CHANGES IN CHILDREN'S TIME USE, INDIA 1998-2019

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Abstract

Using the two waves of the India Time Use Survey, 1998-9 and 2019, we document a 110-minute (30-percent) increase in average daily learning time. The largest offsetting decrease was in work time: 61 minutes. The composition of leisure changed, with television rising by 19 minutes, while talking fell by 10 minutes and games by 17 minutes. We then implement a Gelbach decomposition, showing that 68 minutes of the unconditional learning increase are predicted by demographic covariates. Of these predictors the most important are a child's state of residence and usual principal activity, which captures extensive-margin transitions into schooling.

Keywords: time use; children; education; child labor

JEL codes: J22; I25; J13; J24; O15

1 INTRODUCTION

Childhood investments have large effects on outcomes later in life, including health [Heckman, 2007], labor earnings [Chetty et al., 2011] and accumulation of human capital [Almond et al., 2018]. Such investments plausibly affect macroeconomic growth as well [Mankiw et al., 1992]. Nearly all childhood time use is entangled with investment. Some activities, like schooling or job training, are themselves investments, while others, like leisure, may come at the opportunity cost of investments.[1] Therefore studying children's time use is important, particularly in developing countries.

As a diverse developing country with some 361 million children aged 14 or under as of 2020 [World Bank, 2022a], India comprises a natural setting for such a study. This is doubly so because, in contrast to the intense interest from both policymakers and researchers in studying time spent in school,[2] we know extremely little about how children in India spend their time outside of school.

This paper draws on two waves of the India Time Use Survey (ITUS) to investigate how the allocation of time by children has changed in India between 1998 and 2019, a period of immense economic, social, and political change [World Bank, 2022b, Ahluwalia, 2002, Marelli and Signorelli, 2011, Palshikar et al., 2017]. While the paper pays particular attention to time spent learning, both inside and outside school, it addresses the entire time budget, including work, home production, and leisure (e.g. television). The paper then uses the method of Gelbach [2016] to i) estimate the share of the change that can be predicted by observable characteristics; and ii) decompose the predictable share of the change into the contributions of individual covariates, e.g. sex and age.

We find that mean learning time increased by 110 minutes per day, from 310 minutes in 1998 to 420 minutes in 2019. In proportional terms this is an increase of 30 percent.[3] Conditional on observable child and household characteristics, the unpredicted learning change across waves is 42 minutes.[4] The largest contributors to the discrepancy are usual-activity fixed effects, particularly the indicator for schooling, suggesting that extensive-margin transitions into schooling account for much of the unconditional learning increase. State fixed effects are also quantitatively important predictors of learning time. This suggests that persistent state-specific factors like the bicycle program in Bihar [Muralidharan and Prakash, 2017] and state-level variation in implementation of national policies, like the NREGA public employment scheme [Imbert and Papp, 2015], may matter.[5] Also important for the gap between conditional and unconditional learning changes are dwelling type fixed effects, which plausibly proxy for wealth.[6] These findings are consistent with the long literature on the income-education relationship [Løken, 2010].

As the time constraint always binds, increased learning time must have been offset by declines in other time uses. Work declined by 61 minutes, home production by 23 minutes, and leisure by 26 minutes. Conditional on observables, the unpredicted declines are 20 (work), 14 (home production), and 9 minutes (leisure), respectively. Because usual-activity fixed effects condition on the extensive margin of work, the conditional 20-minute decline in work represents an intensive-margin change.

We also investigate changes in the composition of leisure time. While total leisure decreased between 1998-9 and 2019, time spent watching television increased by 19 minutes. Time spent "talking, conversing, chatting" decreased by 10 minutes, and time spent "playing games and other pastime activities" decreased by 17 minutes. Our results *do not* establish a causal link between increases in television time and decreases in more socially connected forms of leisure. They do, however, suggest that Putnam's *Bowling Alone* hypothesis may warrant investigation in India, a setting quite different from the US context in which it was conceived [Putnam, 2001].

This paper contributes to two literatures. The first is on time allocation in developing countries. Because high-quality time use surveys in developing countries are uncommon, existing literature is relatively sparse. Some papers rely upon public health surveys that were not designed based on survey research in time use. Garg et al. [2020], for example, use the China Health and Nutrition Survey to study the response of work time to extreme temperatures in China. The papers closest to ours are (i) Li [2023], which examines changes in women's work time across the two waves of the ITUS,[7] and (ii) Jagnani [2022], which focuses on the causal effects of child sleep on human capital production using the 1998-9 ITUS. To the best of our knowledge, ours is the first paper to study the full allocation of time among children in a developing country.

The second related literature is on education and child labor in India.[8] As a prominent example, Edmonds et al. [2009] investigates the effects of India's 1991 trade liberalization on the probabilities that a child's principal activity is work or schooling. More recently, Bharadwaj et al. [2020] evaluate India's 1986 ban on child labor, finding that the ban increased the probability of child employment. Our paper makes two contributions to this strand of research. It corroborates previous work on children's usual principal activities and shows how changes in usual activity predict time-use changes. In addition, our study estimates intensive-margin changes in child learning and work over the last two decades.[9]

The rest of the paper proceeds as follows. Section 2 presents a brief overview of the education sector and policies in India relevant to our analysis period. Section 3 describes the ITUS data. Section 4 explains our use of the Gelbach decomposition to study the changes in time use across ITUS waves. Section 5 presents empirical results and Section 6 concludes.

2 INSTITUTIONAL BACKGROUND

India's education sector is subject to both central (federal) and state-level policies. The central government lays down national policies and guidelines that provide an overall framework for national education policies and programs. However, individual state governments have significant leeway in deciding school policies at the local level and implementing national-level programs. For instance, in 1995, the central government initiated the National Programme of Nutritional Support to Primary Education (popularly known as the Midday Meal Scheme) to provide nutritious, in-school meals to all public schools. However, the implementation and coverage of the scheme varied across states, and the program became operational across all states only by 2004 [Singh et al., 2014, Kaur, 2021]. As with the midday meal program, implementation of education and other social sector schemes often varies across states. Our analysis includes state fixed effects to evaluate the role of state-specific factors in predicting the change in children's time-use over the 1998-2019 period.

At the start of our sample period, the central guiding policy governing the education sector was the National Policy on Education (NPE) of 1986. The policy made expanding primary education a national priority and committed to increasing resources allocated towards the education sector. The NPE laid the groundwork for a number of centrally sponsored schemes to increase primary enrollment during the 1990s. In addition to the Midday Meal Scheme mentioned earlier, the central government also launched the District Primary Education Program (DPEP) to target underserved districts [World Bank, 2009]. Evaluations of DPEP have found that it increased school attendance and educational attainment [Jalan and Glinksya, 2013, Azam and Saing, 2017]. These policy efforts resulted in a modest increase in net primary school enrollment from 77 percent in 1990 to 80 percent by 2000 [World Bank, 2022c]. Building on these programs, the central government initiated the National Program for Universal Elementary Education, also known as the Sarva Shiksha Abhiyan (SSA), in 2001. The SSA aimed for universal enrollment of all 6- to 14-year-olds in schools and retention until grade eight. Broadly these educational policies increased school attendance among low-income rural children, particularly girls [Datta Gupta et al., 2018]. The goal of universal education was written into law through the Right to Education (RTE) of 2009. The RTE law made free and compulsory education up to the age of 14 a fundamental, constitutional right.

In conjunction with this increased impetus towards universal education, India also witnessed a strengthening of child labor laws during the course of our sample period. Landmark legislation banning child labor in specific high-risk industries began with the Child Labor (Prohibition and Regulation) Act of 1986. This law made 14 years the uniform age used to define "child" labor and laid down specific penalties for law violations [Bharadwaj et al., 2020]. The initial list of industries and sectors included in the 1986 law expanded to cover more industries in the ensuing years. Finally, by 2016, the Child Labor Act was amended to prohibit the use of child labor in all occupations.

The period corresponding to these policy changes saw net primary enrollment grow to 92 percent by 2013 [World Bank, 2022c], and reach 94.6 percent by 2020 [UNESCO]. While this paper focuses on intensive-margin changes in learning time, our decomposition analysis also provides estimates of changes in children's time allocation associated with the extensive-margin increase in school enrollment over our sample period (see Section 5 and Figure A4).

3 DATA

All data used in this paper are from the India Time Use Survey. Wave one of the ITUS occurred from July 1998 through June 1999 and covered 52 districts in six states: Gujarat, Haryana, Madhya Pradesh, Meghalaya, Odisha, and Tamil Nadu. These states were intended to capture regional variation in time allocations. Households were randomly sampled within each state, and the resulting samples are representative at the state level when used with included sampling weights. Unusually among time-use surveys, the ITUS records time diaries for all household members aged six years or older. In keeping with the recommendations of survey research [Seymour et al., 2017, Field et al., 2022, Giménez-Nadal and Molina, 2022], the ITUS asks respondents for complete 24-hour (1440-minute) time diaries on the day prior to the survey interview. A given respondent was interviewed up to three times, recording a diary for a normal day, an abnormal day (e.g. a festival day), and a "weekly variant" (usually a Sunday).[10] Parents were permitted to assist young children in responding [Jagnani, 2022]. Activities were coded using a nested three-digit classification. For example, in the 1998-9 survey activities 7xx were "learning," and activity 711 was "general education: school/university/other educational institutions attendance." The ITUS survey also included common demographic questions such as sex, monthly expenditure, and religion.

Wave two of the ITUS occurred in 2019 and covered all states in India. Again random sampling was conducted at the household level, and samples are representative at the state level when used with included sampling weights. Again children aged six years or older were included. The format of the 24-hour time diaries was similar to that of the first wave, but an amended activity classification was employed. A given respondent could contribute only one diary, which was classified as covering either a normal or an abnormal day.[11] Respondents could report up to three simultaneous activities for a given period of time, with one identified as primary. To maintain comparability with the 1998-9 ITUS and ensure respondents faced an adding-up constraint, we use only primary activities in this analysis.

Our sample was constructed as follows. Each ITUS wave was restricted to the six states covered in both 1998-1999 and 2019. Because the state of Chhattisgarh was still part of Madhya Pradesh in 1998-1999, it was included in the 2019 sample.[12] The data were further restricted to children aged six to 16 years (school age) and diaries for normal days (which cover both weekdays and weekends in both waves). Our final sample includes 29,865 diaries from just as many children, with 13,969 from 1998-9 and 15,896 from 2019.

