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Selection into Worst Forms of Child Labor: Child Domestics, Porters, and Ragpickers in Nepal

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Abstract: A large literature considers why children work, but little is known about why children participate in activities that are labeled worst forms of child labor. The principal international convention on worst forms of child labor has signatory governments define what activities are worst forms of child labor. Are these government defined worst forms of child labor different from other types of jobs from the perspective of agents making decisions about child time allocation? Existing evidence on the determinants of participation in worst forms largely comes from surveys of children engaged in those activities. This study emphasizes that such evidence alone cannot be informative about the determinants of why children participate in worst forms. Case-control approaches common in medicine are adapted to consider the correlates of participation in worst forms in the context of three activities that the Nepali government has labeled as among the worst forms of child labor in Nepal: child domestic service, portering, and ragpicking. The data are consistent with the view that there are negative amenities associated with these jobs that are partially compensated. However, intrinsic and easily remedied problems in the way data on children in worst forms are collected limit the present analysis, and the considerable limitations of the present study illustrates how current survey efforts aimed at children in worst forms can be improved.

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1. Introduction

Popular horror of the prevalence and persistence of worst forms of child labor in developing countries is nearly universal. 160 countries have ratified ILO Convention 182 "Concerning the Prohibition and Immediate Action for the Elimination of the Worst Forms of Child Labor." Commensurate with this public attention to worst forms is a literature within economics seeking to understand why children are engaged in worst forms of child labor. Policy tends to view worst forms as evidence of victimization. Children are often not free to choose their own time allocation, and one argument for the persistence and prevalence of worst forms is that they reflect parental neglect and indifference to the child's welfare. A second argument is that worst forms are fully compensated with higher wages. That is, parents or children are free to choose different types of work and selection into worst forms is arbitrary. A variation on this argument is that decision-making agents are uninformed about the risks or disamenities associated with worst forms so that full compensation is only ex-ante, not ex-post (Rogers and Swinnerton 2002). A third argument is that worst forms are partially compensated so that there is sorting into worst forms along the marginal utility of income (Dessy and Pallage 2005).

Empirical evidence on selection into the worst forms of child labor is scarce, because worst forms are difficult to capture with randomized sampling. Existing evidence on why children are in worst forms comes largely from research where children engaged in a targeted activity are interviewed, asked about their working conditions and why they participate in the work. In these surveys, children often respond that they are working because either they or their family need the money. However, the fact that children work in worst forms for income does not itself answer the question of why children are working in these activities. Children work in plenty of activities for income, many of which would not be considered hazardous or a worst form of child labor. More generally, it is impossible to understand why children are involved in some activity without talking to children that are not involved in that activity. In order to design policy aimed at preventing child involvement in worst forms of child labor, policy needs to know what factors are associated with entry to worst forms of child labor and whether these correlates of entry differ from correlates of entry into other types of work.

This study argues for analyzing the correlates of participation in worst forms by pooling nationally representative data and survey data from children in worst forms. There is already a well developed statistical literature on inference in contaminated samples (where the probability of being sampled is not random), and the present study applies the simplest of approaches in that literature to consider the correlates of participation in worst forms of child labor. The data on children in the worst forms are pooled with the nationally representative data, and the resulting predicted probabilities of participating in a worst form are adjusted by estimates of the prevalence of the worst form in the population. Inference is limited to child background characteristics that are collected in the survey of children in a worst form and the nationally representative data. As is evident in the application below, the set of overlapping background characteristics and differences in how information on the characteristics are collected limit our ability to infer the correlates of participation in a worst form. It would be simple to modify future data collection efforts to make sure that data on children in worst forms are collected in a manner consistent with existing, nationally representative data.

This study applies this simple approach to examine what child background characteristics make it more likely that a child is observed as short route porters, ragpickers, or domestic servants in Nepal. Each type of work has been defined as a worst form of child labor in Nepal by the Nepali government and explicitly targeted for eradication. Survey data from children engaged in each activity are combined with estimates of the incidence of each in the population and with nationally representative data from Nepal's population census to show how this combination of data can be to infer the correlates of selection into these worst forms of child labor in Nepal. Each activity is considered separately, and findings for children observed in worst forms are compared to results from analyzing selection into regular wage work.

The empirical analysis in this study is descriptive, not causal. Moreover, the analysis is extremely limited by the set of characteristics that overlap in the nationally representative data and data of children in worst forms. That said, some striking patterns are observable in the data. Paternal disability appears to be strongly correlated with child participation in the three worst forms considered herein. The presence of employment opportunities within the child's own household is associated with a diminished risk of entry into worst forms. Such patterns appear in all the worst forms examined in this study, but these correlates of entry into three worst forms do not predict participation in wage work. Given that children rarely work for wages in Nepal, the association between participation and household employment opportunities suggests that children are more likely to be observed in a worst form when the return to the worst form is large relative to other options available to the child. This follows out of any of the main theoretical models used to consider entry to worst forms. The paternal disability findings, however, appear most consistent with Dessy and Pallage's (2005) model of partially compensated wage differentials if paternal disability works primarily through lowering family living standards.

The next section of the study discusses the concept of a worst form of child labor and reviews the existing theoretical literature on why children participate in worst forms. Section three describes the present methods for studying entry into worst forms. Sections four, five, and six apply these methods to the analysis of entry into child domestic service, portering, and ragpicking respectively. Section seven discusses the lessons of the empirical findings and considers the implications of this study's weaknesses for future studies of entry into worst forms of child labor.

