APPENDIX
PERVERSE CONSEQUENCES OF WELL-INTENTIONED REGULATION: EVIDENCE FROM INDIA'S CHILD LABOR BAN

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1. THEORY

1.1. Additional predictions from the one sector model with heterogeneity in sibling age structure

Suppose we maintain all of the assumptions of the model allowing for heterogeneity in sibling age composition as described in Section 3.2 and additionally assume that adult wages are low enough and/or subsistence needs are high enough such that households will provide some child labor in the initial equilibrium. In other words, $w^A \bar{L^A} < C_0$, where again w^A is the adult wage, $\bar{L^A}$ is inelastically supplied adult labor, and C_0 is the subsistence level of consumption. For simplicity of exposition, assume that all households have two children, one of which is working in the initial equilibrium and supplying maximum labor ($L_S = \bar{L_S}$).

As in Section 3.2, we assume that all households have two children and that they send older children to work first. This could be because they incur a higher disutility from sending older children to work, or because older children are more productive than younger children. For simplicity assume that it is the former and all children earn w_C initially. For households with two same-aged children (10-13) that need to supply one child laborer to meet subsistence needs, there is a 50% chance either child works.

As before, the imperfectly enforced ban on child-labor has two potential effects on household income: there is a direct effect on the wage of children under age 14, and a general equilibrium effect that could lead to lower wages for adults and older children aged 14-17 (who are not directly

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affected by the ban). Denote the loss of income for ~~a worker~~ all workers due to general equilibrium effects as G and the additional wage loss for children directly affected by the ban as E. These could also be represented as proportionate declines without loss of generality.

For a 10-13 year old child, we can predict the changes in child labor supply based on the direct and GE effects, which differ by sibling age structure. Note that sibling age structure is important for predicting the effects of the ban because it determines both (1) the size of the income loss generated by the ban and (2) whether a particular child is likely to be the marginal entrant into the labor market when a household experiences an income loss (recall that households prefer to send older children to the market first). These predictions are outlined in Table A1, where ~~as in the main text,~~ $\cancel{w^S}$ ~~and~~ $\cancel{l^S}$ ~~represent~~ we denote *initial* sibling wage and labor ~~, respectively~~as w^S and $\bar{L}^S$, respectively, as in the main text:

TABLE A1. Predicted Extensive Margin Changes in Child Labor for a Child Age 10-13

Age of sibling	Predicted Changes in Child Labor
6-9 (younger): control	No change (already working)
10-13 (same-age): treated	Start working with Pr$= 0.5$ if $w^A\bar{L}^A + w^S\bar{L}^S - 2G - E < C_0$
14-17 (older): control	Start working if $w^A\bar{L}^A + w^S\bar{L}^S - 2G < C_0$
"Balanced" control group (simple avg. of older and younger groups)	Start working with Pr$= 0.5$ if $w^A\bar{L}^A + w^S\bar{L}^S - 2G < C_0$

If there are no general equilibrium effects ($G = 0$), then the decrease in household income is E for treated children, and if this decrease is large enough (such that $\cancel{w^A\bar{L}^A - w^S L^S - 2G - E < C_0}$ $w^A\bar{L}^A + w^S\bar{L}^S - 2G - E < C_0$), then the ban will result in a higher likelihood of working. Note that treated children only have a 50% of being the marginal child to enter the market after the ban because with a 50% chance they were the child already working before the ban. Though control children with younger siblings also experience the same drop in income, they cannot increase their labor supply because they were already working prior to the ban (because they are the oldest child in the household). Therefore comparing treated children to control children with younger siblings results in a positive effect of the ban on child labor supply. In the absence of GE effects, control children with older siblings will not experience a drop in household income. Thus comparing treated children to control children with older siblings also results in a positive effect of the ban on child labor supply (though for different reasons).

When there are general equilibrium effects ($G > 0$), the effects of the ban differ by the control group used. Comparing treated children to control children with younger siblings again leads to a positive effect of the ban. The intuition is the same as in the no GE effects case; while household income falls for both treated and control children, control children cannot increase labor on the extensive margin because they were already working prior to the ban. The ban effect identified in this case includes both direct and indirect (GE) effects of the ban.

However, comparing treated children to control children with older siblings is now more complex. Control children with older siblings experience a household income loss of $2G$. If this loss is large enough such that $\cancel{w^A\bar{L}^A - w^S L^S - 2G < C_0}$$w^A\bar{L}^A + w^S\bar{L}^S - 2G < C_0$, they will need to join the work force. Whether the effect of the ban is larger for the treated group or the control group depends on (1) the size of the GE effect relative to the direct effect and (2) the probability that a treated child is the marginal entrant (here we have assumed that probability is 0.5 for children with a same age sibling, and 1 for children with older siblings). Intuitively, the larger the GE effects, the more likely that household income falls by enough such that even control children with older siblings are forced to work.

If we instead use a "balanced" control group which is made up of both types of control children (those with younger and older siblings), we are more likely to isolate the direct effect of the ban (the effect of the drop in household income due to E). If we assume that the balanced control group is made up of 50% with younger siblings and 50% with older siblings, then the weighted effect of the ban on this control group is that they start working with probability 0.5 if the general equilibrium effects are large enough (again such that $\cancel{w^A\bar{L}^A - w^S L^S - 2G < C_0}$$w^A\bar{L}^A + w^S\bar{L}^S - 2G < C_0$). The intuition is that the balanced control group takes into account the probability of being a marginal entrant and the GE effect on household income. Thus using a balanced control group with both younger (6-9) and older (14-17) siblings can potentially eliminate confounding effects coming from the subtle interaction between age structure and GE wage effects.

1.2. Effects of a Child Labor Ban in a Model with Two Sectors

We consider an economy in which there are two sectors, agriculture and manufacturing (denoted by lower-case subscripts a and m respectively). For simplicity, we drop the assumption of heterogeneous households from the previous section. Firms in these sectors have representative technologies, $Y_m = f_m(L_m)$ and $Y_a = f_a(L_a)$, where L_i is the effective units of labor in sector i. Child labor and adult labor are perfect substitutes up to a constant, γ, which is the same in both sectors; each unit of adult labor is equal to 1 unit of effective labor ($L_i^A = L_i$) and each unit of child labor is worth only γ units of effective labor ($L_i^C = \gamma L_i$). Furthermore, there is an imperfectly enforced ban on child labor, leading to a fine D being applied with probability p, which only applies to the manufacturing sector.[12] Both firms and households are take wages as a given. Normalizing output prices to 1, we can thus say that a firm in sector a is solving

$$\max_{L_a^A, L_a^C} f(L_a^A + \gamma L_a^C) - w_a^A L_a^A - w_a^C L_a^C$$

and a firm in sector m will be solving

$$\max_{L_m^A, L_m^C} f(L_m^A + \gamma L_m^C) - w_m^A L_m^A - (w_m^C + pD) L_m^C.$$

As above, from the first order conditions it can be seen that if both children and adults are working in the agricultural sector, then $w_a^C = \gamma w_a^A$, and if both children and adults are working in the manufacturing sector, then $w_m^C = \gamma w_m^A - pD$.

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[1] A more general specification of the ban allows the probability of detection to vary non-linearly with the level of child labor, i.e. where $p(L)$. Since firms are more likely to be detected the more children they hire, $p(L)$ is increasing in the amount of child labor employed. Here we assume a very simple linear form of $p(L)$, i.e. $p(L) = pL$, where p is a constant. When p is large, a linear function may not be a suitable approximation for $p(L)$ as $p(L)$ may exceed 1 when both p and L are large. However, as discussed in the previous section, enforcement of the ban was perceived to be quite weak and thus p was likely to be very low. In this case, a linear specification as an approximation of $p(L)$ is more justifiable, as there is less concern that $p(L) > 1$.

[2] Note that this definition of imperfect enforcement is as in Basu (2005) and differs from that used in Basu and Van (1998), which specifies that the ban is perfectly enforced for a proportion of firms while the remainder of firms are unregulated. While most of the intuition is similar with this alternate definition of enforcement, the perfect enforcement assumption does change some of the predictions of the model. Most importantly, depending on size of labor demand from the perfectly enforced firms relative to the supply of adult labor, N, there are cases in which an imperfectly enforced ban on child labor (of the Basu and Van (1998) type) could increase adult wages and possibly decrease child labor. However, we model the imperfect enforcement as in the Basu (2005) model because we believe that this is more applicable to the way in which the *actual* 1986 ban was enforced and therefore is the most relevant for our empirical work.

There are N families in the entire economy, each endowed with 1 unit of adult labor which they supply inelastically, and m children who are endowed with 1 unit of labor. In addition to whatever income is provided by children, adult income in each family is assumed to be the average of the wages in each market.[3] Households only supply child labor when otherwise below the subsistence level s, and when they do so, they supply only enough labor to reach s.[4]

1.3. **Complete Mobility**

The case of complete mobility is discussed in Edmonds and Shrestha (2012a). The basic intuition is that without frictions limiting mobility between sectors, labor simply reallocates after a ban in one sector such that child labor flows out of the regulated sector and into the unregulated sector while adult labor flows in the opposition direction. There is no change in the overall level of child labor following a ban in one sector in the complete mobility case.

1.4. **No Mobility**

To move to the case in which we have no mobility, we assume that both children and adults are only able to work in a single sector. The adults still supply labor inelastically, but now only in the sector they have access to, regardless of the wage. Thus, adult labor supply is

$$S_m^A(w_m, w_a) = \begin{cases} 1 \text{ if } k_m^A = 1 \\ 0 \text{ if } k_m^A = 0 \end{cases} \quad \text{and} \quad S_a^A(w_m, w_a) = \begin{cases} 1 \text{ if } k_m^A = 0 \\ 0 \text{ if } k_m^A = 1 \end{cases} \tag{1}$$

where $k_m^A = 1$ if the adult has access to the manufacturing sector, and $k_m^A = 0$ if the adult has access to the agricultural sector. Children face the same incentives as in the complete mobility

[3]This assumption is made to make the modeling of labor supply curves simpler. However, all of the qualitative results of the model go through as long as *either* there is at least partial labor mobility so that changes in the manufacturing market have effects on the agricultural market *or* some children who have access to the agricultural market have household income coming from the manufacturing sector. In the pre-ban data, we see that for those employed in agriculture, 23% live in a household where the head of the household works in manufacturing. Therefore it seems likely that a sizeable portion of the agricultural sector will be affected by the wages being paid in the manufacturing even if there were no mobility between sectors.