Following Li [2023], we created a mapping from three-digit 2019 activity codes to one-digit 1998-9 activity codes. This task was straightforward, requiring no obviously consequential researcher decisions. For example, the 2019 code "620: homework, being tutored, course review, research and activities related to formal education" was mapped to the 1998-9 code "7: learning." Additionally, for our initial description of children's time allocation, we aggregated one-digit 1998-9 codes as follows. "Primary production activities," "secondary activities," and "trade, business, and services" were classified as work. "Household maintenance, management, and shopping for own household," "care for children, the sick, elderly, and disabled for own household," and "community services and help to other households" were classified as home production. "Social and cultural activities, mass media, etc." and "personal care and self-maintenance" were classified as leisure. Learning was not aggregated with other one-digit time uses.

Changes in the survey instrument across the ITUS waves make mapping between three-digit 1998-9 and 2019 codes difficult, particularly for work. Nonetheless, we were able to create a mapping across mutually exclusive and exhaustive time uses within one-digit learning and leisure. For example, the 2019 code "620: homework, being tutored, course review, research and activities related to formal education" was mapped to the 1998-9 code "721: studies, homework, and course review related to general education." Three-digit codes without an obvious match were placed into an "other learning" or "other leisure" category.

Table 1 presents weighted means for our sample by ITUS wave. The share of children reporting school as their usual principal activity increases from 73 percent in 1998-9 to 93 percent in 2019.[13] The 1998-9 ITUS share is similar to the 74.6 percent calculated by Bharadwaj et al. [2020] from the 1987-8 and 1993-4 National Sample Surveys (NSS), but lower than the 85 percent calculated by Edmonds et al. [2009] from the 1999-2000 NSS. This difference may arise from the national sampling frame of the NSS. The 2019 ITUS share is similar to the 94.6 percent share reported by UNESCO for 2020. These comparisons to prior work provide some evidence that the ITUS sample is reasonably representative of broad extensive-margin schooling trends in India. Descriptive statistics for other usual principal activity and state indicators appear in Table A1.

Table 1 also shows that nominal monthly expenditure (in 000 Rupees) increases by a factor greater than three, from 2650 to 9400. Because of the difficulty of measuring income in developing countries, and in keeping with standard practice, ITUS uses consumption expenditure to capture household well-being [Meyer and Sullivan, 2003]. The World Bank [2000] notes that consumption expenditure is the preferred indicator "for practical reasons of reliability and because consumption is thought to better capture long-run welfare levels than current income" (p. 17). The fraction of rural respondents falls from 73 to 71 percent in Table 1, consistent with ongoing urbanization. Household size decreases from 5.5 to 5.0.

Note that the fraction of children in Table 1 with "scheduled tribe" status increases from 14 to 19 percent across ITUS waves. "Scheduled castes" (SC) and "scheduled tribes" (ST) in India consist of groups who have historically been the target of social and economic discrimination stemming from traditional stratifications in Hindu society [Deshpande, 2000]. The 1950 Constitution of India designated these caste and tribe groups as protected under various schedules [Tandon, 2018]. Despite constitutional safeguards and affirmative action policies, on average SC and ST households have lower incomes [Mehta and Shah, 2003], higher mortality [Subramanian et al., 2006] and less sufficient nutrition [Van de Poel and Speybroeck, 2009] compared to the rest of the population.

4 EMPIRICAL STRATEGY

We begin by considering the following two simple regressions.

$$y_{it} = \beta_{base}\, \mathit{Year2019} + \nu_{it} \tag{1}$$

$$y_{it} = \beta_{full}\, \mathit{Year2019} + \mathbf{x}'\boldsymbol{\gamma} + \varepsilon_{it} \tag{2}$$

In these equations y_{it} represents total time spent on a given activity in the 24 hours covered by the diary of individual i in survey year $t \in \{1998, 2019\}$. The indicator *Year2019* equals one for 2019 diaries and it follows that β_{base} is the change in average time spent on the given activity from the 1998-9 wave to the 2019 wave. In equation 1, which we call the base specification, this is the unconditional or unadjusted change over time. Equation 2, the full specification, includes a vector $\mathbf{x}$ of K observable covariates and corresponding parameters $\boldsymbol{\gamma}$, making β_{full} a conditional or adjusted change over time.[14]

The key insight of Gelbach [2016] is that the formula for omitted variable bias in ordinary least squares regression can be used to decompose the difference between β_{full} and β_{base} into the contributions of particular variables (or sets of variables).

$$\beta_{full} - \beta_{base} = \sum_{k=1}^{K} \eta_k \gamma_k \tag{3}$$

In equation 3 the parameters γ_k correspond to elements of $\boldsymbol{\gamma}$ in equation 2. That is, they are the marginal effects from the full regression model. The parameters η_k come from auxilliary regressions of each x_k on the 2019 indicator, controlling for all other variables in $\mathbf{x}$. This decomposition has several desirable properties. First, it is path-independent. One need not make an arbitrary choice of sequence that will influence the estimated contributions of the variables. Second, the Gelbach decomposition adds up: the sum of the variable-specific biases equals the aggregate difference across parameters in the base and full specifications [Fortin et al., 2011]. Finally, Gelbach [2016] shows that this decomposition nests the well-known Blinder-Oaxaca decomposition [Blinder, 1973, Oaxaca, 1973].

An estimator for the elements of the sum in equation 3 is implemented as the Stata package `b1x2` [Gelbach, 2014]. Gelbach [2016] provides an analytical solution for the variance-covariance matrix of this estimator, which allows for a variety of heteroskedasticity- and autocorrelation-robust standard errors. We cluster standard errors at the district level throughout the paper. The provided ITUS sampling weights are employed in both regressions and Gelbach decompositions.

The key assumption required for unbiased aggregate decomposition of β_{base} into a predicted component $\beta_{base} - \beta_{full}$ and a residual unpredicted component β_{full} is ignorability, or "selection on observables" [Fortin et al., 2011]. Informally, in the setting of this paper ignorability stipulates that the distribution of unobservables ε_{it} must be the same in both the 1998 and 2019 ITUS waves after conditioning on $\mathbf{x}$. For the detailed decomposition of equation 3 to be unbiased one must generally make a stronger assumption, restricting the functional form or imposing independence of ε_{it} with respect to *Year2019* and $\mathbf{x}$. As such an assumption is unlikely to hold in our setting, we interpret our detailed decomposition as primarily descriptive.

5 RESULTS

5.1 *Children's Time Allocation*

An aggregate view of changes in children's time allocation appears in Figure 1. Corresponding numerical estimates appear in Table 1. The largest change was in learning time, which rose from 310 minutes in 1998-9 to 420 minutes in 2019. All other high-level aggregate time uses declined. The largest decline was in work, from 78 minutes in 1998-9 to 17 minutes in 2019. Home production also fell, from 49 minutes in 1998-9 to 26 minutes in 2019. Finally, leisure declined from 1003 minutes in 1998-9 to 977 minutes in 2019. The largest component of leisure is sleep, which increased slightly from 568 minutes in 1998-9 to 578 minutes in 2019. Sleep time is of economic interest [Gibson and Shrader, 2018], particularly among children [Jagnani, 2022]. Because there is so little change across ITUS waves, however, in the remainder of this paper we discuss only waking forms of leisure time.

Figure 2 presents uncontrolled and controlled changes in aggregate time uses between 1998-9 and 2019. Estimates from regressions following equations (1) and (2) appear as round markers, with 95 percent confidence intervals represented using whiskers.[15] Corresponding numerical estimates appear in Table 2. Our specification of the full regression (equation 2) comprises all child- and household-level covariates that can be feasibly harmonized across ITUS waves.[16] This covariate set includes all observables that appear in Table 1, plus fixed effects for state, dwelling type, and usual activity.[17] In Figure 2 the change in leisure is small (-26 minutes), and smaller still conditional on covariates (-8.5 minutes, not statistically significant at the five percent level). A similar pattern obtains for home production (-23 minutes unconditional, -14 minutes conditional). The important changes are observed in work and learning. For both of these time uses unconditional changes are large and adding covariates to the regression produces practically meaningful changes in the estimates. The unconditional decline in work is 61 minutes. Conditional on covariates the unpredicted decline is still 20 minutes, with the estimate statistically significant at the five percent level. These work-time changes may influence welfare, as child labor in India is negatively associated with psychosocial measures of well-being like hope and happiness [Feeny et al., 2021]. Learning increases by 110 minutes without covariates, 42 minutes with covariates. The last two decades have seen practically a practically large increase in learning time for Indian children, of which 38 percent cannot be predicted by covariates.

The human capital implications of this increase in learning time are potentially significant. Previous studies using longitudinal time use data find that an additional hour of learning time outside school *per week* has an effect on cognitive skills similar to that of one additional year of parental education [Fiorini and Keane, 2014, Borga, 2019].[18] The conditional increase in learning time we document is much larger than one hour per week and could have contributed to substantial gains in cognitive skills among Indian children over the past two decades.

Last among our aggregated analyses, Figure 3 presents Gelbach decompositions of the changes across ITUS waves in leisure, home production, work, and learning. Round markers give the contribution of a variable, or group of variables, to the predicted change in time use. Using the language of Gelbach [2016], these markers give contributions to omitted variable bias in the uncontrolled regression. In keeping with equation 3, these contributions add to the "Total predicted change" illustrated at the bottom of each panel. Whiskers represent 95 percent confidence intervals. Corresponding numerical estimates appear in Table 3. Taking Figure 3 as whole, most covariates predict little of the changes in time use.[19] For example, the contribution of the female indicator is consistently near zero, and not statistically significant at the five percent level. Two exceptions are apparent. The fixed effects for usual activity predict substantial parts of the changes in all four time uses. In all four cases the sign of usual activity's contribution to total predicted change is the same as the sign of the unconditional change. That is, unexplained time-use changes, net of usual activity, are smaller than raw (unconditional) changes. The largest effects are for work and learning. The influence of state fixed effects is more nuanced. They do not matter for work and home production. For leisure and learning, the contributions of the state fixed effects have signs opposite those of the uncontrolled changes, so unpredicted changes are larger. We note that while the estimated predictive contribution of state fixed effects is sometimes large, the associated confidence intervals contain zero.