2. Why are children in worst forms of child labor?

2.1 What are the worst forms of child labor?

The minimum age convention, C138, places special emphasis on activities that "jeopardise the health safety, or morals of young persons" (Article 3 - section 1) and defines 18 as the minimum age of employment for activities that can be described as such. In 1999, C182 on the Worst Forms of Child Labor asks signatory countries to clarify what types of activities fall under this label and to develop specific plans for their eradication. C182 has proven less controversial than the minimum age conventions, and to date there are 151 signatories.

While it is up to the individual country to identify "worst forms" in their own country, Article 3 of C182 contains several guidelines for what types of activities are to be considered for persons under the age of 18. These include all forms of slavery and "practices similar to slavery." This later clause is noted to include the sale and trafficking of children, debt bondage, serfdom, and forced or compulsory labor including for the purposes of armed conflict. Children in prostitution, pornography, the production or processing of drugs are also noted as being in "worst forms" of child labor. Article 3 (d) is the most ambiguous part of the convention as it allows worst forms to include "work which, by its nature or the circumstances in which it is carried out, is likely to harm the health, safety, or morals of children." Article 4 of the convention is explicit that it is up to individual countries to define what types of work are considered "worst forms" of child labor under this clause. Activities labeled "worst forms" under Article 3(d) of C182 are often labeled as "Hazardous forms of child labor." The companion recommendation document for C182, R190 Worst Forms of Child Labor Recommendation, suggests that these hazardous forms of child labor include:

> "(a) work which exposes children to physical, psychological, or sexual abuse; (b) work underground, under water, at dangerous heights, or in confined spaces; (c) work with dangerous machinery, equipment and tools, or which involves the handling or transport of heavy loads; (d) work in an unhealthy environment which may, for example, expose children to hazardous substances, agents or processes, or to temperature, noise levels, or vibrations damaging to their health; (e) work under particularly difficult conditions such as work for long hours or during the night or work where the child is unreasonably confined to the premises or the employer." (R190, Section II.3.a-e).

Most of the existing evidence on why children work comes from responses to large-scale household surveys (Edmonds 2007 is a recent survey). The advantage of these surveys is that they are randomized so that it is possible to use them for inference about the scope of child labor in a country. However, these instruments are often inappropriate for monitoring the worst forms of child labor in a country. For these difficult to monitor forms of child labor, the ILO and interested organizations conduct specialized surveys that interview only those individuals engaged in the activity. From these targeted surveys, it is possible to guess the extent of worst forms of child labor in a country.

The ILO's SIMPOC estimates that a total of 8.4 million children are involved in child trafficking, in forced or bonded labor, are soldiers, are prostitutes or involved in pornography, or participate in illicit activities (ILO, 2002). 68 percent of these children are in bonded or forced labor. Since hazardous activities are defined at the country level, cross country evidence on their extent is not available. Country level estimates are also typically not available. However, in implementing C182, the ILO has been activity in assisting countries in assessing the prevalence of worst and hazardous forms of child labor as well as in developing plans for the eradication of these activities. Nepal was one of the first countries to initiate one of these "Time Bound Programs," and the findings from the baseline work for this program are illustrative of the types of activities that governments label as hazardous and the prevalence of worst forms in a very poor country.

Estimates of the extent and incidence of worst forms of child labor in Nepal are in Table 1. These estimates are from ILO (2001) and differ slightly from what will be reported below because of differences in data. There are approximately 8 million children below the age of 16 in Nepal, and the ILO estimates that 1.5 percent of these children work in these worst forms of child labor. Most children engaged in worst forms of child labor in Nepal are in hazardous forms of child labor. Child porters and domestic works are the two most common types of “worst forms” of child labor. Among child porters, there are two main types: short distance porters that work in urban markets and bus parks and long distance that work in the countryside. The ILO estimates that typically long distance porters stay and work with their families while short distance porters have often migrated to find work. Estimates are that there are about 42,204 long distance porters and 3,825 short distance porters. 88% are boys. Domestic workers are most prevalent in high status urban households, though domestics typically come from rural areas. In Kathmandu, 1 out of 5 households employ children. The ILO estimates that 43% of employers of child domestics are government or non-government service holders. Domestics are believed to be evenly split between paid (to parents) and unpaid (more correctly, paid in a lump sum) workers. The other children included in Table 1 because of the nature of their employment are children in mines, in the carpet sector, and ragpickers, who pick rags and other rubbish out of garbage dumps for resale.

Bonded laborers and trafficked children both fall under worst forms of child labor as well. Bonded children in Nepal are in bondage either because parents took out debts against the child's future earnings or because they were used as collateral on loans. The ILO estimates that some 17,152 children in bondage in Nepal, although this estimate is controversial because it does not include children whose parents are bonded in a system of bonded labor that pervades western Nepal. Child trafficking is particularly hard to measure and evaluate. According to the ILO (2001), 12,000 girls are trafficked into the commercial sex industry each year in Nepal. By and large, these girls work in brothels in India. Unfortunately, because of the relative rarity of these activities and the challenges of capturing them in randomized surveys, little research exists on whether these activities are rightly viewed as a type of child work (where human rights is more obviously an issue) or whether they should be viewed as some other type of activity altogether.