[4]The model in this paper is a one-period model. In a multiple period setting, binding liquidity constraints would be necessary to generate the following results. Earlier work (see for example Edmonds (2006) and Edmonds et al. (2010)) gives both direct and indirect evidence of the effect of liquidity constraints on child labor in the developing country setting.

case, but now their mobility is also restricted, so

$$S_m^C(w_m, w_a) = \begin{cases} 0 \text{ if } \frac{1}{2}(w_m + w_a) > s \text{ or } k_m^C = 0 \\ \min\left\{\dfrac{s - \frac{1}{2}(w_m + w_a)}{\gamma w_m - pD}, m\right\} \text{ if } \frac{1}{2}(w_m + w_a) \leq s \text{ and } k_m^C = 1 \end{cases} \tag{2}$$

$$S_a^C(w_m, w_a) = \begin{cases} 0 \text{ if } \frac{1}{2}(w_m + w_a) > s \text{ or } k_m^C = 1 \\ \min\left\{\dfrac{s - \frac{1}{2}(w_m + w_a)}{\gamma w_a}, m\right\} \text{ if } \frac{1}{2}(w_m + w_a) \leq s \text{ and } k_m^C = 0 \end{cases} \tag{3}$$

with $k_m^C = 1$ if the child has access to the manufacturing sector, and $k_m^C = 0$ if she has access to the agricultural sector. Finally, for reasons that will be apparent later, we make the technical assumption that a unit change in the equilibrium wage of one sector leads to a change smaller than a unit in the other.

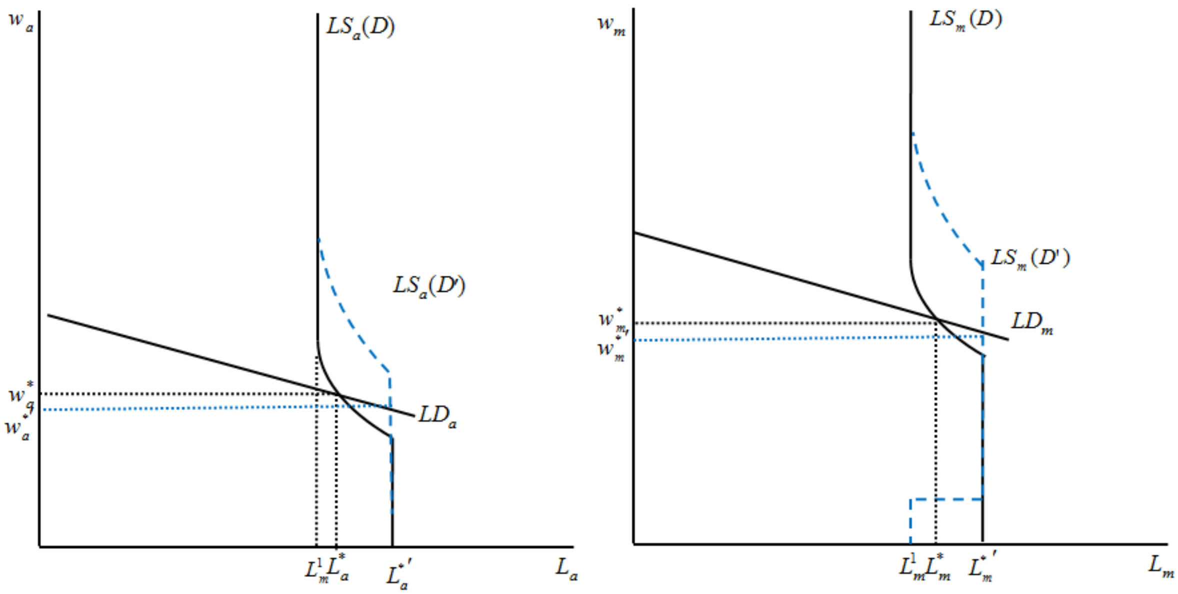
Restricting ourselves to the cases of interest, the pre-ban equilibrium can be seen in with the solid lines in Figure A1.[5] As it has been drawn in this case, the equilibrium wage in manufacturing is higher than that in agriculture, but none of the children or adults in agriculture have access to the manufacturing sector. The total effective supply of child labor is $(L_a^* + L_m^*) - (L_a^1 + L_m^1)$.

The dashed labor supply curves illustrate the post-ban equilibrium. The effect on the manufacturing sector should be intuitive; it looks much like the one sector case of Basu (2005). The lower wage in manufacturing implies that the children in the agricultural sector are receiving less income from their parents[6], inducing them to supply more labor in that sector. This in turn lowers the the wage in agriculture, causing children in manufacturing to work more, etc. until the markets equilibrate. Effective child labor increases by $(L_m^{*\prime} + L_a^{*\prime}) - (L_m^* + L_a^*)$. Wages for children and adults fall proportionally in the agricultural sector, but child wages fall more significantly in manufacturing, because $\frac{\gamma w_m^{*\prime} - pD}{\gamma w_m^*} < \frac{w_m^{*\prime}}{w_m^*}$.

[5]As in earlier work, the one-sector version of this framework allows for multiple equilibria, where an economy can be in either a good equilibrium in which no children work and aggregate firm demand is satisfied by aggregate adult labor supply) or a bad one in which children are forced to work (a possibility raised by many previous works such as Basu and Van (1998), Swinnerton and Rogers (1999), and Jafarey and Lahiri (2002)). It is worth noting that when multiple equilibria exist and an economy is in the "bad" equilibrium, a *perfectly* enforced ban on child labor can jolt the economy to the "good" equilibrium, making households better off (see Basu and Van (1998) for details.)

[6]This general equilibrium labor supply response to the demand shift is formally discussed in Basu et al. (1998).

FIGURE A1. Effect of a ban on child labor in a two sector model assuming no labor mobility.



1.5. **Partial Mobility**

Finally, the partial mobility case assumes that some agents have access to both sectors, while other have access only to agriculture. Adults supply labor inelastically in the sector having the highest wage, conditional on having access to that sector. Thus, adult labor is given by

$$S_m^A(w_m, w_a) = \begin{cases} 1 \text{ if } w_m > w_a \text{ and } k_m^A = 1 \\ q^A \text{ if } w_m = w_a \text{ and } k_m^A = 1 \\ 0 \text{ if } w_m < w_a \text{ or } k_m^A = 0 \end{cases} \tag{4}$$

$$S_a^A(w_m, w_a) = \begin{cases} 1 \text{ if } w_a > w_m \text{ or } k_m^A = 0 \\ 1 - q^A \text{ if } w_a = w_m \text{ and } k_m^A = 1 \\ 0 \text{ if } w_a < w_m \text{ and } k_m^A = 1 \end{cases} \tag{5}$$

where $k_m^A = 1$ implies the adult has access to both sectors, $k_m^A = 0$ implies the adult has access only to the agricultural sector, and q^A is determined in equilibrium if wages are equal in the two sectors.

Child labor is supplied very similarly to the other cases, except that now a family's children may or may not have access to the manufacturing sector. Children supply labor to the sector with the highest wage, conditional on having access to that sector, until they reach subsistence or cannot supply any more labor. Thus, child labor supply is

$$S_m^C(w_m, w_a) = \begin{cases} 0 \text{ if } \frac{1}{2}(w_m + w_a) > s, \gamma w_a > \gamma w_m - pD \text{ or } k_m^C = 0 \\ \min\left\{ q^C \cdot \dfrac{s - \frac{1}{2}(w_m + w_a)}{\gamma w_m - pD}, q^C m \right\} \text{ if } \frac{1}{2}(w_m + w_a) < s, \\ \qquad\qquad \gamma w_m - pD = \gamma w_a, \text{ and } k_m^C = 1 \\ \min\left\{ \dfrac{s - \frac{1}{2}(w_m + w_a)}{\gamma w_m - pD}, m \right\} \text{ if } \frac{1}{2}(w_m + w_a) < s, \\ \qquad\qquad \gamma w_m - pD > \gamma w_a, \text{ and } k_m^C = 1 \end{cases} \tag{6}$$

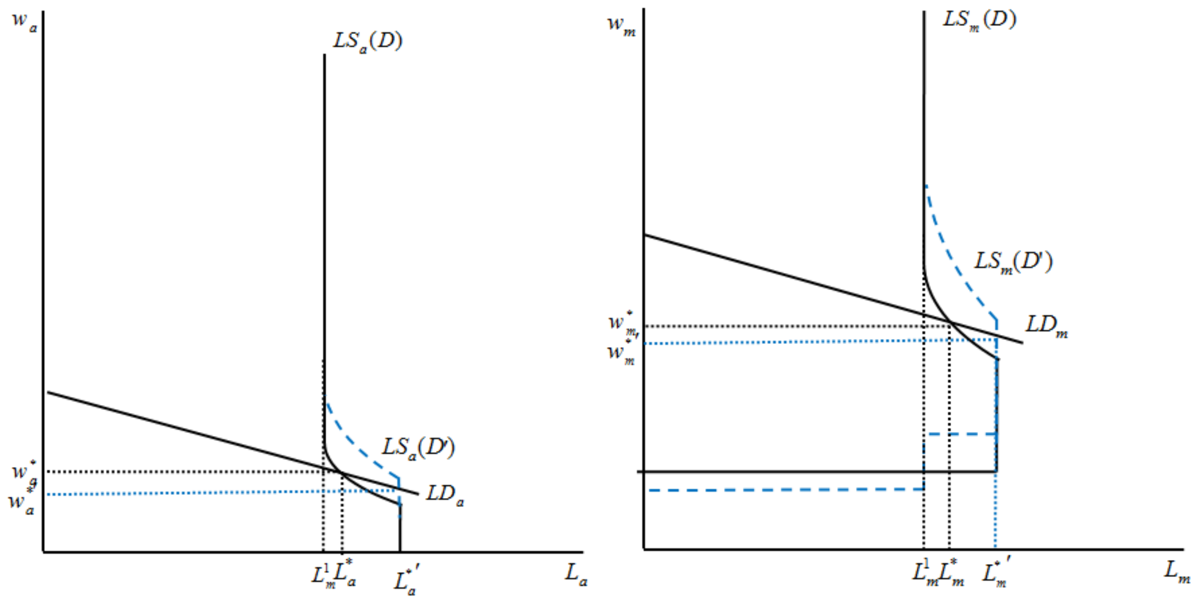
(7)

$$S_a^C(w_m, w_a) = \begin{cases} 0 \text{ if } \frac{1}{2}(w_m + w_a) > s, \gamma w_m - pd > \gamma w_a \text{ and } k_m^C = 1 \\ \min\left\{ (1 - q^C) \cdot \dfrac{s - \frac{1}{2}(w_m + w_a)}{\gamma w_a}, (1 - q^C) m \right\} \text{ if } \frac{1}{2}(w_m + w_a) < s, \\ \qquad\qquad \gamma w_a = \gamma w_m - pD, \text{ and } k_m^C = 1 \\ \min\left\{ \dfrac{s - \frac{1}{2}(w_m + w_a)}{\gamma w_a}, m \right\} \text{ if } \frac{1}{2}(w_m + w_a) < s, \\ \qquad\qquad \text{and } \gamma w_a > \gamma w_m - pD \text{ or } k_m^C = 0 \end{cases}$$

where $k_m^C = 1$ implies the child has access to both sectors, $k_m^C = 0$ implies the child has access only to the agricultural sector, and q^C is determined in equilibrium if wages are equal in the two sectors.