How and why do usual activity and state matter, particularly for work and learning? Figures A1-A4 and Table A2 report estimated fixed effects. By far the most important indicator is for the child's usual activity being school. This covariate predicts a 76-minute reduction in work and an 80-minute increase in learning. The estimated predictive contributions of fixed effects for the usual activity being domestic duties are also practically large and statistically significant. This pattern is consistent with extensive-margin transitions into schooling predicting much–but not all–of the observed changes in work and learning time. Among the state indicators Madhya Pradesh stands out, with the coefficient estimate statistically significant at the ten percent level in three of four cases, but magnitudes are small (seven minutes or less).

5.2 *Children's Learning Time*

To further investigate learning we consider subcategories, learning activities defined at the three-digit level: school attendance, homework, travel for learning, and other learning.[20] Figure 4 shows that school and homework are the largest constituents of learning time. Figure 5 estimates changes in learning activities across ITUS waves. Uncontrolled estimates are positive for all four types of learning. Including covariates decreases the estimates; for homework the point estimate becomes negative, but the confidence interval includes zero. The largest unconditional increase is for school time (72 minutes). A 32-minute unexplained increase remains even after accounting for covariates, including the usual activity fixed effects previously discussed in Section 5.1. This is consistent with intensive-margin increases in school time.

Our Gelbach decomposition does not establish the mechanisms underlying this intensive-margin increase, but some discussion of candidate mechanisms may motivate future research. First, the length of the school day could have increased, holding school type fixed. Second, if private schools have longer days on average, then transitions from public into private schools could have resulted in increased learning time, conditional on usual activity. Third, absenteeism could have decreased, for example because of improved health or better transportation. Fourth, occasional school attendance could have increased among children whose usual principal activity is not school.[21] Fifth, an unobserved variable or an interaction of covariates not included in our regressions could predict the 32-minute unexplained increase. If one is willing to impose the assumptions required for a threefold Blinder-Oaxaca decomposition with 1998-9 as the reference period, results indicate that both covariate and coefficient changes matter (Table A4). A 41 minute school-time increase is attributed to covariate changes, a 37.5 minute increase to coefficient changes, and a 6.5-minute decrease to the interaction. Examining the indicator for a child's usual activity being school, the Blinder-Oaxaca decomposition attributes a 48.8-minute increase to change in the variable, a .7-minute decrease to change in its coefficient, and a .2-minute decrease to their interaction. That is, Blinder-Oaxaca suggests school time is not increasing among children who identify primarily as students.

Lastly in this subsection, Figure 6 implements the Gelbach decomposition for learning activities. As in our aggregate decomposition, fixed effects for usual activity and state generally make the largest contributions to the predicted changes across ITUS waves. Dwelling fixed effects also make practically meaningful, statistically significant contributions for homework, travel, and other learning.[22] It is striking that they retain predictive power even in the presence of indicators for quintiles of monthly household expenditure. One possible reason that wealth proxies predict changes in learning time is that household wealth is an important driver of school choice and education inputs. Despite the increase in public sector resources allocated to education, India has seen an expansion of private participation in the education sector. Survey estimates suggest private school enrollment grew from around 19 percent in 2006 to nearly 26 percent in 2011, even though public schools are free and private schools are not [Muralidharan, 2013]. The increased demand for private schools plausibly reflects parents' perception of the relative quality of public versus private schools. This perception is supported to some extent by observational studies that find children in private schools have higher reading and arithmetic skills than students in government schools [Dubey et al., 2009]. Descriptive evidence also suggests that household wealth predicts private school choice in

India [Kumar and Choudhury, 2021].

5.3 *Children's Leisure Time*

While average leisure time did not exhibit a large change over ITUS waves, it warrants more detailed examination because it is a large share of the time budget for children. Figure 7 shows that television, talking, games, personal hygiene, and eating are all important constituents of leisure in our sample.[23]

Figure 8 examines changes in leisure across ITUS waves. The largest unconditional increase–19 minutes–is for television, and covariates predict very little of this change. There are smaller unconditional increases in eating (12 minutes) and hygiene (7 minutes), with covariates again exhibiting little predictive power. Offsetting unconditional declines are observed in talking (10 minutes), games (17 minutes), and other leisure (47 minutes). Again covariates generally predict small shares of these changes, with one exception: the conditional decline in talking is just 5 minutes, and the estimate is not statistically significant.

While this evidence does not establish any causal relationships, the welfare implications of this trend, with more socially connected time uses like games falling while television time increases, are potentially interesting. On the one hand, socially connected time use is associated with increased prosocial behavior and other forms of non-cognitive development [Meroni et al., 2021]. On the other hand, evidence from natural experiments in the USA and the UK suggests that an increase in television time can result in an increase in test scores [Gentzkow and Shapiro, 2008, Nieto, 2019].[24]

Our Gelbach decomposition of changes in leisure appears in Figure 9. Usual activity indicators are the most important covariates, and dwelling type indicators again show relatively large and statistically significant estimates in some cases. But broadly, Figure 9 accords with Figure 8 in suggesting that covariates predict little of the changes in leisure time uses over ITUS waves.[25]

6 CONCLUSION

We began this paper with the argument that the investment character of children's time use makes it a vital determinant of long-run welfare at both the individual and macroeconomic scales. Time-use investments are plausibly of particular importance in low-income countries. Our analysis takes two initial steps toward understanding time-use investments by children.

First, we document changes in the time allocation of Indian children from 1998 to 2019. These were two decades of thoroughgoing change in India, including increased foreign trade

[Ahluwalia, 2002, Marelli and Signorelli, 2011]. Changes in children's time use over this period are intrinsically interesting.

Second, our analysis decomposes the change in children's time use into unexplained and explained components and further decomposes the explained component into the contributions of particular characteristics. State-specific factors, dwelling type, and usual principal activity all prove quantitatively influential. While these results are primarily descriptive, a decomposition like ours points out potentially fruitful areas for future causal research [Fortin et al., 2011]. For example, perhaps the most striking of our findings is an unexplained 42-minute increase in learning time, which is driven by intensive-margin increases in school time. The effects of such a change on human capital and welfare could be significant and warrant careful study.

Notes

[1] Only an activity without long-run payoffs, and for which the best foregone alternative also lacks long-run payoffs, is not immediately entangled with investment.

[2] For instance, the state of Bihar sought to increase the educational attainment of girls by providing bicycles [Muralidharan and Prakash, 2017]. Economists have randomized the provision of technology-aided after-school instruction [Muralidharan et al., 2019] and remedial education [Banerjee et al., 2007].

[3] $\frac{110}{\frac{1}{2}(310+420)} = .30$

[4] This type of unpredicted change is sometimes described as "unexplained." To avoid any inadvertent suggestion of causal results, we do not use this term.

[5] Three of the seven "star states" that implemented NREGA particularly effectively are in our ITUS sample [Imbert and Papp, 2015]; see Section 3 for details. There is evidence that NREGA affects school enrollment and child labor [Shah and Steinberg, 2021]. State fixed effects also potentially reflect state-level variation in higher education [Jagnani and Khanna, 2020] and infrastructure [Adukia et al., 2020] investments.

[6] The India Time Use Survey classifies dwellings as "kutcha," "semi pucca," "pucca", or "no dwelling." Pucca houses are built of more durable and expensive materials, e.g. cement or brick.

[7] While Li [2023] focuses on women's work time, the paper describes changes in the entire time allocation for adults of both sexes.

[8] Basu [1999] and Edmonds and Pavcnik [2005] survey the broader literature on child labor.

[9] By "intensive-margin changes" we mean changes within usual activity.

[10] As explained below, our analysis does not use abnormal or "weekly variant" diaries.

[11] There was no equivalent of the "weekly variant" from the 1998-9 survey.

[12] Formerly part of Madhya Pradesh, Chhattisgarh became a separate state in 2000.

[13] In Table 1 this indicator variable is labeled "School" for concision, but in survey documents this usual principal activity is given as "Attended educational institution."

[14] Our use of "base" and "full" follows Gelbach [2016].

[15] Confidence intervals are based on standard errors clustered at the district level.

[16] For all regression and decomposition analyses in Section 5, we have estimated alternative specifications including day-of-week and week-of-year indicators. Naturally these predict time use. However the ITUS

sampling procedure makes their covariances with demographics and the 2019 indicator very close to zero, so they make no meaningful difference to the results.

[17]See Section 3 for the details of usual principal activity.

[18]In Section 5.2 we show the unexplained increase in learning time is driven by school, so the cited results from non-school learning provide only rough benchmarks.

[19]This is in contrast with papers like Saffer et al. [2013], which finds that demographic variables predict 30 to 65 percent of racial and gender differences in time spent on physical activity.

[20]See Section 3 for discussion of activity codes.

[21]Intensive-margin increases need not be confined to children whose usual principal activity is school. Indeed the unexplained increase in school time can be interpreted as a weighted average of intensive-margin changes in school time among children whose usual principal activity is school, and children whose usual principal activity is something else.

[22]This is more apparent in Table A5 than in the corresponding Figure 6. Dwelling characteristics are an important component of asset-based measures that researchers generally regard as capturing households' longer-run economic wealth [Sahn and Stifel, 2003, Filmer and Pritchett, 2001].

[23]As discussed in Section 5.1, sleep increased by 10 minutes across ITUS waves. It is omitted from Figure 7 to preserve the legibility of differences across other leisure activities.

[24]However, evidence from Norway suggests otherwise: Hernæs et al. [2019] finds a negative effect of television exposure on cognitive ability and school graduation rates.

[25]A Gelbach decomposition can, in principle, reveal important predicted changes from observables, even when uncontrolled and controlled estimates are close, because the contributions of multiple covariates may offset each other.