2.2 Theory on the determinants of entry

A simple analytical model will help fix ideas in our discussion of the determinants of entry into worst forms. The first issue that any framework of child time allocation must address is the question of who is making decisions. This question of agency in work decisions is unquestionably important when discussing worst forms of child labor. Ultimately, this study does not inform about agency issues, so the present discussion of why children participate in worst forms is framed around an agent making an informed decision about job type without clarifying who the relevant agent might be. A child participates in a worst form of child labor when the decision-making agent's utility is higher than when the child does not:

$$u(y_c, c) + e_c \geq u(y_0, 0) + e_0 \qquad \text{(eq. 2.1)}$$

c is an indicator for whether the child participates in the given worst form, y_c is the agent's income when the child participates in the worst form, and y_0 is the agent's income when the child does not. e_c and e_0 are stochastic, mean zero, error terms that reflect some randomness in the agent's decisions.

Let the decision-maker's utility when the child does not participate in the worst form be represented by an indirect utility function:

$$u(y_0, 0) = v(y_0, p)$$

The agent's relevant income when the child participates in a worst form is the agent's income absent the child's participation plus the net economic gain from having the child in the worst form:

$$y_c = y_0 + w^* \qquad \text{(eq. 2.2)}$$

For analytical clarity, treat the disutility from having the child involved in a worst form as additively separable from the utility owing to the other decisions the agent makes with their income :

$$u(y_c, c) = u(y_0 + w^*, c) = v(y_0 + w^*, p) - \tau \qquad \text{(eq 2.3)}$$

This functional form assumption on preferences is equivalent to assuming that the disutility that parents get from having a child in a worst form is independent from their income (or price) level. Poor families and rich families are made equally worse off by having a child live away and work as a domestic. This does not imply that the marginal utility from having a child in a worst from, relative to not, will be the same for poor and rich families as the marginal utility associated with the child's net economic contribution in the worst form will differ between poor and rich.

The incidence of children involved in worst forms is then:

$$\begin{aligned}\Pr(C=1) &= \Pr\left[v(y_0+w^*,p)-\tau+e_w \geq v(y_0,p)+e_0\right] \\ &= \Pr\left[e_0-e_w \leq v(y_0+w^*,p)-\tau-v(y_0,p)\right]\end{aligned} \qquad \text{(eq. 2.4)}$$

Define $u=e_0-e_w$. u has a cdf *F(u)* and strictly positive density *f(u)*. Thus:

$\Pr(C=1)=F\left[v(y_0+w^*,p)-\tau-v(y_0,p)\right]$. We totally differentiate in order to organize the determinants of different risks of being observed in a worst form of child labor:

$$d\Pr(C=1)= f(u)\left(\left[\frac{\partial v_w}{\partial y}-\frac{\partial v_0}{\partial y}\right]dy_0+\left[\frac{\partial v_w}{\partial p}-\frac{\partial v_0}{\partial p}\right]dp-d\tau+\frac{\partial v_w}{\partial y}dw^*\right) \qquad \text{(eq. 2.5)}$$

With diminishing marginal utility of income, $\partial v_w/\partial y < \partial v_0/\partial y$. Declines in income opportunities open to the child absent participation in the worst forms, tend to push children towards participation in worst forms. The amount of the push depends on the curvature of the indirect utility function. Higher net income available in the worst form also pulls children towards the activity. The extent of the pull depends on the marginal utility of income. Hence, poorer families are more likely to select into worst forms, because they are poorer. The agent's disutility from the activity is also an influence as are prices.

The existing theoretical literature on worst forms can easily be interpreted within this framework. In one view, worst forms are no different than other types of work from the parent or child's perspective, and factors that drive children to select into worst forms are the same factors that drive them to work in the first place. Selection into a worst form occurs because the worst form is the only option available to the child or because all the negative amenities of the worst form are fully compensated (in expectation) through higher wages. The fully compensated view implies that the additional income *w** associated with the worst form is large enough to compensate for the disutility of the job τ.

The fully compensated model implies that the overall incidence of children in worst forms depends on labor demand for those activities as the worker is indifferent between the worst forms and other forms. Dessy and Pallage (2005) argue that worst forms of child labor are partially compensated so that they pay more. Thus, the entry process is similar to other types of work except that poorer households are more likely to select into worst forms, because the marginal utility for the additional income exceeds the disutility of the work. Put another way, there is some (exogenous from the agent's perspective) labor demand for the worst form, and labor supply is driven by the distribution of income absent the worst forms and the disutility to the agent of the work (ignoring price differences). The income available by participation in the worst form is wage that clears this market, and the extent to which the poor dominate those in the worst form depends on the joint distribution of τ and y_0.

In a third view, children in worst forms of child labor enter because of poor information about what the work entails (Rogers and Swinnerton 2002). Thus, ex-ante children select into the work under the assumption that it is similar to other types of work, and there are barriers to exiting. Put another way, the agent underestimates τ. This explanation is most often voiced to explain selection into prostitution, but it may be equally substantive for other worst forms of child labor. A commonly observed correlate of involvement in worst forms is a child migrant living away from home. It is worth noting that in many activities it is not unusual to see children working by their parent's side. Ragpicking is one example.

The popular view of entry into worst forms as victimization of the child presumes that $\tau=0$. Without any disamenity to the agent associated with the work, child labor will flow to whatever type of work pays the highest wage. In equilibrium, then wages paid to children in worst forms should be identical to that of other working children from the same community. If labor is immobile, the prevalence of worst forms across communities will differ with variation in labor demand for other activities. With labor market imperfections that impede the perfect substitution of family and non-family labor, differences within communities in participation in worst forms would be driven by differences in the availability of own family employment opportunities. Note that this, in turn, implies that the equilibrium wages paid to children in worst forms would be below (weakly) the shadow value of child time in family activities.