The solid lines in Figure A2 show the equilibrium in the partial mobility case before the ban has been imposed. The agricultural sector looks very similar to the single sector case. The manufacturing sector has a higher wage since those in the agricultural sector can't shift. The flat

FIGURE A2. Effect of a ban on child labor in a two sector model assuming partial labor mobility.

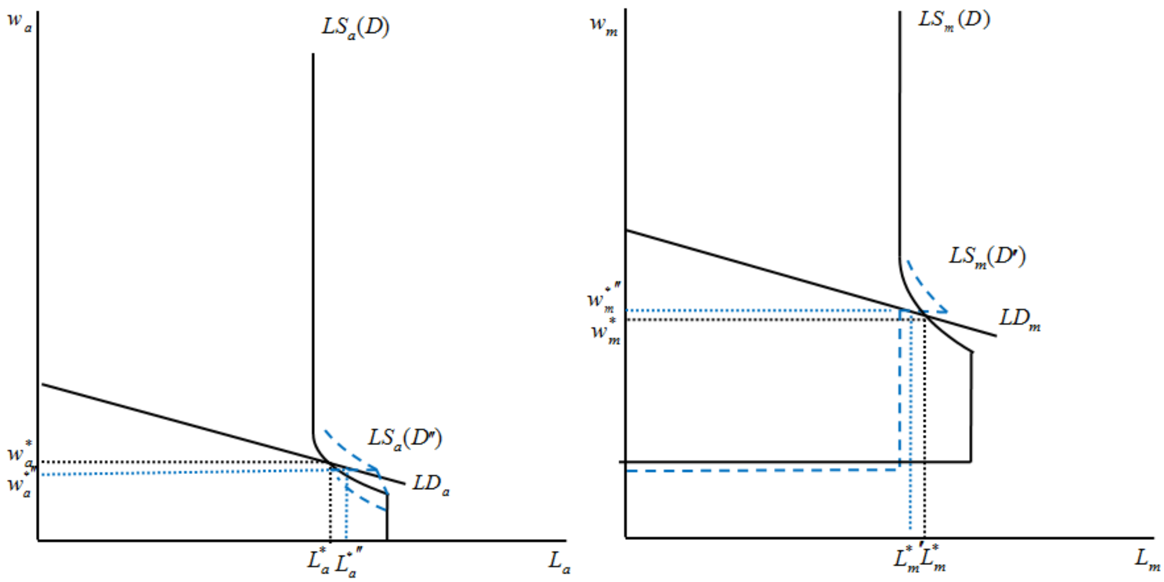


Case I: $\gamma w_m^{*\prime} - pD > \gamma w_a^*$

portion of the labor supply curve in manufacturing comes from the fact that if wages in manufacturing fall below those in agriculture, all manufacturing workers shift to the agricultural sector. The total effective child labor is once again $(L_a^* + L_m^*) - (L_a^1 + L_m^1)$.

The post ban equilibrium can be split up into three different cases, effectively differentiated by the relationship between the initial effect of the ban on child wages in both sectors. The first case, in which child wages are still higher in manufacturing (i.e.$\gamma w_m' - pD' > \gamma w_a'$) can be seen with the dashed portion of Figure A2. Since child wages are still higher in manufacturing, adult wages must also still be higher in manufacturing, none of the children or adults who have access to the manufacturing sector will switch to the agricultural sector. The increase in the fine lowers the wage for children in manufacturing, increasing labor supply in that sector and lowering the equilibrium wage. Similar to the no mobility case, this lower wage in manufacturing increases the labor supply of children in agriculture, because they need to work more to make up for their parents' lower income. This again leads to an iterated increase in labor supply in both markets until the markets equilibrate in an equilibrium with increased effective labor supplied and lower equilibrium wages in both sectors. Since adult labor supply has not changed, this implies that effective

FIGURE A3. Effect of a ban on child labor in a two sector model assuming partial labor mobility.



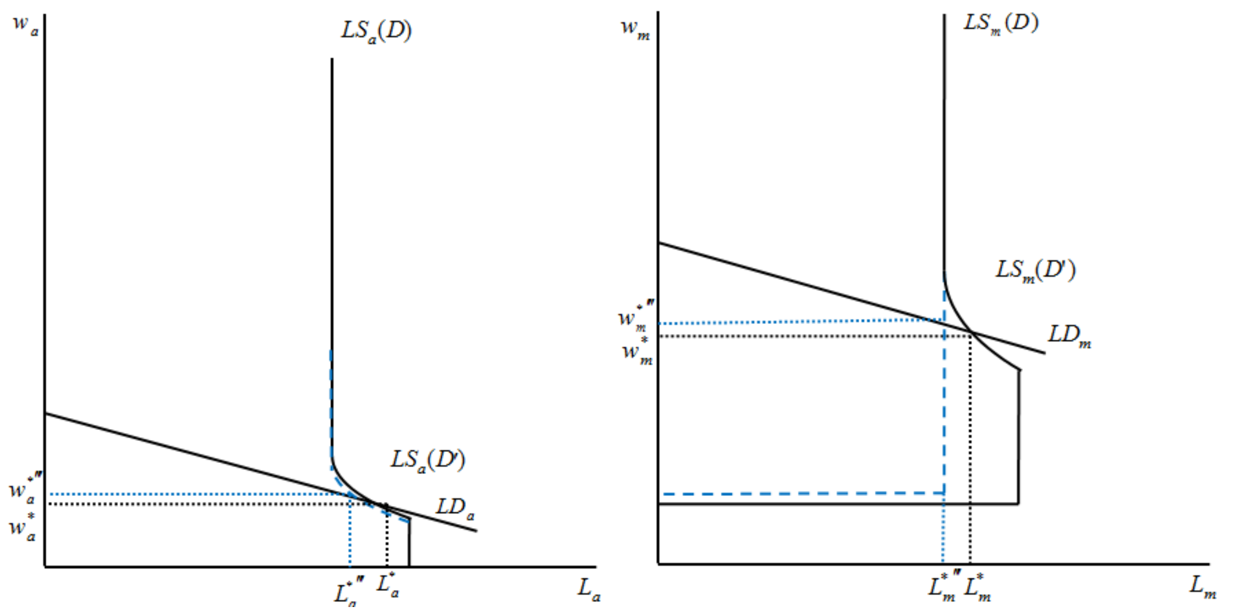
Case II: $\gamma w_m^{*\prime} - pD = \gamma w_a^*$

child labor has increased in both sectors. Finally, we can see that wages have fallen for children more in the manufacturing sector than they have in the agricultural sector, because $\frac{\gamma w_m^{*\prime} - pD}{\gamma w_m^*} < \frac{w_m^{*\prime}}{w_m^*}$.

Figure A3 shows the pre and post ban equilibria in the case in which the ban initially equates child wages in the two sectors ($\gamma w_m'' = \gamma w_a''$). In this case, children are now indifferent between working in agriculture and working in manufacturing. However for families with children who initially worked in manufacturing, wages are now lower so more children must work to achieve subsistence consumption. Total labor supply shifts out, lowering wages in both sectors. The end result is more child labor and lower wages though child wage has fallen by a larger proportion relative to adult wages in manufacturing (not in agriculture where adult and child labor fall by the same proportion).

Figure A4 shows one potential illustration of the final case, in which the equilibrium child wage in agriculture is higher than the equilibrium child wage in manufacturing ($\gamma w_m''' - pD < \gamma w_a'''$). Intuitively, one could think of this as the case in which the government set p and D high enough to push children out of the manufacturing market. The effect on labor supply in the manufacturing sector is simple; only adults work in the sector for any wage, and if the wage falls below

FIGURE A4. Effect of a ban on child labor in a two sector model assuming partial labor mobility.



Case III: $\gamma w_m^{*\prime} - pD < \gamma w_a^*$

the wage in agriculture, all of the adults will leave. Labor supply in the agricultural sector looks as if it would if all children *only* have access to the agricultural sector. Wages unambiguously rise in manufacturing. If this wages increase is large enough to reduce overall child employment, this leads to a reduction in agricultural labor supply and wages rise in that sector as well. However, if the manufacturing wage increase is not enough to reduce the number of working children, the labor supply curve will shift out in agriculture, lowering wages in that sector. The combination of the two effects - higher manufacturing wages but lower agricultural wages - leads to an ambiguous overall effect of the ban on levels of child labor.

2. DATA

2.1. **Additional Rounds of the NSS**

The 42nd round of the NSS was collected between July 1986 and June 1987. The 42nd round is unique from the employment rounds in that its focus is on "participation in education" rather than on employment. (There are several other modules in this round but none that focuses on employment.) While there exist some employment data in this round, the nature of the employment questions and sampling frame are somewhat different from the employment round questions and thus the employment variables are not consistent across the two subsets of data. Most notably, in all of the rounds *other than* the 42nd Round, employment information is reported for all children 6 and older. In the 42nd Round employment information is reported only for children who are not currently enrolled in school, regardless of how much time they spend in school. Thus child employment variables in the 42nd round are likely to undercount working children relative to the employment rounds. Even considering these caveats, this round of the NSS is potentially useful for evaluating the short-term impacts of the ban because it encompasses the six months immediately preceding and following the Child Labor Act (enacted in December 1986); thus the changes in child time allocation during this time are unlikely to capture long-term trends due to factors other than the 1986 Act.

For the purpose of robustness checks, we also make use of a second additional dataset comprised of the consumption rounds (Schedule 1) of the NSS. These were conducted only in the years *following* the passage of the 1986 Act. These include rounds 45, 46, 47, 48 and 49 which span the period 1989-1993 (there are no consumption rounds available prior to 1986). The consumption rounds contain somewhat limited information on employment (and also lack some controls, such as religion) but include more detailed information on household expenditure.

2.2. **Child-level variables**

All measures of child time allocation are based on the child's reported "principal usual activity". Each child is reported as having an exclusive principal activity. The reference period for usual activity is the 365 days prior to the survey. A "current status" is also reported for each child with virtually the same possible classifications as for usual status but with the reference period being the week prior to the survey. Current status is not available in the 42nd round of the NSS. All of the main results for the employment sample reported in the paper are robust to using child time allocation variables based on current status rather than usual status.