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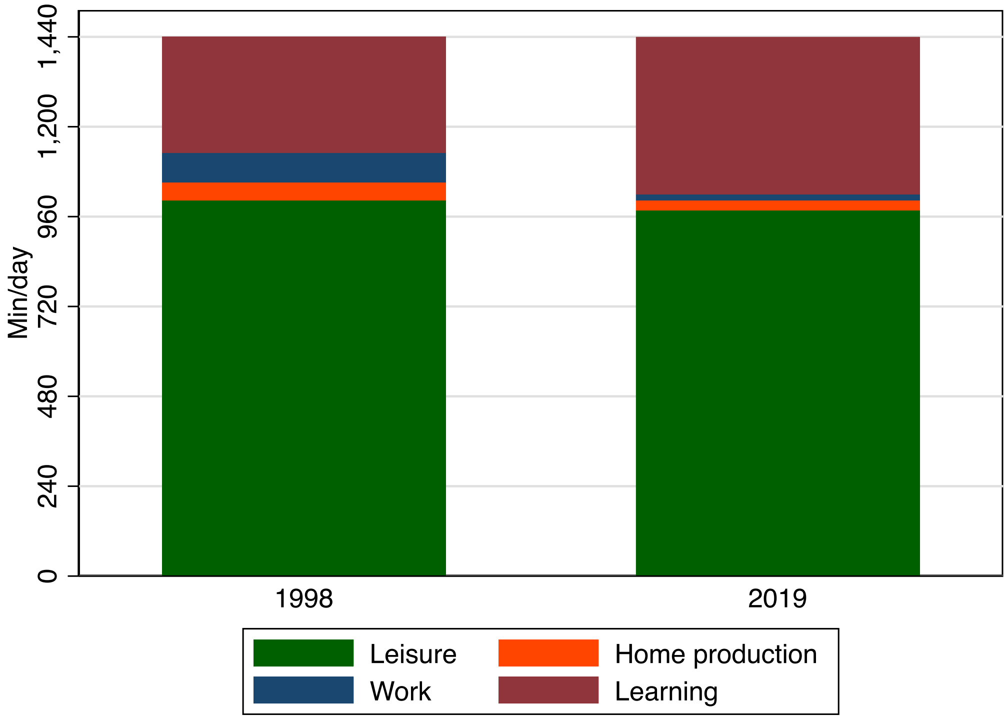
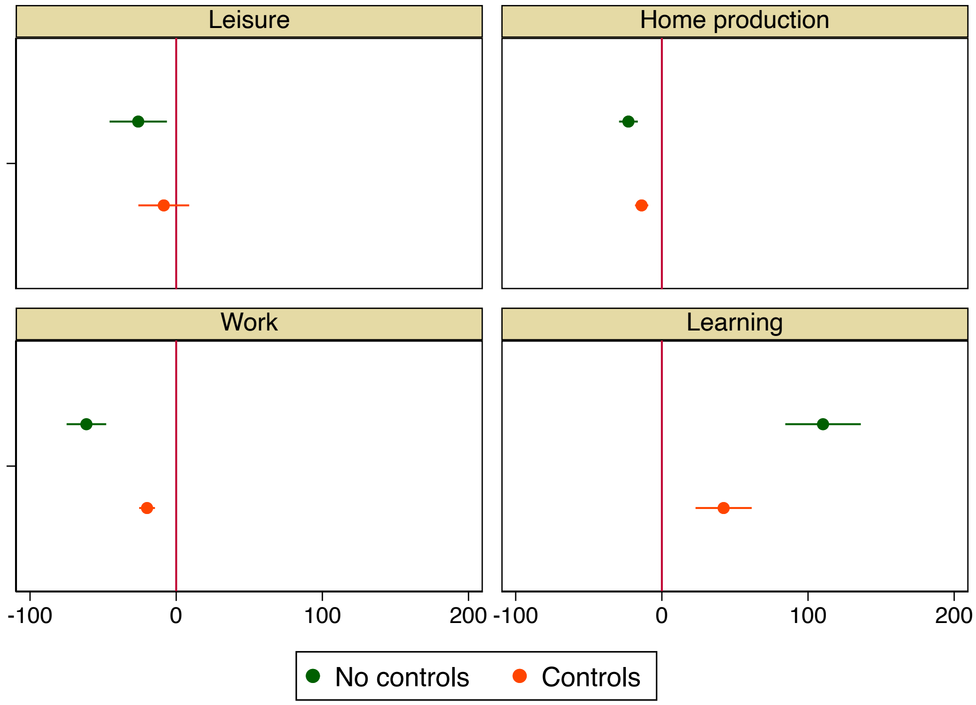
7 Figures

Figure 1: Children's time allocation, 1998-2019



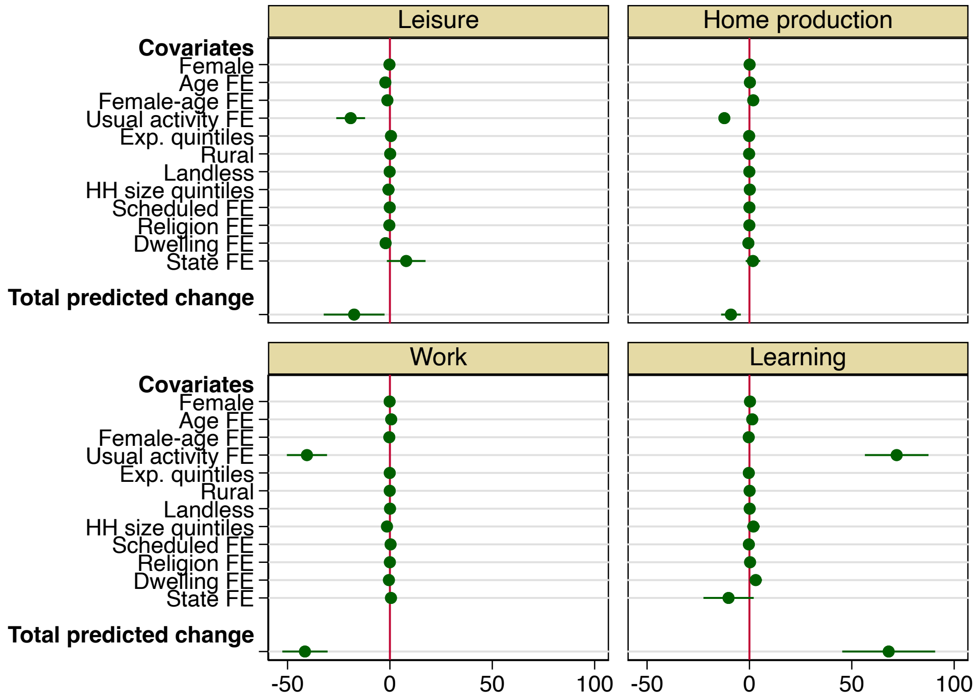
Data are from the 1998-9 and 2019 ITUS. Each diary covers exactly 1,440 minutes (24 hours). Classification is based on 1-digit 1998 activity codes: 8-9 leisure, 4-6 home production, 1-3 work, and 7 learning. Weighted means computed using ITUS sampling weights. Table 1 presents these weighted means in numerical form.

Figure 2: Children's time use changes, 1998-2019



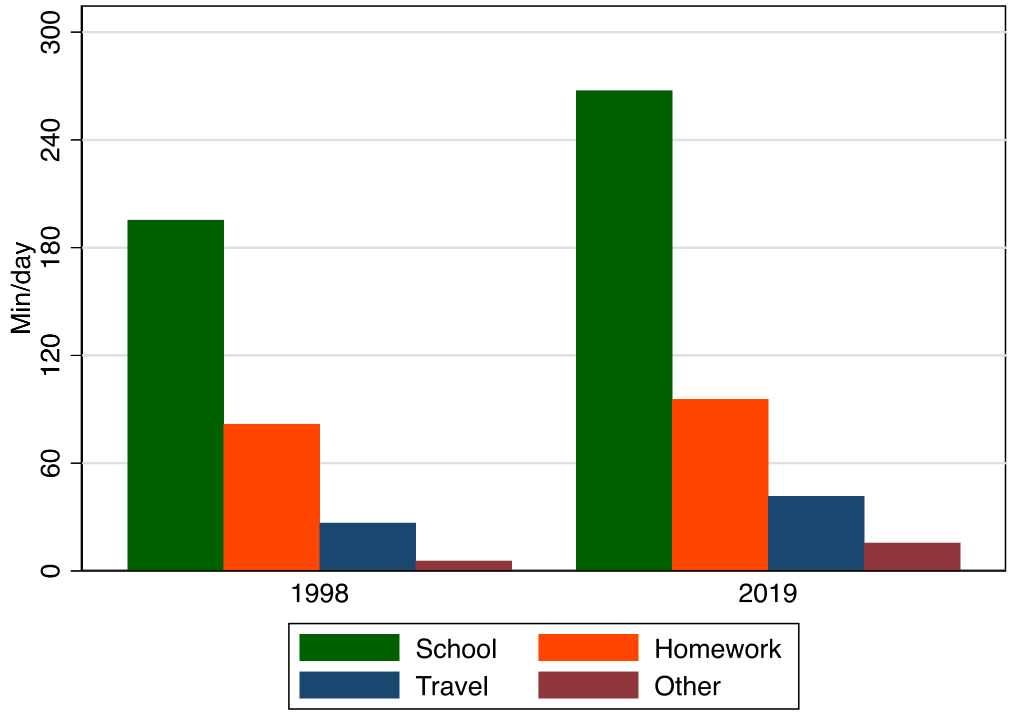
Data are from the 1998-9 and 2019 ITUS. Classification is based on 1-digit 1998 activity codes: 8-9 leisure, 4-6 home production, 1-3 work, and 7 learning. Round markers represent the change in weighted mean duration from 1998-9 to 2019, with and without covariates. Sampling weights are from the ITUS. Markers correspond to regression estimates in Table 2. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level.