In principal, testing between these competing models of entry into worst forms is transparent. The fully compensated model implies that selection into worst forms is arbitrary so that when one identifies a population with the same opportunities to participate in the worst form and other activities at the same wages, one can test whether participation is correlated with observable household characteristics. This is distinguishable from the partially compensated model, because the partially compensated model implies that entry should be negatively correlated with household living standards absent the child's involvement in the worst form. The victimization model differs from the partial compensation model in the income elasticity of participation as well, but it can be differentiated from the fully compensated model in that it does not imply that participants are paid more. Note that to test between these models, one requires information on what the agent's income would be absent the child's involvement in the worst form, and one needs to be able to identify both the child's wage when involved in the worst form as well as what the child's wage could be absent involvement in worst forms. Thus, separating competing explanations for why children are engaged in worst forms requires constructing the counterfactual of what children and their families would be doing absence the child's involvement in a worst form of child labor. The next section describes how to compute this. In the subsequent sections, it is obvious that the available data is too limited to conclusively distinguish between competing theories.

3. Methodology for examining selection into worst forms

Why are children engaged in worst forms of child labor (WFCL)? Empirically, this is a hard question to answer, because WFCL are relatively rare. The probability that random sampling captures children engaged in any given WFCL is typically low. Hence, data collection can be prohibitively costly and statistical power is always a concern. Researchers have had to turn to other data sources. The most common approach is inherently qualitative. Researchers find children engaged in a worst form and interview them to find out about their circumstances. Sometimes these interviews are unstructured, but often researchers follow a survey questionnaire which can permit quantitative analysis.

It is impossible to learn about why children are in worst forms from only interviewing children in worst forms. Consider some factor D that influences selection into activity C. The researcher is interested in knowing how factor D increases the probability that a child with other characteristics X enters into activity C. When D is discrete, this is: $P\left[C=1 \middle| D=1, X\right]-P\left[C=1 \middle| D=0, X\right]$. Neither probability can be computed in the set of C=1. Put another way; let's say a child in an interview remarks that they are engaged in activity C because of factor D ("I am a ragpicker, because my dad lost his job"). There may be lots of children that experience factor D that do not select into C (lots of children have a parent loose a job without becoming a ragpicker), but without data on children not in C there is no way to compute the increased chance of engaging in C with a change in D.

The problem of drawing inference about rare events is not unique to worst forms of child labor. Most observational inference in medicine is made under precisely these circumstances, and this study applies these approaches to rare events from epidemiology to the study of selection into worst forms of child labor. These techniques do not appear to have been applied to the analysis of selection into worst forms before. The present discussion draws heavily from papers such as Prentice and Pyke (1979), King and Zeng (1999), and Manski (1999).

Let C_i be an indicator that child i is involved in the given worst form of interest. D_i is the covariate of interest. In the present discussion, D_i is binary, but the discussion generalizes to when D_i takes more than two values. Our interest is in estimating the impact of D_i on the probability that child i is involved in the given worst form. Later attention will be placed on estimating this probability conditional on other confounding variables that are correlated with both C_i and D_i.

There are three main outcomes of potential interest.

1. Absolute risk. How likely is an individual with D_i to be involved in the given worst form:

$$\pi_i = \Pr\left(C = 1 \middle| D_i\right). \qquad \text{(eq. 3.1)}$$

2. Relative risk. How much more likely is a child with D=1 to be observed in activity Y than a child with D=0:

$$R = \frac{\Pr\left(C = 1 \middle| D = 1\right)}{\Pr\left(C = 1 \middle| D = 0\right)}. \qquad \text{(eq. 3.2)}$$

3. Attributable risk. How much does an individual's risk of engaging in Y increase with a change in D from 0 to 1:

$$A = \Pr\left(C = 1 \middle| D = 1\right) - \Pr\left(C = 1 \middle| D = 0\right). \qquad \text{(eq. 3.3)}$$

Each of these outcomes is potentially of considerable interest to researchers and policy. For example, absolute risk is of interest to assess how likely a child with a given characteristics is to be in a WFCL. An index of vulnerability to WFCL would be constructed entirely through combining measures of absolute risk. Researchers interested in how participation in WFCL differs with variation in observable characteristics will be most concerned with relative or attributable risk. Relative risk is the most straightforward to estimate. However, relative risk can often be misleading to interpret in the context of low probability events. For example, suppose that the probability of observing a child in a WFCL is extremely low when a certain characteristic D is not present (e.g. 0.00001) and suppose the probability is higher when the characteristic is present (e.g. 0.0001) but still so small as to not be substantive. Estimates of relative risk in this case would be very large (10) even though the probabilities are so small as to not be substantive. Hence, at a minimum, relative risk should never be considered without attention to the baseline absolute risk. In contrast, attributable risk gives a direct measure of how much a child's risk of being involved in a WFCL changes with an observed characteristic. Consequently, it is the outcome of interest most often.

Estimating absolute, attributable, or relative risk requires data on both cases (subjects where C=1) and controls (C=0). When data on both cases and controls can be collected in a single randomized survey, standard cohort comparison techniques are available. However, typically the incidence of most forms of WFCL is such that a survey would need to be extremely large in scale to recover engaged children using random sampling. Thus, a more common situation is to have separately collected data on children not engaged in the WFCL (the control data) and data on children engaged in the activity (the case data). The case data do not need to be obtained through randomized sampling, but estimating absolute or attributable risk requires knowledge of the probability a child engages in the WFCL. This is most easily assessed if the case data collection is designed, in part, to estimate this parameter. Moreover, whatever sampling procedure generates the case data, sampling must be independent of the covariates *D* of interest except in as much as D is correlated with selection into the case data. Put another way, the data generation process can generate bias if it is correlated with covariates of interest for reasons other than that the covariates are correlated with selection into worst forms.