Aside from the activities that we study in Tables 3 and 4, the other potential categories for child time in the NSS include "Other" (15.6% in 1983), "Too young to attend school/work/seek work" (80.8%) and a few less prevalent activities (e.g. begging, prostitution, disabled etc. which account for the final 3.6%). Thus the increase in child labor force participation seems to come largely from a decrease in unpaid household activities, other activities and being considered "too young" rather than from schooling. The category "Too young to attend school/work/seek work" is available only for the 38th round (1983) after which it is combined with "Other". Therefore we cannot study the impact of the ban on the classification of children as being "too young."

We classify as children working banned versus non-banned occupations based on the 3-digit NIC codes reported for each employed child (according to the principal usual activity); however for the data on days spent working we have only 1-digit NIC codes to match to activities so the banned versus non-banned occupation classifications are much coarser. These are matched to the list of processes and occupations listed as banned in the 1986 Act as of 1993. As stated in the 1986 Act, all children working in family enterprises are not classified as working in banned industries, regardless of the NIC code. Over time, other processes have been added to the "prohibited list" of regulated industries under the 1986 Act. Relatively few of these changes occur between 1986 and 1994. The majority (and more substantive) of the changes to the "prohibited list" occur after 1994, including the prohibition of child employment in domestic work and dhabas (eateries) which were added in October 2006. Note that the identification of the empirical effects of the ban is based solely on age (or sibling age) and year and not sector, so the results in the paper should not be affected by any changes to the "prohibited list".

As stated in the paper the NSS modules include information days spent in each activity, though the distributions displayed in Figures A5 and A6 make clear that the data contain very little variation over and above the extensive margin. Moreover, the data on days in each activity are likely to be reported with some noise, as virtually all children who report attending school report doing so for 7 days a week, even though India's standard school week covers only 5 days. For that reason, we focus most of our analysis on the principal usual activity reported for each child, which we believe captures mostly the extensive margin of participation in activities.

However, even changes in the principal usual activity could potentially capture in part changes on the intensive margin in the sense that they are based on a child's *primary* activity. For example, if a child goes from primarily attending school to primarily working, this is coded as going from "Any Economic Activity"=0 to "Any Economic Activity"=1, even if the change in status was due to a shift in days devoted to each activity (for example, from full-time schooling and part-time work to full-time work and part-time schooling). The pre-ban data on days spent engaged in economic activity for those whose principal usual activity is *not* work (Figure A7) suggest that this is possible, given that there is a non-negligible mass of children working an intermediate number of days. Assuming that the principal usual activity corresponds to the activity that comprises the majority of a child's time, this means that the usual status of these children could change in response to an increase in work days, though it is worth noting that of all children (aged 10-13) whose principal status is not working in the 1983 round, only 1.2% report spending some time working in the past week.

The data also contain very limited information on secondary activities. More specifically, secondary activities are only reported if they are "gainful" and thus are not reported if they include schooling or unpaid activities. In the pre-ban period, 4.4% of all children ages 10-13 who are primarily engaged in non-economic activities such as school report some form of gainful secondary activity. This again suggests a pool of children whose primary activities could shift from non-work to work due to an increase in work hours resulting in a new primary activity classification. In light of these additional sources of data, it seems reasonable that our results reflect in part an intensive margin effect of the ban.

2.3. **Household-level variables**

We examine the responses of several household-level measures of welfare in Table 10 of the main paper. We now describe these measures in more detail.

Our first measure, per capita expenditure, is one of the most widely used indicators of household welfare and is used for Indian and global poverty measurement. Note that this is the only household outcome available in the 42nd Round. Our second measure, per capita food expenditure, is highly correlated with per capita expenditure (0.92) but may vary if poor households adjust to shocks by lowering non-food intake more than food intake. Our third measure, caloric intake per capita, is moderately correlated with food expenditure per capita (0.54) but can vary if households adjust to a drop in food expenditure by switching from foods that are more expensive per calorie to foods that are cheaper per calorie. Our fourth measure, the staple share of calories, is proposed by Jensen and Miller (2010) as a measure of household nutritional adequacy in the presence of caloric needs that are unknown or variable across households. Their logic is that if households attach a high disutility to having caloric intake below caloric needs, they will substitute towards the cheapest sources of calories (staples). The staple share is thus an inverse indicator of household welfare, and consistent with this we find a negative correlation (-0.57) with per capita expenditures. Finally, our fifth measure is a household asset index constructed as the principal component of a set of variables that capture the quality and quantity of housing, the type of energy used for cooking and lighting, and the quantity of electricity used (which is likely to be correlated with the number of appliances and durables used by the household). If households adjust to negative income shocks by selling assets, using electric appliances less intensively, or letting the quality of their assets deteriorate then we might expect deterioration in the asset index for households affected by the ban. While the asset index is correlated with per capita expenditures (0.50) and other flow measures of welfare, it uses an entirely different source of variation across households. Thus while measurement error may be correlated across the other measures, it is unlikely to be correlated across our expenditure/consumption flow measures and our asset measure.

We calculate monthly per capita expenditures using Schedule 1.0 of the National Sample Survey (NSS) of India, which is directly linked to the employment data for all households in our sample (both Schedules 1 and 10 were collected in 1983, 1987-8, and 1993-4). The survey is based on a 30-day recall of household consumption for a detailed list of items. Information is collected on both quantities and expenditures and includes home produced goods (which have expenditures imputed at the farm-gate price). Our per capita expenditure measure excludes rent and taxes but includes all food, alcohol and tobacco, energy, clothing and footwear, service, non-durable and durable expenditure. Real values (expressed in 1982 rupees) are nominal values deflated by the average wholesale price index reported by the Government of India for the respective year. We calculate monthly per capita food expenditures using only the food items from the survey and exclude alcohol. To construct caloric intake at the household level we convert the recorded quantities into calories using the standard caloric conversion factors that have been used for this purpose in the past (Gopalan et al. (1980)). We supplement this with data from other sources in a few cases. For some food items quantities and/or caloric conversion factors are not available so we use the imputation procedure described in detail in the appendix of Li and Eli (2013). We use the "liberal" conversion factor and impute using all food factors rather than the group factors. Our calorie calculations include calories from alcohol. We calculate a "staple share of calories" measure as the ratio of calories from cereals and cereal substitutes to calories from all sources (including alcohol). In our regression analysis we define "1 - staple share of calories" as a positive indicator of welfare for reasons we discuss later. We also construct a household wealth/asset index using data on housing and some proxies for durable ownership. Although the 43rd and 50th NSS consumption modules record ownership of many different household durables, these data are missing for the 38th round so we are forced to rely on proxies such as the source of energy for lighting and cooking and household electricity ownership. To calculate the asset index, we calculate the principal component of the following set of discrete variables – source of cooking energy, source of lighting energy, floor type, wall/building type, house condition – and the continuous variables covered area and quantity of electricity used.

3. Additional Results and Robustness Checks

3.1. **Clustering methods: Wild Cluster Bootstrap with Webb Weights**

In Online Appendix Tables A3 and A4 we use a wild cluster bootstrapping procedure outlined in Cameron et al. (2008). Specifically, we create a counterfactual distribution of t-statistics under the null hypothesis of no effect of the ban. To do this, we run the regression of our outcome of interest on all of our covariates *except* the interaction "Under14XPost-1986" (our "ban" variable) and then calculate the residuals. For each of 999 iterations, we (i) create a "wild" outcome which is the predicted outcome under the null and the aforementioned residual multiplied by Webb weights to reflect the low number of clusters (Webb (2013)) and then (ii) regress the "wild" outcome on our complete set of covariates including "Under14XPost-1986" and store the resulting t-statistic. This gives us a distribution of the t-statistic for "Under14XPost-1986" under the null hypothesis of no effect. The p-value we calculate draws on the comparison of our observed t-statistic to the null distribution.

3.2. **Implied changes in child productivity**

We observe a net zero impact of the ban on household expenditure, despite the increase in child work.[7] To back out an implied change in child productivity, we use our additional results that other observable components of household income - adult labor income and assets - also do not change in response to the ban. We do not observe saving, transfers or other non-labor income in the data. Assuming that percentage change in household expenditure and other non-child labor components are zero implies that the increase in child work and decrease in child productivity must exactly offset each other (in percentage terms). To calculate the increase in child labor supply at the household labor we separately estimate the effects on the proportion of working children ages 6-9 and 10-13 at the household level.[8] The effect for the 6-9 age group is a 25.3% increase over the pre-ban mean and for the 0-13 age group it is 6.54% (results available upon request). We then calculate the proportion of child labor derived from each age group to use as weights (0.115 and 0.885) for ages 6-9 and 10-13, respectively. The overall effect on child labor supply at the household level is then the weighted average of the effects for the 6-9 and the 10-13 age groups: $0.8846 * 0.0654 + (1 - 0.8846) * 0.2532 = 0.0871$.

3.3. **Wage results by sector**

A further prediction of the model is that the declines in child wages are larger in banned activities than in non-banned activities. Unfortunately there are no detailed industry codes associated with wages that we can use to differentiate between earnings in banned and non-banned

[7]This holds for both the full sample of households and the restricted sample of households with at least one child aged 6-17.

[8]Labor supply responses at the household level must be estimated separately by age group because the definition of treatment changes as the age group for the outcome changes. Specifically when estimating the effect of the ban on the proportion of children ages 6-9 working, the treatment variable is whether the household has at least 1 child in the age range 10-13. However when the outcome is the proportion of children age 10-13 the treatment is whether the household has at least 2 children ages 10-13 because all children in the sample have at least 1 child age 10-13 (otherwise the outcome variable is undefined). These definitions are consistent with the sibling-based definition of treatment.

sectors. In light of this, we separate the samples into non-agricultural wages (to which the ban broadly applies) and agricultural wages (to which the ban does not apply).[9]

We find larger relative decreases in wages for children in non-agricultural jobs likely to be affected by the ban, though the difference is not significant for any of the age bands we consider (Online Appendix Table A19). The overall decline for children is statistically significant level for only non-agricultural earnings for all age ranges except the most narrow (column 5).

3.4. **Endogenous changes in household composition**

A related concern is that household structure may respond endogenously to the ban itself; to see whether this is the case, we regress household demographic variables on the household-level treatment variable as defined in the previous section. The results in Online Appendix Table A14 indicate that there is only one statistically significant endogenous response of household demographics to the ban (out of eight). Moreover, the effect is very small in magnitude; household size decreases by 0.029 members (0.5% of the pre-ban mean). Thus we do not find evidence that the ban had any meaningful effect on household characteristics.