Figure 3: Gelbach decompositions of children's time use changes, 1998-2019



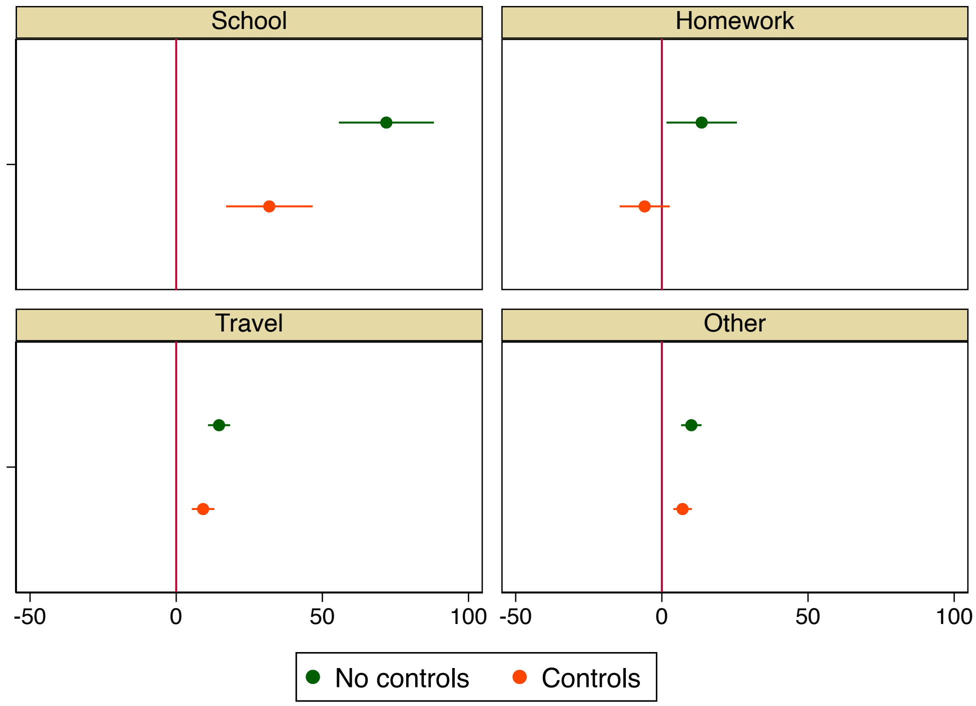
Data are from the 1998-9 and 2019 ITUS. Classification is based on 1-digit 1998 activity codes: 8-9 leisure, 4-6 home production, 1-3 work, and 7 learning. Round markers represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Markers correspond to Gelbach estimates in Table 3. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level. State and usual activity fixed effects are disaggregated in Figures A1 through A4.

Figure 4: Children's learning time, 1998-2019



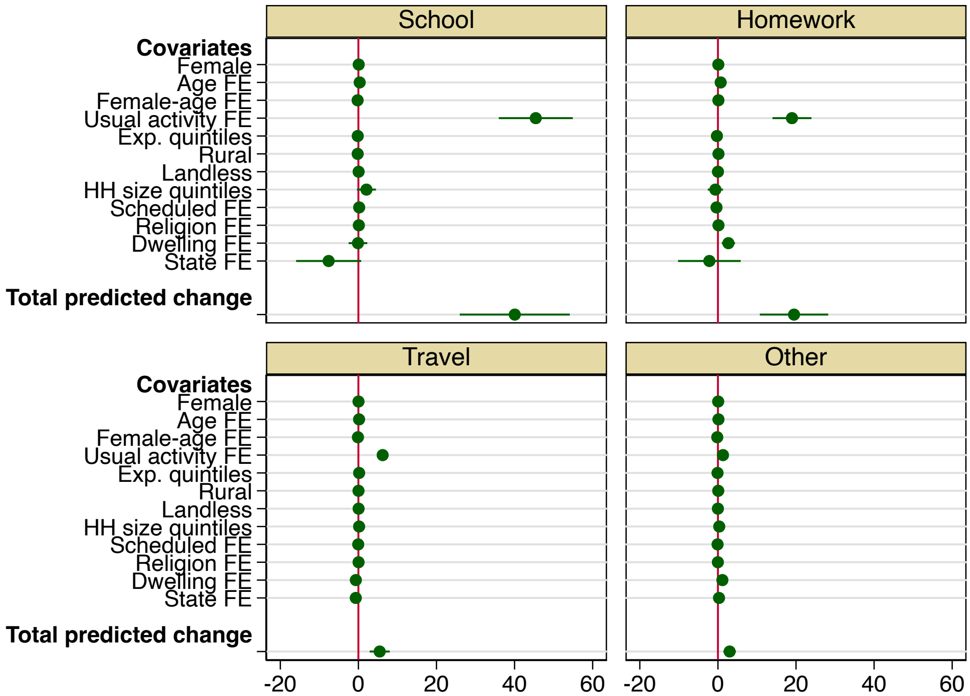
Data are from the 1998-9 and 2019 ITUS. Weighted means correspond to "school/university attendance," "homework, being tutored, course review, research and activities related to formal education," "traveling time related to learning," and all others under learning (1998 single-digit code 7). Sampling weights are from the ITUS.

Figure 5: Children's learning changes, 1998-2019



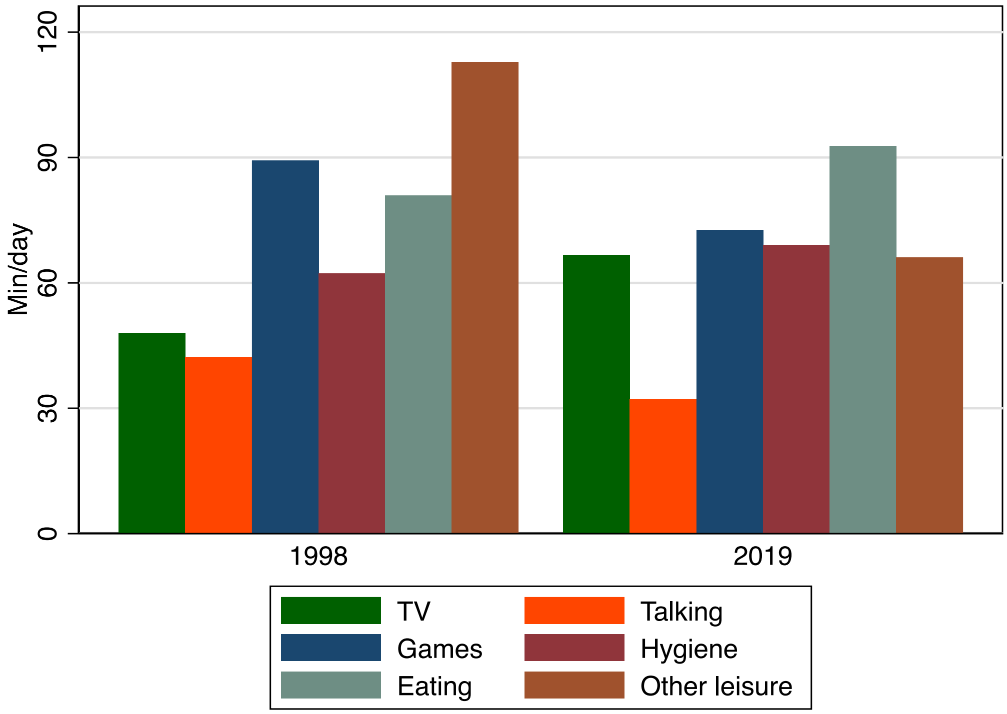
Data are from the 1998-9 and 2019 ITUS. Categories are "school/university attendance," "homework, being tutored, course review, research and activities related to formal education," "traveling time related to learning," and all others under learning (1998 single-digit code 7). Round markers represent the change in weighted mean duration from 1998-9 to 2019, with and without covariates. Sampling weights are from the ITUS. Markers correspond to regression estimates in Table A3. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level.

Figure 6: Gelbach decompositions of children's learning changes, 1998-2019



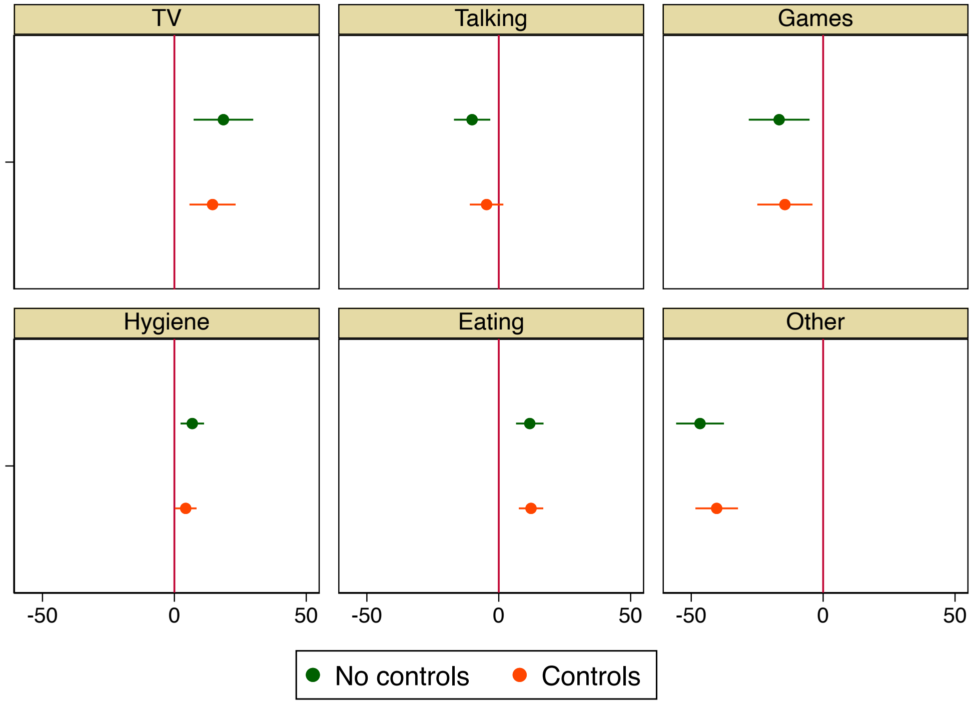
Data are from the 1998-9 and 2019 ITUS. Categories are "school/university attendance," "homework, being tutored, course review, research and activities related to formal education," "traveling time related to learning," and all others under learning (1998 single-digit code 7). Round markers represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Markers correspond to Gelbach estimates in Table A5. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level.