Ideally, the survey instrument used to collect data on the case and control populations will be identical. In practice, it is rare that similar case and control data exist. It will only be possible to compute any of the risk parameters of interest for covariates that appear in both the case and control data. Moreover, a common problem is that even when there are similar questions, the case and control data will be answered by different people. Often case data is collected by interviewing children while most household surveys and censuses (typical sources of control data) interview household heads or their spouses. Biases from differences in respondents can be as substantive as biases from different framing of questions, and these dissimilarities make it very challenging to assess the risk parameters of interest.

The classic case – control approach makes the rare events assumption to estimate relative risk. That is, the case and control data are pooled, and it is assumed that the probability of observing a case individual tends to zero (conditional on observed characteristics) in the limit. This assumption allows the researcher to interpret the odds ratio from a logit of participation in the WFCL on observable characteristics as an estimate of relative risk. The appeal of this approach is that it is possible to estimate relative risk without identifying absolute risk in the population. However, the rare events assumption is problematic. The existence of case data implies that the probability of observing a case is not zero, and the rare events assumption implies that attributable risk is zero.

Knowledge of the probability of observing a case in the population substantially improves estimation. Let λ denote the incidence of the worst form in the population, and let $\bar{C}$ be the fraction of the case –control pooled data that is from the case data. In order to estimate parameters such as absolute risk and attributable risk, the constant from the logit needs to be corrected to reflect the difference between λ and $\bar{C}$. Specifically, the regression's intercept in the logit β_0 needs to be adjusted as :

$$\beta_0 - \ln\left[\left(\frac{1-\lambda}{\lambda}\right)\left(\frac{\bar{C}}{1-\bar{C}}\right)\right] \qquad \text{(eq. 3.4)}$$

This result is attributable to Manski and Lerman (1977) or Prentice and Pyke (1979). The intuition behind this adjustment is that in general the ratio of case to control observations in the pooled data will not correspond to the ratio expected in the population. Hence, the intercept term needs to be rescaled so that predicted probabilities match what would be observed if all of the population data existed.

Sometimes researchers will not have an estimate of the incidence rate in the population. Theoretical work in econometrics such as Manski (1999) considers cases where there is no prior information about the range of plausible values of λ. However, at a minimum, researchers will have some idea of a plausible range of values for incidence in the population. Let λ_L and λ_H

indicate the lower and upper values of the plausible range of λ. King and Zeng (1999) suggest computing bounds on possible values of absolute and relative risk by estimating either at both λ_L and λ_H. Because absolute and relative risk are positive monotone functions of λ, computing either at the lower and upper values of λ defines bounds on the range of possible absolute and relative risks.

Attributable risk is more difficult, because it is not a positive monotone function of λ. Define $A(\lambda_k)$ as the estimate of attributable risk associated with an estimated incidence of λ_k. King and Zeng (1999) suggest checking for whether λ_L and λ_H are in a monotone region of attributable risk by evaluating whether attributable risk appears to have the same derivative with respect to λ at both its high and low values. This can be checked by verifying that the signs of $A(\lambda_{L+\varepsilon}) - A(\lambda_L)$ and $A(\lambda_{H+\varepsilon}) - A(\lambda_H)$ are the same. When λ_L and λ_H are in a monotone region of A, then bounds can be calculated as:

$$A \in \left\{ \min\left(A(\lambda_L), A(\lambda_H)\right), \max\left(A(\lambda_L), A(\lambda_H)\right)\right\}. \qquad \text{(eq. 3.5)}$$

Sometimes, population prevalence rates will be in a non-monotone region of attributable risk. In this case, King and Zeng (1999) show that bounds on attributable risk are given by:

$$A \in \left\{ \min\left(A(\lambda_L), A(\lambda_0), A(\lambda_H)\right), \max\left(A(\lambda_L), A(\lambda_0), A(\lambda_H)\right)\right\}. \qquad \text{(eq. 3.6)}$$

where $A(\lambda_0) = \frac{\sqrt{\omega}-1}{\sqrt{\omega}+1}$ and ω is the odds ratio:

$$\omega = \frac{\Pr(C=1|D=1)\Pr(C=0|D=0)}{\Pr(C=0|D=1)\Pr(C=1|D=0)}. \qquad \text{(eq. 3.7).}$$

In what follows, econometric work focuses on presenting estimates of attributable risk. Attributable risk is the focus of this study, because the primary aim of the empirical work is to identifier indicators associated with increased risk of participating in a worst form. Hence, the size of the increased risk associated with a given factor of interest is important. In the present case, attributable risk is computed using prior correction (eq. 3.4) to compute absolute risks and in turn compute the difference. All empirical work is implemented using the regression code available freely from King and Zeng (2001).

4. Analyzing Entry into a Worst Form: Child Domestics in Nepal

4.1 Data on Domestics (case data)

Child domestic workers are defined as children working in an employer's house with or without wages. They typically wash, cook, clean, care for children or elders, and help in other domestic related duties. The government of Nepal classifies child domestic work as a "worst form" of child labor. Domestics often live in isolation as it is unusual for households to employ multiple domestics, and domestics are often confined to their employer's premises. Domestics have little recourse to address issues over emotional deprivation and verbal or physical abuse. This confinement, isolation, and potential for abuse are the reasons why child domestic work is viewed as a worst form by the government. See Mukharjee et al (2004) for a more detailed presentation of the work environment of domestics.