3.5. **Secular time trends and falsification tests**

Finally we test for secular time trends unrelated to the ban for treated and control children using only data from the post-ban era. In particular, we run a falsification test by estimating our main specifications but using 1987-8 as the "pre" and 1993-4 as the "post" period. The results (displayed in Appendix Table A15) indicate that imposing a false ban date does not lead to significant "effects" of the ban for children ages 6-9 or ages 10-13. Hence, it appears that the policy change specific to 1986 is driving our results.

3.6. **Evidence of inelastic adult (and young adult) labor supply**

One of the main assumptions in the Basu (2005) and Basu and Van (1998) models is that adults supply labor inelastically. Hence, in response to lower child wages, we should not expect to

[9]Reported wages do not necessarily correspond to the reported "usual" or primary activity used to construct our employment variables. Wage data contain 1-digit NIC codes. "Non-agricultural" activities encompass all codes other than agriculture, such as manufacturing and mining.

see a response from adults (or in our framework, "young adults" who may be considered children by households but are classified as adults in the definitions set forth in the 1986 Act). In Online Appendix Table A20, we show that this is precisely the case. Individuals above the age of 14 do not show any increases or decreases in labor supply in response to the ban.

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4. Appendix Figures and Tables

FIGURE A5. Distribution of days spent in any economic activity in previous week (Ages 10-17, 1983).

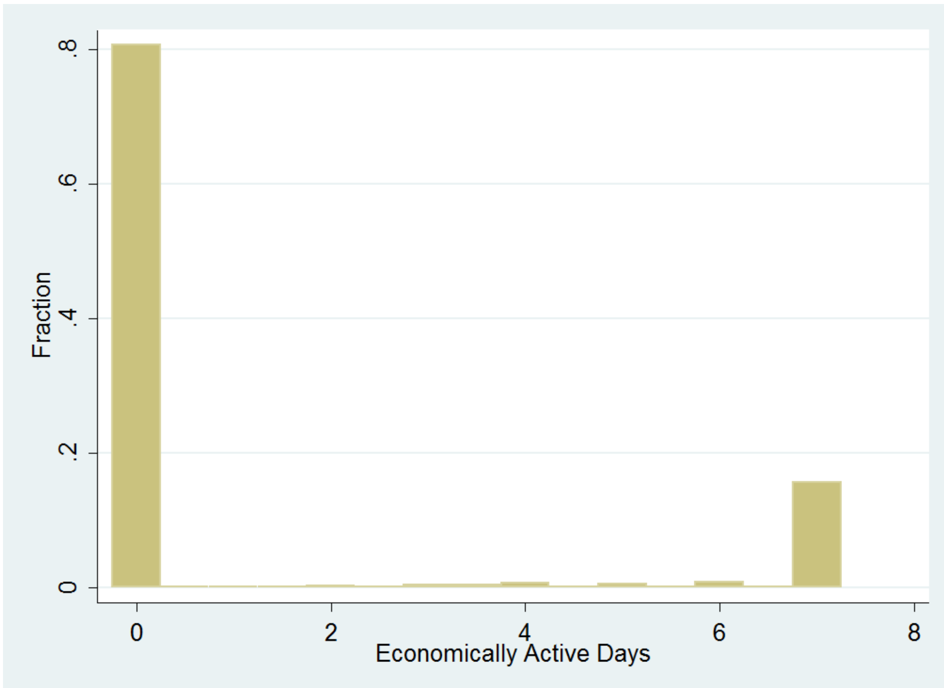


FIGURE A6. Distribution of days spent attending school in previous week (Ages 10-17, 1983).

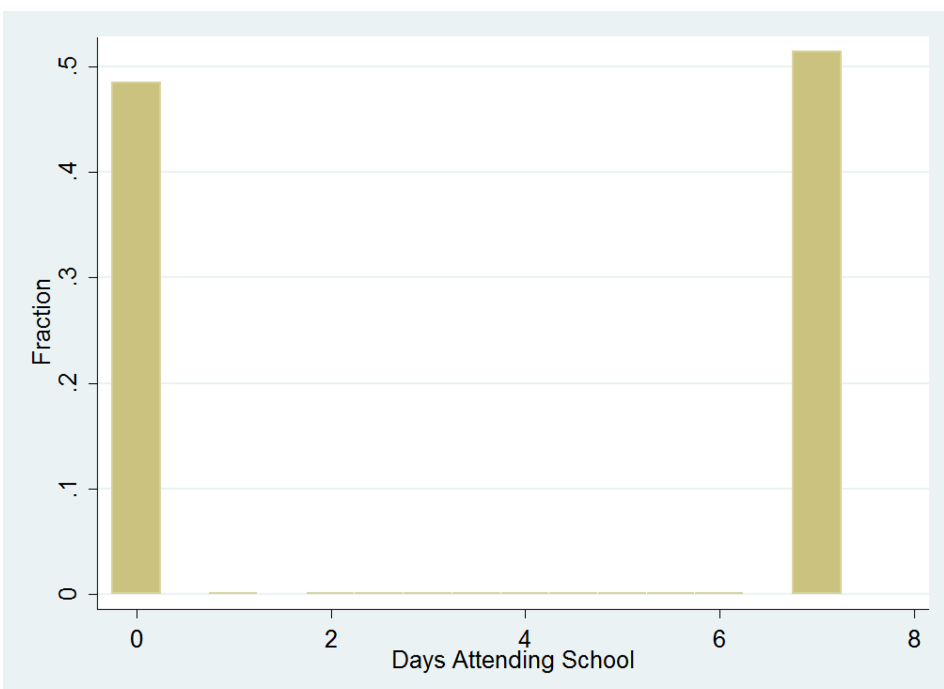
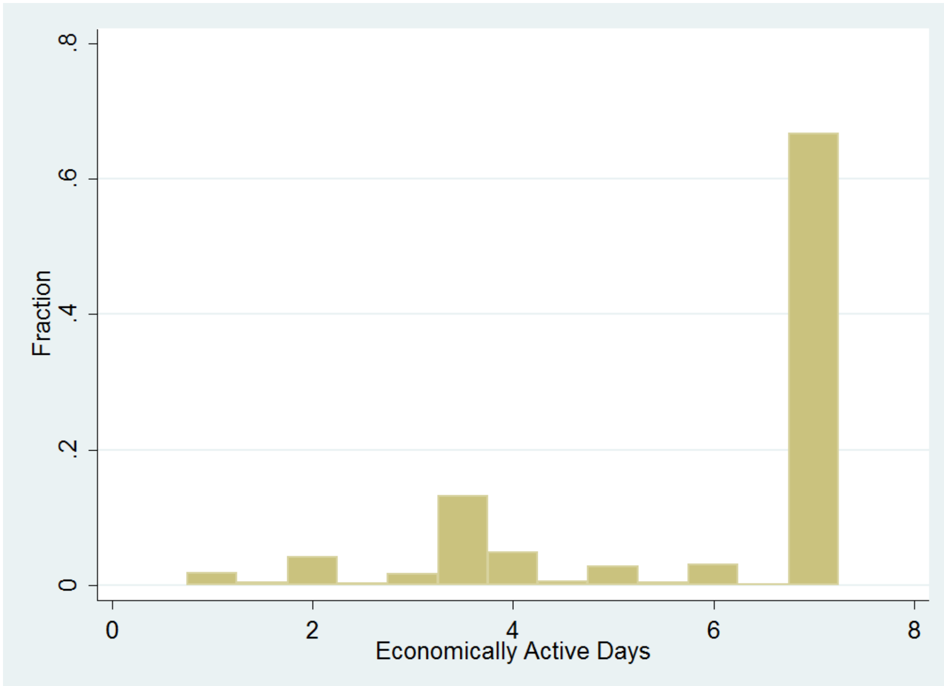
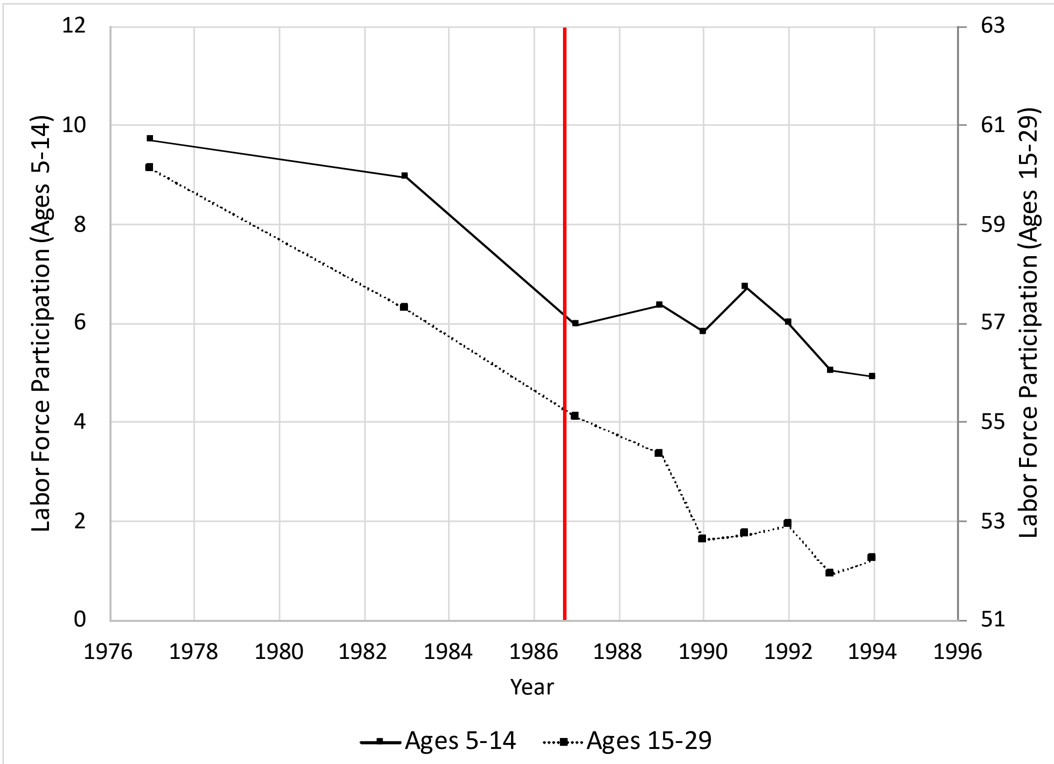


FIGURE A7. Distribution of days spent in any economic activity in previous week, conditional on principal usual status *not* being economic activity (Ages 10-13, 1983).



This distribution of days worked in the past *week* is for the sample of children ages 10-13 in 1983 whose principal usual status (based on a recall period of the past *year*) is not engaging in economic activity but who have spent at least some time in economic activity in the past week. The mass of children who worked 7 days in the previous week but whose principal status is not working may be due to the difference in recall periods (previous 365 days to the survey for principal usual status versus previous 7 days for days spent in each activity). Note that only 1.2% of children ages 10-13 in 1983 whose principal usual status is *not* working report spending some time working in the past week.