Figure 7: Children's leisure time, 1998-2019



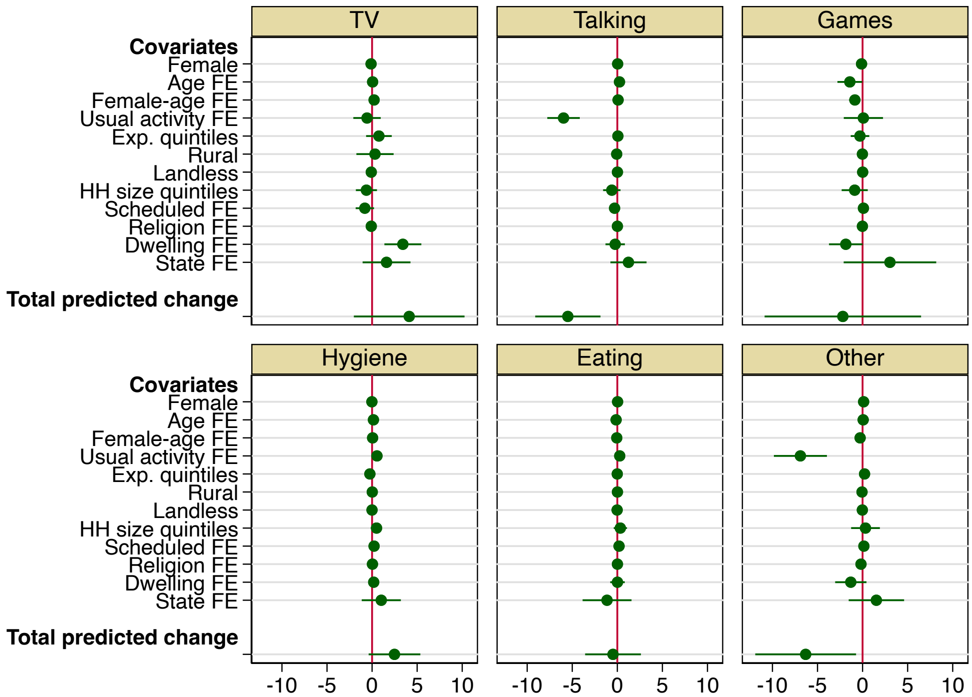
Data are from the 1998-9 and 2019 ITUS. Weighted means correspond to "watching/listening to television and video," "talking, conversing, chatting," "playing games and other pastime activities," "personal hygiene and care," "eating and drinking," and all other waking uses under leisure (1998 single-digit codes 8-9). Sleep is excluded from the figure to preserve legible scale. Sampling weights are from the ITUS.

Figure 8: Children's leisure changes, 1998-2019



Data are from the 1998-9 and 2019 ITUS. Categories are "watching/listening to television and video," "talking, conversing, chatting," "playing games and other pastime activities," "personal hygiene and care," "eating and drinking," and all other waking uses under leisure (1998 single-digit codes 8-9). Round markers represent the change in weighted mean duration from 1998-9 to 2019, with and without covariates. Sampling weights are from the ITUS. Markers correspond to regression estimates in Table A6. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level.

Figure 9: Gelbach decompositions of children's leisure changes, 1998-2019



Data are from the 1998-9 and 2019 ITUS. Categories are "watching/listening to television and video," "talking, conversing, chatting," "playing games and other pastime activities," "personal hygiene and care," "eating and drinking," and all other waking uses under leisure (1998 single-digit codes 8-9). Round markers represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Markers correspond to Gelbach estimates in Table A7. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level.

8 Tables

Table 1: ITUS descriptive statistics

	1998	2019
Leisure	1003.0	977.0
Home prod.	49.0	26.1
Work	78.1	16.7
Learning	309.9	420.2
Female	0.46	0.47
Age	11.3	11.5
School	0.73	0.93
Monthly exp.	2.65	9.40
Rural	0.73	0.71
Landless	0.57	0.56
Household size	5.47	4.98
Scheduled tribe	0.14	0.19
Scheduled caste	0.16	0.17
Hinduism	0.90	0.91
Islam	0.063	0.053

Data are from the 1998-9 and 2019 ITUS. Weighted means are computed using sampling weights from the ITUS. Time-use classification is based on 1-digit 1998 activity codes: 8-9 leisure, 4-6 home production, 1-3 work, and 7 learning. Time-use units are minutes per day. The variable labeled "School" indicates a child's usual principal activity is "Attended educational institution." Descriptive statistics for other usual principal activity and state indicators appear in Table A1. Monthly expenditure is given in thousands of nominal Rupees (000 Rs). Female, rural, landless, scheduled tribe, scheduled caste, Hinduism, and Islam are proportions (shares). Household size is a count of people.

Table 2: Children's time use changes, 1998-2019

	Leisure	Leisure	Home prod.	Home prod.	Work	Work	Learning	Learning
2019 survey	-26.0***	-8.50	-22.9***	-13.8***	-61.4***	-19.9***	110.3***	42.3***
	(9.94)	(8.81)	(3.25)	(2.30)	(6.86)	(2.74)	(13.1)	(9.74)
Female		-14.3		5.42*		-9.29		18.2
		(12.7)		(3.19)		(7.86)		(12.5)
Rural		-8.76		10.0***		5.04		-6.28
		(7.89)		(2.27)		(3.18)		(7.28)
Landless		12.2*		4.84*		-4.64***		-12.4**
		(6.40)		(2.46)		(1.74)		(6.16)
Scheduled tribe		-1.77		-0.35		6.58*		-4.46
		(10.7)		(2.89)		(3.56)		(9.53)
Scheduled caste		1.17		2.97		0.42		-4.56
		(6.42)		(2.06)		(2.57)		(6.35)
Hinduism		-22.9		-2.12		12.3**		12.7
		(14.3)		(3.90)		(5.26)		(15.7)
Islam		4.08		1.02		13.7***		-18.8
		(20.7)		(4.25)		(5.15)		(21.0)
Age FE	No	Yes	No	Yes	No	Yes	No	Yes
Female-age FE	No	Yes	No	Yes	No	Yes	No	Yes
Usual activity FE	No	Yes	No	Yes	No	Yes	No	Yes
Exp. quintiles	No	Yes	No	Yes	No	Yes	No	Yes
HH size quintiles	No	Yes	No	Yes	No	Yes	No	Yes
Dwelling FE	No	Yes	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	29859	29859	29859	29859	29859	29859	29859	29859

Data are from the 1998-9 and 2019 ITUS. Classification is based on 1-digit 1998 activity codes: 8-9 leisure, 4-6 home production, 1-3 work, and 7 learning. Each column presents estimates from a weighted linear regression, with time use in minutes as the dependent variable and an indicator for the 2019 ITUS survey as the regressor of primary interest. Sampling weights are from the ITUS. Odd columns correspond to equation 1 and even columns to equation 2. Estimates correspond to Figure 2. Standard errors in parentheses are clustered at the district level. * $p < .1$, ** $p < .05$, *** $p < .01$.

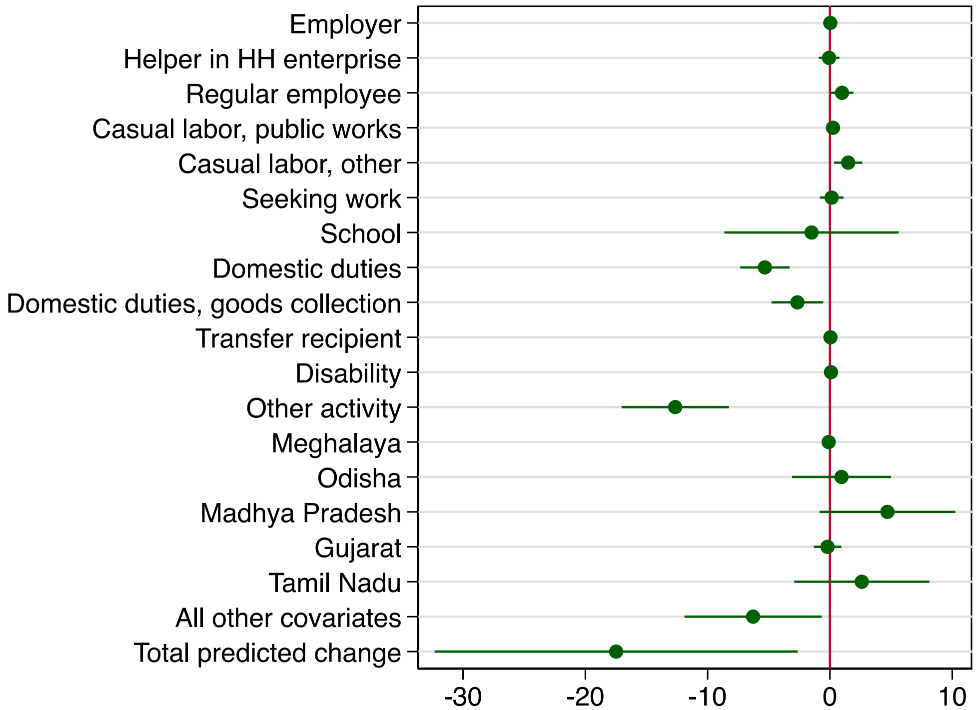
Table 3: Gelbach decompositions of children's time use changes, 1998-2019

	Leisure	Home prod.	Work	Learning
Female	-0.23	0.086	-0.15	0.29
	(0.25)	(0.087)	(0.16)	(0.26)
Age FE	-2.22**	0.23**	0.63**	1.36**
	(0.92)	(0.12)	(0.29)	(0.63)
Female-age FE	-1.22**	1.86***	-0.29	-0.35
	(0.56)	(0.68)	(0.17)	(0.31)
Usual activity FE	-19.2***	-12.2***	-40.5***	71.9***
	(3.59)	(1.36)	(5.01)	(7.93)
Exp. quintiles	0.53	-0.14	-0.079	-0.31
	(0.50)	(0.23)	(0.15)	(0.56)
Rural	0.13	-0.15	-0.074	0.092
	(0.39)	(0.47)	(0.23)	(0.34)
Landless	-0.13	-0.051	0.049	0.13
	(0.40)	(0.16)	(0.15)	(0.41)
HH size quintiles	-0.69	0.17	-1.43	1.95
	(1.51)	(0.64)	(1.12)	(1.59)
Scheduled FE	-0.074	0.017	0.33	-0.27
	(0.55)	(0.16)	(0.27)	(0.50)
Religion FE	-0.27	-0.031	-0.014	0.31
	(0.42)	(0.051)	(0.13)	(0.42)
Dwelling FE	-2.10	-0.50	-0.48	3.08**
	(1.37)	(0.72)	(0.47)	(1.55)
State FE	7.95*	1.71	0.53	-10.2
	(4.82)	(1.80)	(0.81)	(6.26)
Total predicted change	-17.5**	-9.03***	-41.5***	68.0***
	(7.58)	(2.45)	(5.64)	(11.6)
Observations	29859	29859	29859	29859

Data are from the 1998-9 and 2019 ITUS. Classification is based on 1-digit 1998 activity codes: 8-9 leisure, 4-6 home production, 1-3 work, and 7 learning. Estimates represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Estimates correspond to markers in Figure 3. Standard errors in parentheses are clustered at the district level. * $p < .1$, ** $p < .05$, *** $p < .01$.