Interestingly, there is little popular stigma against employing a domestic. This permits precise estimates of the incidence of domestic workers from the population census. The 2001 population and housing census captured 29,556 domestics age 6-18. This corresponds to roughly 0.4 percent of children in Nepal. Fourty-nine percent of all domestics are in Kathmandu. Fostered domestic workers are primarily urban phenomena. These 29.6 thousand domestics correspond to nearly 3 percent of Nepal's urban children.

The Child Domestic Workers survey (CDW) was conducted in 2003 by the ILO and the Central Bureau of Statistics in Nepal (ILO 2004). Urban areas in Nepal were stratified based on population, and blocks of households were randomly selected. Within each selected block, lists of residents were collected for each household in the block. Detailed questionnaires on the domestic's background, work conditions, etc. were administered to sampled domestics. Because of the randomized nature of this survey and the transparency of the survey design, it is possible to use the CDW to construct estimates of the urban child domestic population in 2003. The CDW finds 35,286 child domestics aged 6-18 in Nepal in 2003 (Sharma 2005), or 0.5 percent of children. This corresponds to 18.7 percent of all children estimated to be involved in a worst form of child labor in Nepal.

4.2 Data on Non-Domestics (control data)

The population and housing census of 2001 is used for the control sample. While the census includes information on domestics, no information is available on their background. Hence, it is not possible to conduct an analysis of selection into domestic service in the census. Moreover, because domestics can be explicitly identified in the census, it is easy to exclude them from the control sample and thereby be assured of the validity of the assumption that the control sample is uncontaminated.

However, an important, substantive issue with the census is that it is only possible to discern familial relationships for children of the household head. This introduces non-random selection bias into the control sample by eliminating children who live in households where a parent is not codified as the head. This could be a problem for inference if whether a parent is coded as a household head in the census is correlated with selection into domestic service and other observable household characteristics. Parental death is one potential concern. A child who has experienced a parental death is less likely to have a parent coded as the household head (mechanically, they have one fewer parent who could be a household head). If parental death is associated with other background characteristics and selection into domestic service, any estimates of attributable risk associated with the background characteristics could be severely biased. Unfortunately, there appears to be no obvious solution to this problem.

The census also requires two additional restrictions. First, information on economic activities is not collected for children below age 10. An estimated 1, 517 children 6-9 work as domestics in Nepal based on the CDW survey, but it is impossible to draw inference about what drives selection into these activities using the census as a source of control data. Second, education data is incomplete on children above age 14 in the census because of an odd skip pattern in the questionnaire. The CDW found an estimated 12,350 domestics age 15 and above, and again it will not be possible to consider this older population in the analysis. Thus, children 10-14 are the focus of the present study. This corresponds to an estimated 21, 659 working child domestics in the CDW survey or 0.72 percent of children 10-14 in Nepal.

4.3 Differences in Child Characteristics

Table 2 begins with a comparison of child characteristics of child domestics for the CDW and children who are not domestics in the census. Census children are trifurcated into children involved primarily in wage work, primary in home enterprise work, or no form of work. This later category includes children who work in domestic service in their own home, children who are inactive, and children are primarily students. For each classification of child, means and standard errors are reported. Both are corrected for sample design and weighted to be nationally representative. For each activity category in the census data, the hypothesis that the mean of the row characteristic in the census is different from the mean of the row characteristics in the CDW is tested. A * indicates the difference in means is statistically significant at 10 percent, and ** indicates the difference is significant at 5 percent.

The top row of table 2 counts the actual number of children observed in each (column) category. Thus, there are 486 observed child domestics 10-14 in the CDW data and 6,900 children in the census observed working for wages. The second row weights each observation by its inverse sampling probability to compute population estimates. Note that the CDW is unusual in that it is feasible to compute national estimates from the CDW. It will be more common in other applications to only be able to describe the target group for which data is available. There are an estimated 21,659 domestics 10-14 and 63,143 wage workers.

Ethnicity and caste are intertwined in Nepal, and the census identifies over 100 ethnic groups. The CDW records six different categories, and hence the census has been grouped to match the CDW. The Tharu are a middle status ethnic group indigenous to the Terai (plains) of Nepal. The Newari are also of middle status. They are typically characterized as the earliest inhabitants of the Kathmandu valley, and today they are primarily located in the Kathmandu valley of Nepal. A number of Hindu occupational castes are grouped under Dalit, and they are among the lowest status populations in Nepal. There would be considerable stigma against a high status individual having a Dalit inside their house. Muslims in Nepal are of relatively low status, although they are more apt to be welcomed into a high status Hindu house than would a Dalit. Most ethnic groups in Nepal have their own language, and it is not unusual to observe uneducated individuals speaking both Nepali and their native language. Table two reports whether an individual's native language is Nepali, Tharu, or something else.

Information on child schooling is reported by indicators for whether the child attends school currently, is able to read and write (self-assessed), has completed some school, standard five, or post primary schooling. Schooling categories are cumulative, so a child that has completed post primary has also completed primary, etc. An important caution in the descriptive statistics is that the CDW data are self-reported by a child to a survey enumerator whereas the census is administered to a household head by a local official, often a school teacher.

A comparison of child domestics with children in wage work is illustrative. Domestics are more likely to be female. This is not surprising. The types of activities performed by domestics are typically assigned to women in households, and women in Nepal have fewer labor market opportunities, making domestic service one of the few occupations open to young girls that will be bring income from outside their family. Domestics are more likely to be of high caste or Tharu than wage workers who are more apt to be Dalit or "other". As high status households are most apt to employ domestics, it makes sense that the domestics should come from ethnic groups whose presence in high status households is socially acceptable. The difference in incidence rates between domestics and wage work is such that there are actually more high caste children working as domestics than in wage work (9,017 v. 5,935). The Tharu are an especially interesting group. They are roughly 8 percent of the Nepali population, but they constitute 29 percent of domestics. This group is interesting, because a system of debt-bondage is pervasive in the indigenous Tharu population (see Edmonds and Sharma 2005 for discussion).