FIGURE A8. National trends in labor by age group (5-14 versus 15-29) from 1977-1994.



Data by age group, sex, and sector (rural, urban) are collected by the Central Statistical Organisation, Ministry of Statistics and Programme Implementation, Govt. of India. and reported by IndiaStat (www.indiastat.com). Age groups are as reported by IndiaStata and are *not* chosen by the authors; note that they do not perfectly align with the age restrictions of the 1986 Act. Additional data from the 1981 and 1991 Censuses are used to aggregate the labor force participation data to the national level; data from the IndiaStat survey is matched to the closest Census in absolute terms. The horizontal axis marks out the first calendar year of each corresponding survey, even if the survey spans two calendar years; for example the first survey was conducted in 1977-78 and is thus marked at 1977 (not 1978). Labor Force Participation of age groups 5-14 and 15-29 are plotted using separate axes with different intercepts but the scale for both axes is the same.

FIGURE A9. Age distribution pre- and post-ban.

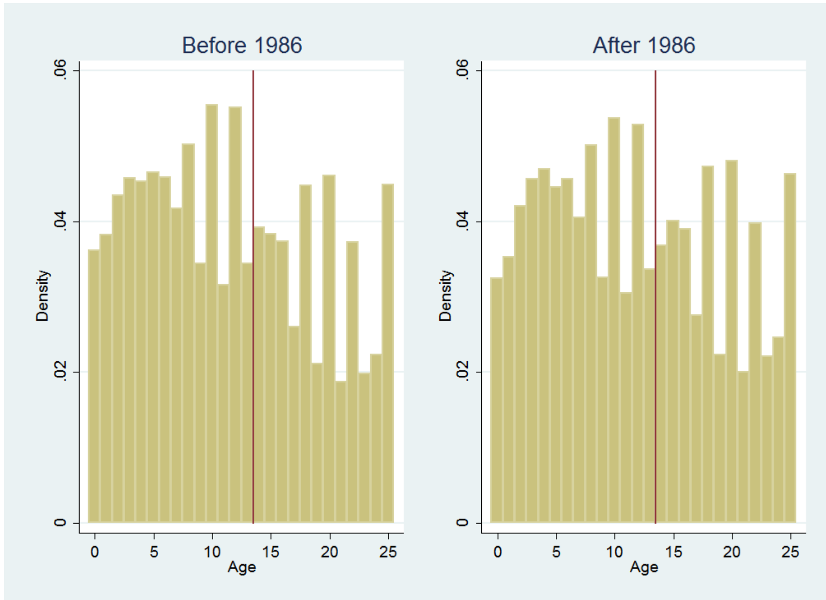


FIGURE A10. Age distribution pre- and post-ban for children working in banned occupations.

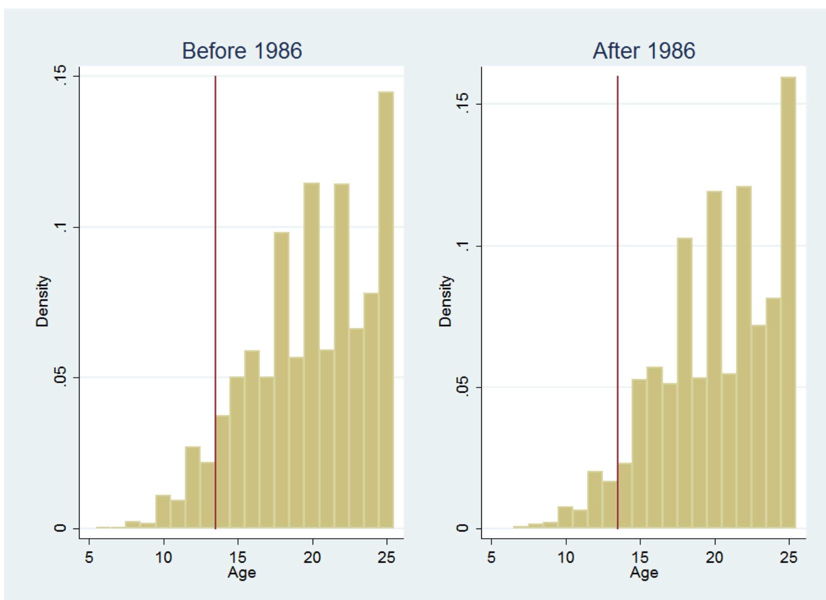


TABLE A2. Measures of Child Time Allocation

	N	%
Any Economic Activity		
Unpaid Economic Activity	N	%
Self-employed, HH Enterprise	3,472	2.11
Helper, HH Enterprise	5,279	3.21
Paid Employment		
Regular wage/salary employee	1,193	0.73
Casual Wage Labor, Public Works	50	0.03
Casual Wage Labor, Other	3,613	2.2
Total Engaged in Any Economic Activity	13,607	8.28
Attending School	113,941	69.39
Unpaid Household Services		
Domestic duties only	7,402	4.51
Domestic duties + free collection of goods	6,458	3.93
Total Engaged in Unpaid Household Services	13,860	8.44
Other		
Too young to work/attend school/seek employment	7,189	4.38
Did not work but was available for work	372	0.23
Not able to work due to disability	182	0.11
Old and disabled	174	0.11
Rentiers, Pensioners, etc.	14	0.01
Beggars, prostitutes, etc.	56	0.03
Others	14,759	8.99
Not reported	46	0.03
Total Other	15,603	9.51
Total	164,200	100

Categories based on the usual principal status and are mutually exclusive. Sample includes all children aged 10-13 across three employment rounds of the NSS: the 38th (January - December 1983), 43rd (July 1987 - June 1988), and 50th (July 1993 - June 1994).

TABLE A3. Alternate Clustering Methods

	Dependent Variable: Any Economic Activity					
	Standard Cluster by Age-Round	Standard Cluster by State	Standard Cluster by Age	Wild Cluster Bootstrap by Age	Standard Cluster by Under 14-Post	Wild Cluster Bootstrap by Under 14-Post
	(1)	(2)	(3)	(4)	(5)	(6)
Under14XPost	0.026***	0.026***	0.026***	0.026**	0.026***	0.026
	(0.005)	(0.005)	(0.007)	N/A	(0.000)	N/A
No. of clusters	24	31	8	8	4	4
p-value	0.000	0.000	0.005	0.010	0.000	0.176
Observations	327,233	327,233	327,233	327,233	327,233	327,233

Columns (4) and (6): Wild cluster bootstrap is implemented as in Cameron, Gelbach and Miller (2008) but using the 6-point distribution weights presented in Webb (2012) due to the low number of clusters. See the Online Appendix for full details on bootstrapping methods. “Under14” is a dummy variable that takes the value of 1 if the child is under 14 years of age. Sample consists of all individuals related to the household head aged 10-17. Controls: gender, gender of household head, age of household head, urban status, number of adult females, number of male children, number of female children, number of children under 5, number of children ages 6-9 as well as the following fixed effects: age, family size, household head’s education level, religion, survey round, survey quarter, state.

TABLE A4. Simple Estimates of the Effects of the Ban - Narrower Age Ranges

	Dependent Variable: Any Economic Activity			
	Ages 10-17	Ages 11-16	Ages 12-15	Ages 13-14
	(1)	(2)	(3)	(4)
Under14XPost	0.026***	0.024***	0.019**	0.011
CRVE (age-round)	(0.005)	(0.004)	(0.004)	(0.003)
Bootstrap p-value	0.000	0.006	0.030	0.340
Number of Clusters	24	18	12	6
Pre-Ban Mean	0.118	0.138	0.154	0.167
Observations	327,233	241,301	169,995	72,964
R-squared	0.182	0.177	0.160	0.136

*** p<0.01, ** p<0.05, * p<0.1 based on the p-value using the Wild Cluster Bootstrap method. “Under 14” is a dummy variable that takes the value of 1 if the child is under 14 years of age. Controls: gender, gender of household head, age of household head, urban status, number of adult females, number of male children, number of female children, number of children under 5, number of children ages 6-9 as well as the following fixed effects: age, family size, household head’s education level, religion, survey round, survey quarter, state. Sample consists of all individuals related to the household head aged 10-17. CRVE: Standard errors are given by the conventional cluster-robust estimate of the variance matrix, where the cluster level is age-survey round. Bootstrap p-values are calculated using the Wild cluster bootstrap method (Cameron, Gelbach and Miller (2008)) using the 6-point distribution weights presented in Webb (2012). Pre-Ban mean is for children under the age of 14 only.

TABLE A5. Excluding Post Rounds

	Dependent Variable: Any Economic Activity					
	Excluding Round 43 (1987-8)			Excluding Round 50 (1993-4)		
	Simple Estimate	Sibling-based Estimate		Simple Estimate	Sibling-based Estimate	
	Ages 10-17	Ages 6-9	Ages 10-13	Ages 10-17	Ages 6-9	Ages 10-13
	(1)	(2)	(3)	(4)	(5)	(6)
Under14XPost	0.030***	0.004***	0.008**	0.023***	0.004***	0.009***
	(0.006)	(0.001)	(0.003)	(0.004)	(0.001)	(0.003)
Survey Years Included	1983 (pre-ban), 1993-4 (post-ban)			1983 (pre-ban), 1987-8 (post-ban)		
Observations	209,425	115,834	112,691	230,032	129,805	124,414
R-squared	0.190	0.026	0.109	0.184	0.026	0.109

*** p<0.01, ** p<0.05, * p<0.1 Columns (1) and (4): “Under14”=dummy for whether child is under 14. Sample: all related to the HH head aged 10-17. SEs clustered by age-survey round. Columns (2), (3), (5) and (6): “Under14”=dummy for whether the child has at least one sibling age 10-13. Sample: all related to the HH head with at least one other (related) HH member age 6-17. SEs clustered by HH. Controls: gender, gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9; and the following fixed effects: age, family size, HH head’s educ., relig., survey round, survey quarter, state. Columns (2), (3), (5) and (6): for each age 0-25, we include a separate variable which counts the no. of household members of that specific age.

TABLE A6. Simple Estimates of the Effects of the Ban
Round 42: July 1986 - June 1987

	Any Economic Activity	Any Economic Activity	Unpaid Economic Activity	Paid Employment	Enrolled in School	Unpaid Household Services
	(1)	(2)	(3)	(4)	(5)	(6)
Under14XPost	0.004	0.003	-0.002	0.006**	-0.017***	-0.001
	(0.029)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)
Pre-Ban Mean of Dep. Var.	0.059	0.059	0.034	0.024	0.743	0.093
Observations	90,248	90,248	90,248	90,248	90,248	90,248
R-squared	0.045	0.141	0.086	0.082	0.248	0.212
Controls?	No	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1 “Under 14” is a dummy variable that takes the value of 1 if the child is under 14 years of age. Controls: gender, gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9; and the following fixed effects: age, family size, HH head’s educ., survey quarter, district. Pre-Ban mean is for children under 14 only. Standard errors are clustered by age-quarter.

