.0748)	(0.1367)	(0.3636)	(0.0433)	(0.0675)	(0.1063)	(0.1891)	(0.3951)	(0.0443)	(0.0738)	(0.1272)	(0.2009)
Panel C: Girls 6–10													
Labor demand	−0.1192	−0.0238	0.0067	0.0029	0.0266	0.0036	−0.0218	−0.0055	0.1396	0.0431	0.1317	−0.0092	−0.0261
index t+1	(0.3031)	(0.0511)	(0.0852)	(0.5011)	(0.0979)	(0.1673)	(0.1643)	(0.1382)	(0.4846)	(0.1016)	(0.1594)	(0.1733)	(0.1194)
Panel D: Girls 11–16													
Labor demand	−0.0587	0.0066	−0.0149	0.1835	0.0014	0.0731	0.067	0.0421	0.3906	0.0042	0.0852	0.1851	0.1161
index t+1	(0.6022)	(0.0823)	(0.1354)	(0.3935)	(0.0513)	(0.0804)	(0.1277)	(0.1809)	(0.4570)	(0.0551)	(0.0911)	(0.1540)	(0.2112)

[a]Each regression model controls for age, year of interview and district fixed effects, as well linear state trends, and trends in baseline district characteristics (proportion of rural, ST, SC, and illiterate population in the district, average years of education, proportion of population under the poverty line, and female and male labor force participation rate). [b]Standard errors in parentheses, clustered at the district level. Total number of clusters = 533. [c] * denotes 10% significance level; ** denotes 5% significance level. [d]Panel A has 256,698 observations. Panel B has 255,114 observations. Panel C has 215,305 observations. Panel D has 211,406 observations.

Appendix Table 3: Heterogeneity in the treatment effect by mother's education

	Years of education	Currently in school	On track	Reading Score	Math score
Panel A: Boys 6–10					
Labor demand index	2.5217**	0.0162	0.5572**	4.1132**	3.1772**
	(0.7990)	(0.0843)	(0.2153)	(1.1792)	(1.0695)
Labor demand index*Mother	0.0054**	0.0006**	0.0016**	0.0204**	0.0189**
yrs education ≥8	(0.0004)	(0.0000)	(0.0001)	(0.0006)	(0.0005)
Panel B: Boys 11–16					
Labor demand index	1.2876	0.0832	0.2999	1.1859	0.429
	(1.5144)	(0.1903)	(0.3755)	(0.8732)	(1.0649)
Labor demand index*Mother	0.0251**	0.0025**	0.0063**	0.0134**	0.0152**
yrs education ≥8	(0.0010)	(0.0001)	(0.0002)	(0.0005)	(0.0005)
Panel C: Girls 6–10					
Labor demand index	2.6733**	0.1201	0.4948**	5.1780**	3.4513**
	(0.9134)	(0.1066)	(0.2161)	(1.2981)	(1.2317)
Labor demand index*Mother	0.0059**	0.0007**	0.0018**	0.0211**	0.0195**
yrs education ≥8	(0.0004)	(0.0000)	(0.0001)	(0.0006)	(0.0006)
Panel D: Girls 11–16					
Labor demand index	3.2420**	0.1276	0.4957	2.4444**	1.6178
	(1.4849)	(0.2120)	(0.3259)	(0.9948)	(1.1753)
Labor demand index*Mother	0.0293**	0.0031**	0.0071**	0.0147**	0.0174**
yrs education ≥8	(0.0011)	(0.0001)	(0.0002)	(0.0005)	(0.0006)

[a]Each regression model controls for age, year of interview and district fixed effects, as well linear state trends, and trends in baseline district characteristics (proportion of rural, ST, SC, and illiterate population in the district, average years of education, proportion of population under the poverty line, and female and male labor force participation rate), as well as an indicator for the child's mother having completed eight or more years of schooling. [b]Standard errors in parentheses, clustered at the district level. Total number of clusters = 533. [c] * denotes 10% significance level; ** denotes 5% significance level. [d]Panel A has 256,698 observations. Panel B has 255,114 observations. Panel C has 215,305 observations. Panel D has 211,406 observations.

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Supplementary Material: The online version of this article offers supplementary material (https://doi.org/10.1515/bejeap-2020-0281).