Self-reported schooling is substantially greater among domestics than wage workers. Schooling attendance is greater than any other working students and literacy rates and schooling completion are similarly elevated relative to both children working for wages or in home enterprises. This may reflect the reporting biases of domestics or that many domestics receive schooling as a part of their compensation package. Indeed, some statistical evidence and ample anecdotal evidence suggests that access to schooling is an important motivation in sending children to work as domestics (see Sharma 2005). That said, one has to be concerned that it is likely that a domestic responding to an ILO enumerator may give different answers than a parent in the census being asked questions by a local school teacher.

4.4 Differences in Background Characteristics

There is some evidence in the background characteristics that children are more likely to be domestics when other employment opportunities are scarce. Table 3 looks at how child background characteristics for children in the census differ from those observed for domestics. Wage work is most prevalent in the Terai whereas domestics are most prevalent in the hill areas. This hints at a degree of non-substitutability between wage work and domestic work that will be revisited later. Domestics are also less likely to come from households that own farmland than are children who are not working or children who work in family enterprises. That is, domestics seem to be coming from backgrounds where wage work and alternatives to wage work is relatively scarce.

The parents of domestics are less likely to have self employment than are parents of wage workers. Table 4 summarizes parental background characteristics (problems in the parental wage employment data in the CDW prevent its use herein). Three percent of domestics have a father who works in a family business while 11 percent of wage workers do. The difference for mothers is similar. Two percent of domestics have a mother with a small business while 10 percent of wage workers do. Domestics have a higher incidence of fathers who are disabled and a lower incidence of mothers who are disabled than any population group in the census. A domestic is seven times more likely to report that a father is disabled than is a child working for wages. However, a child working for wages is more than three times as likely to report a mother who is disabled. This is interesting, because a disabled father is likely to be associated with diminished family income while a disabled mother might raise the household's labor demand for domestic services. The incidence of disability is so low that only the difference in maternal disability between domestics and wage workers is statistically significant, but these disability patterns might be suggestive of the circumstances that lead a family to send a child to be a domestic.

4.5 Attributable Risk Estimates for Domestics

Estimates of attributable risk are in Table 5A for background characteristics that are likely to be associated with income generating activities in the sending family. Attributable risk is computed as described in the methodology section, following King and Zeng (2001). Specifically, the census and CDW data are pooled. An indicator that a child is a domestic is regressed (using a logit) on age, gender, ethnicity, language, geographic belt (hills, mountain, plains), development region (east, central, mid-west, west, far-west), and other controls that vary across specifications. The logit is estimated using prior correction (eq. 3.4) with a bias correction for small samples. Attributable risk is then computed by estimating the differences in absolute risk level as computed with (eq. 3.3). Standard errors are corrected for clustering in sample design.

In the first column of table 5A, attributable risk is computed from a regression on the variable indicated by the row in addition to the other controls listed in the preceding paragraph. That is, column 1 contains estimates of attributable risk from 15 separate regressions. In the column marked "conditional", all fifteen controls are included in one regression simultaneously, and attributable risk is computed for a difference from zero to one in the row variable. Predicted probabilities from a logit regression depend on what values of the other included controls are used. In table 5A, all controls other than the indicated row variable are evaluated at their mean when the row variable moves from zero to one. Confidence intervals are reported for both unconditional (each row variable in a separate regression) and conditional estimates of attributable risk. Obviously, attributable risk can only be computed when there is some variation in selection associated with the covariate. That is, conditional on the row variable, children must be observed both in and out of domestic service. This point is not substantive in Table 5A, but it will be important in some applications.

It is critical to remember that causal parameters are not being computed. Attributable risk is the change in probability of observing a domestic associated with a change from 0 to 1 (or mean to mean plus one) in the row variable. That is, it is an observational statistic based on existing data, and it cannot be used to predict out of sample changes in the incidence of child domestic service with changes in row variables. This point is illustrated in a comparison of the interpretation of the findings in the first column of table 5A to the interpretation of results in the column labeled "conditional". In column one, children from households with agricultural land are nearly 3 percentage points less likely to be observed as a domestic than children from families without land. The scale of the change in risk associated with being a domestic is enormous for an activity with an incident rate of 0.72 percent. The "conditional" column hints at part of the reason why this magnitude appears so large. Owning farmland is associated with a number of other background characteristics that also reduce the probability of a child being a domestic. When a small set of the possibly relevant background characteristics are captured in the conditional specification, the risk attributable to owning land declines in magnitude by approximately one third.

Several individual observable characteristics are associated with large variation in the incidence of domestic service (column 1 of table 5A). In addition to owning agricultural land, having a father who owns a small business or who can read or write, or having a mother who owns a small business all are associated with substantively lower participation rates in domestic work. The largest variation in the risk of domestic service is attributable to variation in father's disability status. Having a disabled father is associated with a nearly ten-fold increase in the chance of observing the child as a domestic.

The specification that pools all (row) common characteristics allows the consideration of how changes in multiple covariates at the same time are associated with changes in the probability that a child is a domestic. This is more informative than the attributable risks reported in the conditional attributable risks in Table 5A, because it is unlikely that a father who is disabled is as likely to work in the formal wage sector as the average worker. In the present context, this is important since estimates of attributable risk depend on the value of all included covariates. More informative attributable risk calculations are in Table 5B.