TABLE A7. Sibling-based Estimates of the Effects of the Ban on Child Activities in Previous Week (Days)

Panel A: Children Ages 6-9							
	Any Economic Activity (1)	Employment in Banned Occ. (2)	Employment in Non-Banned Occ. (3)	Unpaid Econ. Activity (4)	Paid Employment (5)	Attending School (6)	Unpaid Household Services (7)
SibUnder14XPost	0.041***	0.001	0.040***	0.040***	-0.001	-0.060	0.016
	(0.011)	(0.003)	(0.011)	(0.010)	(0.005)	(0.041)	(0.012)
Pre-Ban Mean of Dep. Var.	0.112	0.005	0.112	0.091	0.019	4.026	0.161
Observations	152,882	152,882	152,882	152,882	152,882	152,882	152,882
R-squared	0.025	0.003	0.025	0.021	0.007	0.260	0.024

Panel B: Children Ages 10-13							
	Any Economic Activity (1)	Employment in Banned Occ. (2)	Employment in Non-Banned Occ. (3)	Unpaid Econ. Activity (4)	Paid Employment (5)	Attending School (6)	Unpaid Household Services (7)
SibUnder14XPost	0.054***	0.012*	0.054***	0.041**	0.013	-0.064*	0.000
	(0.021)	(0.007)	(0.021)	(0.018)	(0.012)	(0.033)	(0.022)
Pre-Ban Mean of Dep. Var.	0.770	0.105	0.671	0.524	0.232	4.155	0.900
Observations	164,200	164,200	164,200	164,200	164,200	164,200	164,200
R-squared	0.096	0.015	0.097	0.064	0.045	0.257	0.132

*** p<0.01, ** p<0.05, * p<0.1 The classification of banned & non-banned occupations in this table is much coarser than in Table 4 because days worked data are reported with 1-digit rather than 3-digit NIC codes. “SibUnder14” is a dummy variable for whether the child has at least 1 sibling age 10-13. Controls: gender, gender of HH head, age of HH head, urban status, no. of adult females, no. of male children, no. of female children, no. of children under 5, no. of children ages 6-9 and the following fixed effects: (own) age, family size, HH head’s education level, religion, survey round, survey quarter, state. Additionally for each age 0-25, we include a separate variable which counts the number HH members of that specific age. Sample consists of all individuals related to the HH head with at least one other (related) HH member age 6-17. Standard errors are clustered by HH.

TABLE A8. Effects of the Ban on Child Wages Allowing for Changes in Returns to Skill over Time

	Dependent Variable: Log(Real Wage)	
	Baseline	Including EducXPost Interactions
	(1)	(2)
Under14XPost	-0.078***	-0.147***
	(0.023)	(0.025)
Observations	33,731	25,718
R-squared	0.392	0.358

*** p<0.01, ** p<0.05, * p<0.1 Each column uses individuals related to the household head in the specified age range. “Under14” is a dummy variable that takes the value of 1 if the child is under 14 years of age. Real values (expressed in 1982 rupees) are nominal values deflated by the average wholesale price index reported by the Government of India for the respective year. Wages are trimmed of the top and bottom 1% of values within each round. Controls: gender, gender of household head, age of household head, urban status, number of adult females, number of male children, number of female children, number of children under 5, number of children ages 6-9 as well as the following fixed effects: age, family size, household head’s education level, religion, survey round, survey quarter, state, industry. Column (2) additionally controls for for interactions between dummy variables for all education levels and “Post." Standard errors are clustered by age-survey round.

TABLE A9. Effect of the Ban on Household Outcomes - Alternate Sample

	Log Total Expenditure Per Capita (1)	Log Food Expenditure Per Capita (2)	Log Daily Calories Per Capita (3)	(1-Staple Share of Calories) (4)	Asset Index (5)
Child10-13 XPost	-0.008 (0.006)	-0.000 (0.005)	-0.002 (0.004)	-0.001 (0.002)	0.009 (0.023)
Pre-Ban Mean of Dep. Var.	4.555	4.145	7.611	0.286	-0.738
Observations	140,130	138,816	138,872	138,612	139,092
R-squared	0.350	0.332	0.165	0.480	0.529

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. "ChildUnder14" is a dummy variable that takes the value of 1 if there is at least one child age 10-13 in the household. Sample consists of households with at least one child in the sibling-based DID samples (i.e. with one child aged 6-13 and with at least one sibling age 6-17), trimmed of the top and bottom 1% of values of the dependent variable within each round. Robust standard errors reported. Controls: gender of household head, age of household head, urban status, number of adult females, number of male children, number of female children, number of children under 5, number of children ages 6-9 as well as the following fixed effects: family size, household head's education level, religion, survey round, survey quarter, state. Additionally we include controls for sibling age as follows: for *each* age 0-25, we create a separate variable which counts the number household members of that specific age.

TABLE A10. Alternate Sibling Samples (Ages: 10-13)

Dependent Variable: Any Economic Activity						
	Baseline Specification (1)	All Empl. and Cons. Rounds (2)	Round 42 (July 1986- June 1987) (3)	Excluding Children whose "Treatment-Generating" Sibling is Younger (4)	Only Children with Siblings Ages 8-15 (5)	Only Unmarried Children of HH Head (6)
SibUnder14	0.008***	0.010***	0.001	0.022***	0.007**	0.007**
Xpost	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Survey Years	1983, 1987-8	All Rds.	July 1986	1983, 1987-8	1983, 1987-8	1983, 1987-8
Included	1993-4	1983-1994	- June 1987	1993-4	1993-4	1993-4
Pre-Ban Mean						
of Dep. Var.	0.115	0.115	0.058	0.103	0.112	0.113
Observations	164,200	212,715	44,910	122,034	144,340	137,633
R-squared	0.106	0.110	0.040	0.098	0.106	0.107

*** p<0.01, ** p<0.05, * p<0.1 Cols (1),(4)-(6): Sample period includes Rounds 38, 43 and 50 (1983, 1987-8, 1993-4). Col (2): Employment and consumption rounds of the NSS: 38, 43, 45, 46, 47, 48, 49, 50 (1983-1994). Col (3) uses Round 42 (1987-8) only. Col(4): Note that the definition of Economic Activity differs from all other columns; defined only for children who do not attend school (see Section 5.1 and Online Appendix for more details). Col(4): Sample excludes all children who are older than their sibling aged 10-13. Col (5): Sample is further restricted to only children with siblings ages 8-15. Col (6): Sample includes only unmarried children of the household head (restriction applies to siblings as well). For all columns: SEs clustered by HH. Controls: gender, gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9; and the following fixed effects: age, family size, HH head's educ., relig., survey round, survey quarter, state. Additionally for *each* age 0-25 we include a separate variable which counts the no. household members of that specific age.

TABLE A11. Allowing the Effect of Sibling Age to Differ over Time and by Treatment Status

	Dependent Variable: Any Economic Activity					
	Using Age of Sibling Closest to 13/14 Cutoff			Using Age of Nearest Sibling		
	Effect of Sibling Age Is Allowed to Differ...			Effect of Sibling Age Is Allowed to Differ...		
	...in Each Survey Round	...by Treatment Status	...by Treatment Status and Survey Round	...in Each Survey Round	...by Treatment Status	...by Treatment Status and Survey Round
	(1)	(2)	(3)	(4)	(5)	(6)
SibUnder14	0.008***	0.009***	0.008***	0.008***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	162,883	162,883	162,883	164,200	164,200	164,200
R-squared	0.105	0.105	0.105	0.105	0.105	0.105

*** p<0.01, ** p<0.05, * p<0.1. "SibUnder14"=dummy variable for whether the child has at least one sibling in age 10-13. Cols (1)-(3): Controls include age of sibling closest to the 13/14 cutoff (using younger siblings' ages in the case of a tie) as well as interactions with treatment status and/or survey round dummies (as indicated above each column). Cols (4)-(6): Controls include age of sibling closest to own age as well as interactions with treatment status and/or survey round dummies (as indicated above each column). Sample: all aged 10-13 related to the HH head with at least 1 (related) HH member aged 6-17. Controls for all columns: gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9, and the no. of household members of each age 0-25; and the following fixed effects: family size, HH head's educ., relig., survey round, survey quarter, state. SE are clustered by household.

TABLE A12. Redefining Work-Eligible Age

	Dependent Variable: Any Economic Activity			
	Baseline	Placebo Tests		
	"Banned"= Ages 10-13 (1)	"Banned"= Ages 1-4 (2)	"Banned"= Ages 5-9 (3)	"Banned"= Ages 14-17 (4)
SibUnder14XPost	0.008***	0.002	-0.006	0.004
	(0.003)	(0.004)	(0.005)	(0.004)
Pre-Ban Mean of Dep. Var.	0.115	0.125	0.125	0.125
Observations	164,200	78,973	78,973	78,973
R-squared	0.105	0.103	0.103	0.103

*** p<0.01, ** p<0.05, * p<0.1. "SibUnder14"=dummy variable for whether the child has at least one sibling in specified age range. Sample for Col (1): all aged 10-13 related to the HH head with at least one (related) HH member aged 6-17. Sample for Cols (2)-(4): all aged 10-13 related to the HH head with at least one (related) HH member aged 6-17, excluding all "treated" children with siblings ages 10-13. Controls (all columns): gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9, and the no. of household members of *each* age 0-25 as separate variables; and the following fixed effects: family size, HH head's educ., relig., survey round, survey quarter, state. SE are clustered by household.

TABLE A13. Accounting for Differential Birth Spacing

	Dependent Variable: Any Economic Activity			
	Restricted Sample: Only Those with a Sibling within 3 Yrs. of Own Age (1)	Average Sibling Age Gap and Interaction with Post (2)	Age Gap to Oldest Sibling and Interaction with Post (3)	Age Gap to Youngest Sibling and Interaction with Post (4)
SibUnder14XPost	0.006*	0.006*	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	136,944	164,200	164,200	164,200
R-squared	0.104	0.105	0.105	0.105

*** p<0.01, ** p<0.05, * p<0.1. "SibUnder14"=dummy variable for whether the child has at least one sibling in age 10-13. Sample (all columns except (1)): all aged 10-13 related to the HH head with at least one (related) HH member aged 6-17. Col (1): Sample is further restricted to children with at least one sibling within 3 years of own age. Cols (2)-(4) Age Gap is calculated as the absolute number of years between self and all/oldest/youngest sibling. Controls (all columns): gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9, and the no. of household members of *each* age 0-25 (as separate variables); and the following fixed effects: family size, HH head's educ., relig., survey round, survey quarter, state. SE are clustered by household.