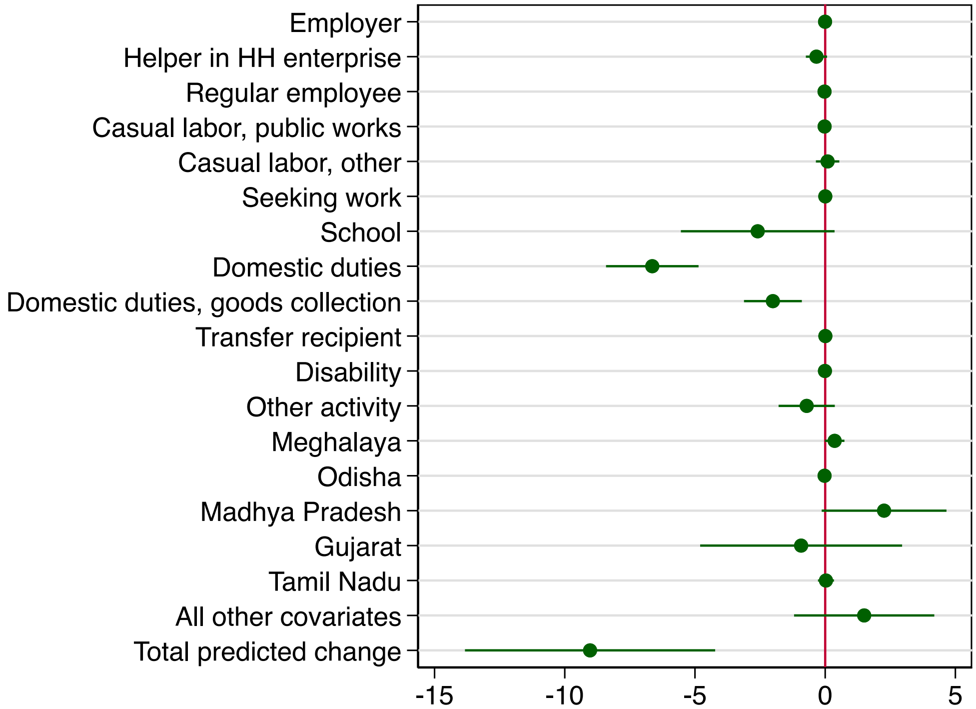
Appendix A Additional figures

Figure A1: Gelbach decomposition showing FE, leisure, 1998-2019



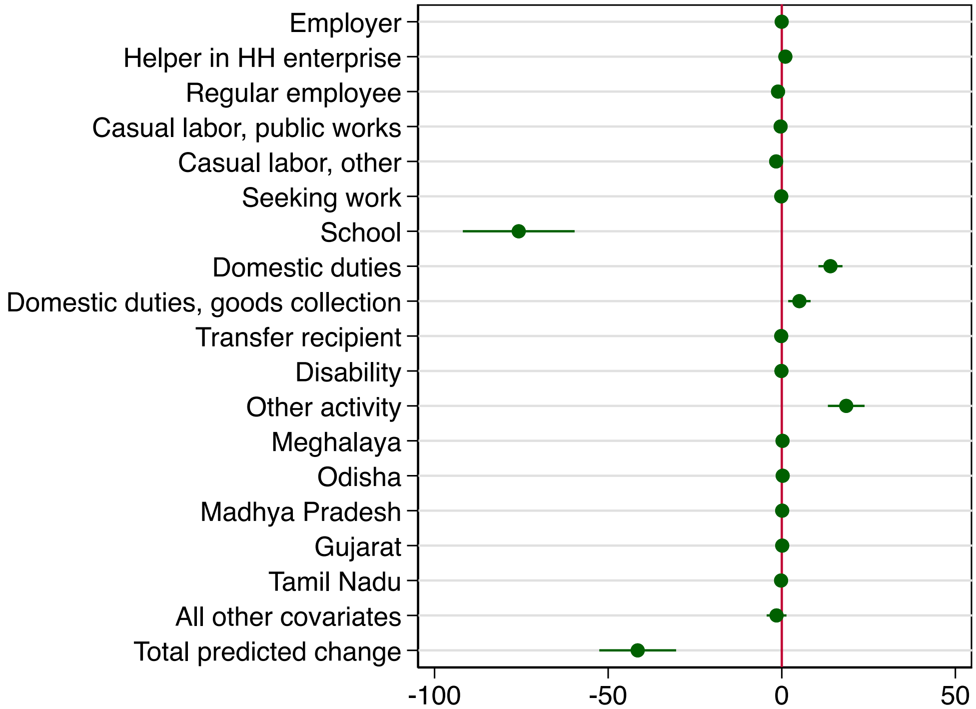
This is an alternative presentation of the leisure results in Figure 3. Round markers represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level. Corresponding numerical estimates are in Table A2.

Figure A2: Gelbach decomposition showing FE, home production, 1998-2019



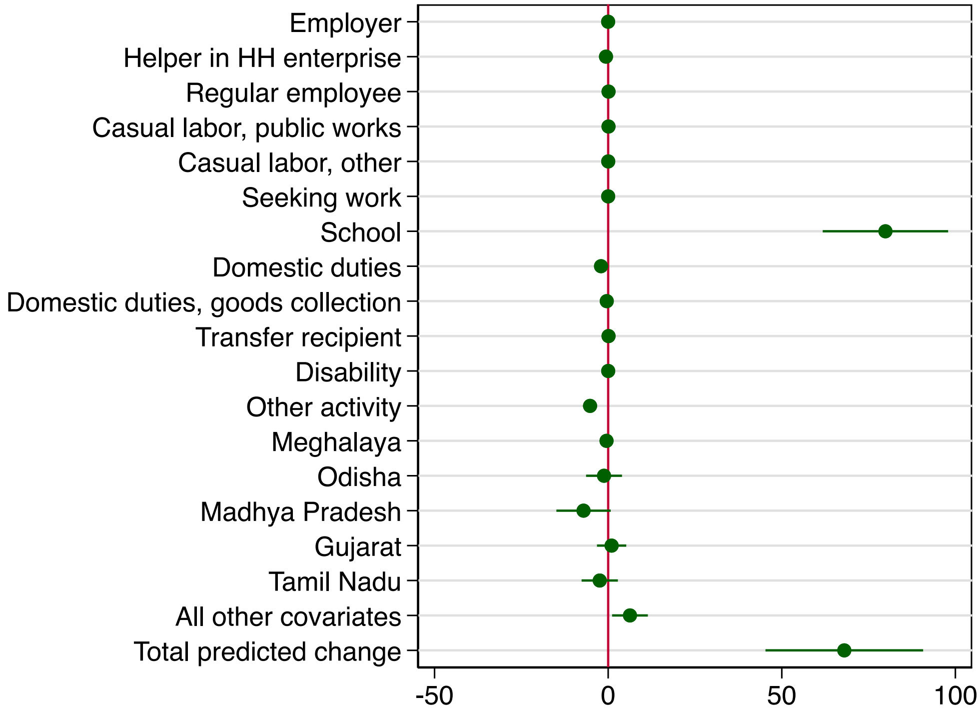
This is an alternative presentation of the home production results in Figure 3. Round markers represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level. Corresponding numerical estimates are in Table A2.

Figure A3: Gelbach decomposition showing FE, work, 1998-2019



This is an alternative presentation of the work results in Figure 3. Round markers represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level. Corresponding numerical estimates are in Table A2.

Figure A4: Gelbach decomposition showing FE, learning, 1998-2019



This is an alternative presentation of the learning results in Figure 3. Round markers represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Whiskers represent 95 percent confidence intervals based on standard errors clustered at the district level. Corresponding numerical estimates are in Table A2.

Appendix B Additional tables

Table A1: ITUS descriptive statistics, usual activity and state indicators

	1998	2019
Self-employed	0.0094	0.0021
Employer	0.00021	0.000052
Helper in HH enterprise	0.029	0.0083
Regular employee	0.012	0.0029
Casual labor, public works	0.0050	0.0010
Casual labor, other	0.035	0.0078
Seeking work	0.0053	0.0057
School	0.73	0.93
Domestic duties	0.068	0.024
Domestic duties, goods collection	0.033	0.0069
Transfer recipient	0.00016	0.00056
Disability	0.0022	0.0024
Other activity	0.066	0.0097
Haryana	0.090	0.068
Meghalaya	0.0068	0.017
Odisha	0.17	0.15
Madhya Pradesh	0.26	0.38
Gujarat	0.25	0.21
Tamil Nadu	0.22	0.17

Data are from the 1998-9 and 2019 ITUS. Weighted means are computed using sampling weights from the ITUS.

Table A2: Gelbach decompositions showing FE, 1998-2019

	Leisure	Home prod.	Work	Learning
Employer	0.033	-0.0043	-0.022	-0.0067
Helper in HH enterprise	-0.072	-0.33	1.03**	-0.62*
Regular employee	0.99**	-0.024	-1.08*	0.11
Casual labor, public works	0.25	-0.022	-0.33	0.10
Casual labor, other	1.49**	0.093	-1.62***	0.029
Seeking work	0.14	0.0045	-0.15	0.00094
School	-1.50	-2.59*	-75.8***	79.8***
Domestic duties	-5.32***	-6.64***	14.0***	-2.06***
Domestic duties, goods collection	-2.66**	-2.01***	5.07***	-0.41
Transfer recipient	0.043	0.0071	-0.16	0.11
Disability	0.089	-0.0091	-0.096	0.016
Other	-12.6***	-0.71	18.6***	-5.21***
Meghalaya	-0.10	0.36*	0.21*	-0.47
Odisha	0.95	-0.023	0.26	-1.19
Madhya Pradesh	4.70*	2.26*	0.13	-7.09*
Gujarat	-0.20	-0.92	0.13	0.99
Tamil Nadu	2.60	0.030	-0.21	-2.43
All other covariates	-6.28**	1.50	-1.50	6.28**
Total predicted change	-17.5**	-9.03***	-41.5***	68.0***
Observations	29859	29859	29859	29859

This is an alternative presentation of the results in Table 3. Graphical analogs appear in Figures A1 through A4. Data are from the 1998-9 and 2019 ITUS. Classification is based on 1-digit 1998 activity codes: 8-9 leisure, 4-6 home production, 1-3 work, and 7 learning. Estimates represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Standard errors in parentheses are clustered at the district level. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A3: Children's learning changes, 1998-2019