TABLE A14. Falsification Test: Effect of the Ban on Demographics

	Child is Male (1)	HH Size (2)	Head is Male (3)	Head Age (4)	Head has at least Sec. Educ. (5)	Hindu HH (6)	Number of Females (7)	Number of Children (8)
ChildUnder14	-0.004	-0.002	-0.001	-0.219**	0.002	-0.006*	0.007	-0.006
XPost	(0.003)	(0.006)	(0.002)	(0.091)	(0.003)	(0.003)	(0.009)	(0.005)
Pre-Ban Mean								
of Dep. Variable	0.529	6.268	0.914	44.611	0.127	0.783	3.045	3.203
Observations	327,233	230,029	230,029	230,029	230,029	230,029	230,029	230,029
R-squared	0.268	0.941	0.261	0.337	0.150	0.210	0.622	0.897

*** p<0.01, ** p<0.05, * p<0.1. "ChildUnder14" is a dummy variable for whether there is at least 1 child age 10-13 in the HH. Sample: HHs with at least one member ages 6-17. Robust SE reported. Controls: gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9; and the following fixed effects: family size, HH head's educ., relig., survey round, survey quarter, state. For each age 0-25, we include a separate variable which counts the no. household members of that specific age.

TABLE A15. Checking for Differential Trends using only Post-Ban Data

	Dependent Variable: Any Economic Activity	
	Ages 6-9 (1)	Ages 10-13 (2)
SibUnder14XPost1988	-0.000	-0.002
	(0.001)	(0.003)
Observations	98,591	106,937
Observations	98,591	106,937
R-squared	0.020	0.091

*** p<0.01, ** p<0.05, * p<0.1. "Post1988" is a dummy variable which takes the value of 1 after June 1988. Only post-ban (1987-8 and 1993-4) rounds included. "SibUnder14"=dummy variable for whether the child has at least one sibling age 10-13. Sample: all related to the HH head with at least one (related) HH member age 6-17. SEs are clustered by HH. Controls: gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9; and the no. siblings of each age 0-25; and the following fixed effects: family size, HH head's educ., relig., survey round, survey quarter, state. Additionally we include separate variables which counts the number of household members of each age from 0-25.

TABLE A16. Accounting for State Policies and Differential Effects of Economic Growth on Children

	Dependent Variable: Any Economic Activity					
	Includes State GDP Index X Under14		States with No Change in Besley-Burgess Labor Classifications (1983-1994)		States with Below Median OB Intensity	
	Ages 6-9	Ages 10-13	Ages 6-9	Ages 10-13	Ages 6-9	Ages 10-13
	(1)	(2)	(3)	(4)	(5)	(6)
SibUnder14XPost	0.007***	0.009**	0.005***	0.013***	0.003*	0.009**
	(0.002)	(0.004)	(0.001)	(0.003)	(0.002)	(0.004)
Pre-Ban Mean of Dep. Variable	0.016	0.114	0.011	0.093	0.009	0.083
Observations	152,021	163,307	122,960	133,544	62,807	68,925
R-squared	0.025	0.104	0.015	0.081	0.012	0.072

*** p<0.01, ** p<0.05, * p<0.1 Cols (1)-(2): State-level GDP (yearly) is calculated using state-level census data as reported by IndiaStat (http://www.indiastat.com). The base year for the index is 1983. Cols (3)-(4): Sample excludes states that have experienced any labor regulation reform during the period 1983-1994 as defined in Besley and Burgess (2004): Andhra Pradesh, Madhya Pradesh, and Rajasthan. Cols (5)-(6): Intensity of Operation Blackboard figures taken from Chin (2005). "SibUnder14"=dummy for whether the child has at least 1 sibling age 10-13. Controls for all columns: gender, gender and age of HH; urban status; counts of adult females, male children, female children, children under 5, children ages 6-9; and the following fixed effects: age, family size, HH head's educ., relig., survey round, survey quarter, state. In addition to the listed controls, for each age 0-25, we include a separate variable which counts the no. of households members of that specific age. SEs are clustered by HH. Sample: all related to the HH head with at least one other (related) HH member age 6-17.

TABLE A17. Simple Estimates Omitting Children Ages 13 and 14

	Any Economic Activity	Any Economic Activity	Employment in Banned Occ.	Employment in Non-Banned Occ.	Unpaid Economic Activity	Paid Employment	Attending School	Unpaid Household Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Under14XPost	0.029	0.030***	0.003**	0.028***	0.009**	0.022***	0.015***	-0.011**
	(0.026)	(0.005)	(0.001)	(0.005)	(0.004)	(0.002)	(0.005)	(0.004)
Pre-Ban Mean of Dep. Var.	0.195	0.195	0.020	0.174	0.116	0.079	0.524	0.16
Observations	254,269	254,269	253,882	253,882	254,269	254,269	254,269	254,269
R-squared	0.078	0.195	0.033	0.172	0.098	0.105	0.307	0.214
Controls?	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1 “Under14” is a dummy variable that takes the value of 1 if the child is under 14 years of age. Column 1 includes only a Post-ban dummy, the “Under14” dummy, and an interaction between “Under14” and Post. Controls: gender, gender of household head, age of household head, urban status, number of adult females, number of male children, number of female children, number of children under 5, number of children ages 6-9 as well as the following fixed effects: age, family size, household head’s education level, religion, survey round, survey quarter, state. Sample consists of all individuals related to the household head aged 10-17, *omitting ages 13 and 14*. Standard errors are clustered by age-survey round. Pre-Ban mean is for children under the age of 14 only. Columns 4 and 5: Smaller sample sizes are due to missing NIC codes. Employment in non-banned occupations includes all unpaid economic activity within the household and paid employment in non-banned occupations.

TABLE A18. Sibling-based Estimates Omitting Children with Siblings Ages 13 and 14

	Any Economic Activity (1)	Employment in Banned Occ. (2)	Employment in Non-Banned Occ. (3)	Unpaid Econ. Activity (4)	Paid Employment (5)	Attending School (6)	Unpaid Household Services (7)
Panel A: Children Ages 6-9							
SibUnder14XPost	0.006*	0.000	0.005*	0.007**	-0.001	0.014	0.003
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.011)	(0.003)
Pre-Ban Mean of Dep. Var.	0.017	0.001	0.016	0.014	0.003	0.552	0.022
Observations	78,217	78,205	78,205	78,217	78,217	78,217	78,217
R-squared	0.024	0.004	0.024	0.020	0.008	0.326	0.023
Panel B: Children Ages 10-13							
	Any Economic Activity (1)	Employment in Banned Occ. (2)	Employment in Non-Banned Occ. (3)	Unpaid Econ. Activity (4)	Paid Employment (5)	Attending School (6)	Unpaid Household Services (7)
SibUnder14XPost	0.008*	0.001	0.007	0.009**	-0.001	-0.001	-0.010**
	(0.005)	(0.002)	(0.005)	(0.004)	(0.003)	(0.007)	(0.005)
Pre-Ban Mean of Dep. Var.	0.132	0.011	0.120	0.086	0.046	0.590	0.134
Observations	78,487	78,421	78,421	78,487	78,487	78,487	78,487
R-squared	0.114	0.018	0.106	0.069	0.058	0.272	0.142

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ "SibUnder14" is a dummy variable for whether the child has at least 1 sibling age 10-13. Controls: gender, gender of household head, age of household head, urban status, number of adult females, number of male children, number of female children, as well as the following fixed effects: (own) age, family size, household head's education level, religion, survey round, survey quarter, state. Additionally we include controls for sibling age as follows: for *each* age 0-25, we create a separate variable which counts the number household members of that specific age. Sample consists of all individuals related to the household head with at least 1 other (related) household member age 6-17, *excluding children with siblings exactly age 13 or 14*. Standard errors are clustered by household.

TABLE A19. Effects of Ban on Child Wages by Sector

	Dependent Variable: Log(Real Wage)				
	Ages 6-21	Ages 7-20	Ages 8-19	Ages 9-18	Ages 10-17
	(1)	(2)	(3)	(4)	(5)
Non-Ag SectorXUnder14XPost	-0.036	-0.029	-0.022	-0.013	-0.014
	(0.055)	(0.055)	(0.049)	(0.049)	(0.036)
Under14XPost	-0.045	-0.049	-0.054	-0.056	-0.037
	(0.037)	(0.036)	(0.035)	(0.035)	(0.030)
Total Effect for Non-Ag Sector	-0.081**	-0.079*	-0.076*	-0.068*	-0.051
p-value for Total Effect (Non-Ag)	0.046	0.058	0.053	0.086	0.153
Observations	33,731	30,566	23,648	20,696	14,848
R-squared	0.392	0.378	0.357	0.343	0.313
Controls?	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1 "Non-Ag Sector" refers to all 1-digit NIC classifications other than agriculture. Each column uses individuals related to the household head in the specified age range. "Under14" is a dummy variable that takes the value of 1 if the child is under 14 years of age. Real values (expressed in 1982 rupees) are nominal values deflated by the average wholesale price index reported by the Government of India for the respective year. Wages are trimmed of the top and bottom 1% of values within each round. Controls: gender, gender of household head, age of household head, urban status, number of adult females, number of male children, number of female children, number of children under 5, number of children ages 6-9 as well as the following fixed effects: age, family size, household head's education level, religion, survey round, survey quarter, state, industry. Standard errors are clustered by age-survey round.

TABLE A20. Effects on Other Ages

	Dependent Variable: Any Economic Activity					
	Ages 14-17	Ages 18-25	Ages 26-35	Ages 36-45	Ages 46-55	Ages 56+
	(1)	(2)	(3)	(4)	(5)	(6)
ChildUnder14	-0.007	-0.002	0.000	-0.010***	-0.001	0.003
XPost	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)	(0.006)
Mean of Dep. Var.	0.292	0.520	0.608	0.677	0.664	0.385
Observations	138,537	173,481	189,540	166,627	92,837	84,433
R-squared	0.195	0.337	0.488	0.516	0.508	0.423

*** p<0.01, ** p<0.05, * p<0.1 "ChildUnder14" is a dummy variable that takes the value of 1 if there is at least one child age 10-13 in the household. Controls: gender, gender of household head, age of household head, urban status, number of adult females, number of male children, number of female children, number of children under 5, number of children ages 6-9 as well as the following fixed effects: (own) age, family size, household head's education level, religion, survey round, survey quarter, state. Additionally we include controls for sibling age as follows: for *each* age 0-25, we create a separate variable which counts the number household members of that specific age. Sample consists of all individuals related to the household head living with at least one (related) household member age 6-17. Standard errors are clustered by household.