	School	School	Homework	Homework	Travel	Travel	Other	Other
2019 survey	71.9***	31.9***	13.6**	-5.88	14.7***	9.20***	10.1***	7.09***
	(8.23)	(7.50)	(6.10)	(4.34)	(1.92)	(1.95)	(1.77)	(1.60)
Female		5.35		6.61		1.77		4.44
		(9.86)		(4.38)		(2.44)		(2.69)
Rural		12.1**		-10.6***		-2.24		-5.53***
		(6.02)		(3.96)		(1.93)		(1.98)
Landless		-6.26		-1.69		-4.91***		0.44
		(4.15)		(2.71)		(1.09)		(1.00)
Scheduled tribe		4.16		-6.19		-0.84		-1.59
		(6.55)		(4.68)		(1.94)		(2.11)
Scheduled caste		-0.10		-4.36		0.28		-0.37
		(4.52)		(2.85)		(1.12)		(1.51)
Hinduism		-2.05		11.8		1.59		1.40
		(7.96)		(7.87)		(2.52)		(2.04)
Islam		-14.7		-3.70		-3.04		2.56
		(13.1)		(7.86)		(2.93)		(2.87)
Age FE	No	Yes	No	Yes	No	Yes	No	Yes
Female-age FE	No	Yes	No	Yes	No	Yes	No	Yes
Usual activity FE	No	Yes	No	Yes	No	Yes	No	Yes
Exp. quintiles	No	Yes	No	Yes	No	Yes	No	Yes
HH size quintiles	No	Yes	No	Yes	No	Yes	No	Yes
Dwelling FE	No	Yes	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	29859	29859	29859	29859	29859	29859	29859	29859

Data are from the 1998-9 and 2019 ITUS. Categories are "school/university attendance," "homework, being tutored, course review, research and activities related to formal education," "traveling time related to learning," and all others under learning (1998 single-digit code 7). Each column presents estimates from a weighted linear regression, with time use in minutes as the dependent variable and an indicator for the 2019 ITUS survey as the regressor of primary interest. Sampling weights are from the ITUS. Odd columns correspond to equation 1 and even columns to equation 2. Estimates correspond to Figure 5. Standard errors in parentheses are clustered at the district level. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A4: Blinder-Oaxaca decomposition of children's school time change, 1998-2019

	School time
Overall	
2019 survey	267.4***
	(5.85)
1998 survey	195.5***
	(7.31)
Difference	71.9***
	(8.49)
Endowments	41.0***
	(6.87)
Coefficients	37.5***
	(6.89)
Interaction	-6.54
	(5.78)
Endowments	
Usual activity is school	48.8***
	(5.19)
Coefficients	
Usual activity is school	-0.71
	(9.91)
Interaction	
Usual activity is school	-0.19
	(2.62)
Observations	29859

Data are from the 1998-9 and 2019 ITUS. Dependent variable is "school/university attendance." Sampling weights are from the ITUS. Standard errors in parentheses are clustered at the district level. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A5: Gelbach decompositions of children's learning changes, 1998-2019

	School	Homework	Travel	Other
Female	0.085	0.10	0.028	0.070
	(0.16)	(0.094)	(0.041)	(0.063)
Age FE	0.33*	0.71*	0.18*	0.14
	(0.18)	(0.38)	(0.11)	(0.11)
Female-age FE	-0.20	0.13	-0.11	-0.17*
	(0.20)	(0.14)	(0.079)	(0.096)
Usual activity FE	45.4***	19.0***	6.22***	1.30***
	(4.83)	(2.55)	(0.67)	(0.26)
Exp. quintiles	-0.16	-0.24	0.19	-0.093
	(0.32)	(0.23)	(0.21)	(0.15)
Rural	-0.18	0.15	0.033	0.081
	(0.56)	(0.50)	(0.12)	(0.27)
Landless	0.066	0.018	0.051	-0.0046
	(0.21)	(0.062)	(0.16)	(0.018)
HH size quintiles	2.06*	-0.64	0.19	0.34
	(1.24)	(1.00)	(0.22)	(0.29)
Scheduled FE	0.20	-0.36	-0.038	-0.082
	(0.36)	(0.26)	(0.11)	(0.12)
Religion FE	0.13	0.15	0.046	-0.012
	(0.18)	(0.24)	(0.059)	(0.033)
Dwelling FE	-0.11	2.69***	-0.65**	1.15**
	(1.22)	(0.87)	(0.29)	(0.47)
State FE	-7.62*	-2.19	-0.67	0.28
	(4.25)	(4.09)	(0.79)	(0.46)
Total predicted change	40.1***	19.5***	5.46***	3.00***
	(7.19)	(4.47)	(1.31)	(0.82)
Observations	29859	29859	29859	29859

Data are from the 1998-9 and 2019 ITUS. Categories are "school/university attendance," "homework, being tutored, course review, research and activities related to formal education," "traveling time related to learning," and all others under learning (1998 single-digit code 7). Estimates represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Estimates correspond to markers in Figure 6. Standard errors in parentheses are clustered at the district level. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A6: Children's leisure changes, 1998-2019

	TV	TV	Talking	Talking	Games	Games	Hygiene	Hygiene	Eating	Eating	Other	Other
2019 survey	18.6***	14.5***	-10.1***	-4.61	-16.7***	-14.5***	6.79***	4.31**	11.8***	12.2***	-46.7***	-40.4***
	(5.73)	(4.43)	(3.49)	(3.22)	(5.84)	(5.30)	(2.26)	(2.08)	(2.64)	(2.35)	(4.59)	(4.09)
Female		-6.96		2.42		-7.01		-1.10		1.99		7.53
		(5.84)		(3.40)		(6.84)		(2.06)		(3.66)		(7.32)
Rural		-22.3***		4.57**		1.22		-1.50		-1.02		4.10
		(3.53)		(2.17)		(3.98)		(1.27)		(1.67)		(3.78)
Landless		8.44***		-1.21		-1.11		0.27		1.83		2.16
		(2.29)		(1.63)		(2.49)		(0.99)		(1.15)		(2.95)
Sched. tribe		-15.0***		-6.15*		2.36		4.91***		3.30		1.73
		(4.33)		(3.33)		(5.30)		(1.72)		(2.41)		(4.65)
Sched. caste		-5.60		0.077		-1.69		-1.76		2.54*		5.47*
		(3.60)		(1.91)		(3.47)		(1.06)		(1.39)		(2.86)
Hinduism		-3.22		-7.23**		4.61		-0.97		-5.71		-8.48
		(4.90)		(2.82)		(5.06)		(2.65)		(4.11)		(9.65)
Islam		5.82		-8.39**		6.42		-5.43*		-7.25		8.91
		(6.81)		(4.14)		(8.87)		(3.04)		(4.52)		(10.9)
Age FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Female-age FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Usual activity FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Exp. quintiles	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
HH size quintiles	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Dwelling FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	29859	29859	29859	29859	29859	29859	29859	29859	29859	29859	29859	29859

Data are from the 1998-9 and 2019 ITUS. Categories are "watching/listening to television and video," "talking, conversing, chatting," "playing games and other pastime activities," "personal hygiene and care," "eating and drinking," and all other waking uses under leisure (1998 single-digit codes 8-9). Each column presents estimates from a weighted linear regression, with time use in minutes as the dependent variable and an indicator for the 2019 ITUS survey as the regressor of primary interest. Sampling weights are from the ITUS. Odd columns correspond to equation 1 and even columns to equation 2. Estimates correspond to Figure 8. Standard errors in parentheses are clustered at the district level. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A7: Gelbach decompositions of children's leisure changes, 1998-2019

	TV	Talking	Games	Hygiene	Eating	Other
Female	-0.11	0.038	-0.11	-0.018	0.031	0.12
	(0.12)	(0.064)	(0.13)	(0.034)	(0.060)	(0.15)
Age FE	0.062	0.24	-1.41**	0.15**	-0.13	0.068
	(0.14)	(0.17)	(0.70)	(0.076)	(0.086)	(0.31)
Female-age FE	0.23*	0.087	-0.85***	0.063	-0.059	-0.27
	(0.13)	(0.075)	(0.32)	(0.056)	(0.070)	(0.28)
Usual activity FE	-0.56	-5.97***	0.092	0.54**	0.27	-6.90***
	(0.78)	(0.92)	(1.11)	(0.25)	(0.31)	(1.50)
Exp. quintiles	0.76	0.065	-0.29	-0.24**	-0.0042	0.22
	(0.73)	(0.28)	(0.52)	(0.10)	(0.13)	(0.20)
Rural	0.33	-0.067	-0.018	0.022	0.015	-0.060
	(1.05)	(0.22)	(0.096)	(0.078)	(0.053)	(0.20)
Landless	-0.088	0.013	0.012	-0.0029	-0.019	-0.023
	(0.27)	(0.045)	(0.047)	(0.014)	(0.061)	(0.082)
HH size quintiles	-0.63	-0.61	-0.87	0.50	0.34	0.33
	(0.60)	(0.49)	(0.74)	(0.32)	(0.38)	(0.81)
Scheduled FE	-0.80	-0.30	0.097	0.22	0.19	0.15
	(0.52)	(0.29)	(0.30)	(0.21)	(0.17)	(0.25)
Religion FE	-0.090	0.011	-0.018	0.044	0.015	-0.17
	(0.11)	(0.084)	(0.089)	(0.060)	(0.069)	(0.24)
Dwelling FE	3.42***	-0.24	-1.86*	0.18	0.018	-1.30
	(1.05)	(0.55)	(0.95)	(0.29)	(0.41)	(0.89)
State FE	1.61	1.24	3.04	1.02	-1.14	1.53
	(1.35)	(1.02)	(2.62)	(1.11)	(1.39)	(1.57)
Total predicted change	4.12	-5.49***	-2.19	2.49*	-0.48	-6.31**
	(3.13)	(1.85)	(4.43)	(1.46)	(1.58)	(2.85)
Observations	29859	29859	29859	29859	29859	29859

Data are from the 1998-9 and 2019 ITUS. Categories are "watching/listening to television and video," "talking, conversing, chatting," "playing games and other pastime activities," "personal hygiene and care," "eating and drinking," and all other waking uses under leisure (1998 single-digit codes 8-9). Estimates represent the contributions of covariate groups to the difference between: i) the uncontrolled change in weighted mean duration from 1998-9 to 2019; and ii) the change in weighted mean duration from 1998-9 to 2019, controlling for covariates. Sampling weights are from the ITUS. The contributions of all covariate groups sum to the Total predicted change. Estimates correspond to markers in Figure 9. Standard errors in parentheses are clustered at the district level. * $p < .1$, ** $p < .05$, *** $p < .01$.