Table 5B reports estimates of attributable risk with changes in multiple risk factors simultaneously. In the first columns, all probabilities are calculated for households with average probability of holding land, and in the second columns, everything is computed for households without any landholdings. Several scenarios are considered in Table 5B. The first two rows consider a move from father (mother in row 2) who is not disabled that has population means for all labor related variables to a father (mother) that is disabled and cannot work. The second set of results considers variation in literacy rates among mothers and fathers who have no formal schooling. The third set of results considers increases in work in family businesses.

The largest predictor of domestic service is paternal disability in landless households. Similarly paternal literacy seems to substantially reduce the probability a child is observed as a domestic (although the magnitude of the decline in attributable risk associated with paternal literacy is about a fifth of the increase associated with paternal disability). Both paternal illiteracy and paternal disability are likely to be associated with diminished living standards, much more so than maternal disability or illiteracy. In contrast, maternal disability lowers the probability that a child is observed as a domestic. This likely reflects that most domestics are girls, and maternal disability raises the return on the girl's time within her own home. Hence, the relative return to sending her as a domestic is lower with maternal disability. Similarly, employment opportunities within the household lower the risk that the child is observed as a domestic. In general, attributable risk estimates are larger in magnitude for landless households.

Table 5C is an interesting contrast to the findings for selection into domestics. In particular, 5C mimics 5B in form but computes attributable risk of selection into wage work. That is 5C is based on a logit regression of an indicator that a child participates in wage work on all the row variables in the conditional column of Table 5A as well as all the controls described in the table notes using prior correction and the small sample bias correction. Interestingly, paternal literacy is associated with reduced wage work (much more so than maternal literacy), similar to what was observed for domestics. In contrast to what was observed in domestics, parent participation in home enterprises is associated with an increased risk of wage labor participation by the child in landless households especially, and maternal disability is associated with an increased risk of wage work rather than the observed decreased risk of being a domestic. Thus, the contrasting results in 5C and 5B suggest the possibility that response of worst forms and more common forms of child labor may differ in how the react to changes in the family's environment.

5. Analyzing Entry into a Worst Form: Short Route Porters

5.1 Data on Porters

For many areas of Nepal, porters are critical for transporting consumer goods, getting business output for market, and delivering construction materials to remote areas. Porters are typically classified as long route and short route porters, and the two types of porters appear to be somewhat segmented. This study focuses on short route porters. Short route porters are typically contracted at spot markets in local markets and bus parks.

Portering is considered a worst form of child labor, because children often carry heavy loads, across difficult terrain, for long hours. In the data used in this study, short route porters report working approximately 10 hours per day for 6 days a week on average. Two thirds of short route porters report averaging roughly 10 routes per day that range in weight from 10 to 50 kilograms (although one has to be suspect about self-reported load weights). Sixty percent report not wearing protective gear such as boots, gloves, or pads on the head.

The short route porter (SRP) survey was conducted in urban areas of Nepal as that is where short route portering is concentrated. Rather than sampling households as in the CDW survey, the SRP survey sampled work sites: markets and bus parks. Out of an estimated 423 market centers and bus stops, a random sample of porters was interviewed in 97 randomly selected market centers and 15 randomly selected bus parks. When appropriately weighted, the SRP survey suggests a total of 5,087 short route child porters age 6-17 in Nepal in 2003. A total of 30 of these are below the age of 10, and most are age 14 or more. In the present study, we focus on short route porters age 10-14. There are an estimated 1,404 short haul porters age 10-14 in urban Nepal in 2003.

5.2 Differences in Child Characteristics

As with the analysis of child domestics, the population census is used to create a control sample. The difficulties associated with identifying parents in the census are still a substantive problem in the analysis of selection into portering. An additional problem is that it is not possible to identify in the census whether a child is a porter. Hence, it is necessary to assume that no porters are sampled in the 11% public use sample of the census used in this analysis. To the extent that some of the control children are (unobserved) porters, our estimates of selection into portering could be severely biased.

Children engaged in short route portering appear similar to children involved in other forms of wage work. Table 6 compares child characteristics of short route porters from the SRP and children in the census who live with a parent (this restriction is important in the subsequent discussion). Census children are trifurcated into children involved primarily in wage work, primary in home enterprise work, or no form of work. For each classification of child, means and standard errors are reported. Both are corrected for sample design and weighted to be nationally representative. For each activity category in the census data, the hypothesis that the mean of the row characteristic in the census is different from the mean of the row characteristics in the SRP is tested. A * indicates the difference in means is statistically significant at 10 percent, and ** indicates the difference is significant at 5 percent.

Short route porters differ from wage workers in that they are more likely to be high status, more likely to speak Nepali, and less likely to be Muslim. These differences likely reflect that short route porters are only interviewed in urban areas, and tend to be from those some areas. That is, most short route porters in the survey are not in-migrants to urban areas. Thus, populations of rural origin (such as Muslims or non-Nepali speaking populations) are less present in the SRP. The reported completed schooling of porters is also higher than other wage workers. Whether this reflects reporting bias or something about those who select into portering is unclear.

5.3 Differences in Background Characteristics

Porters are more likely to be from hill areas than wage workers. Table 7 summarizes various child background characteristics. It is not surprising that porters are more prominent in hill areas, less prominent in plains, as the road infrastructure around the Terai's mid sized cities are generally better than in the hill areas. Moreover, porters are more active in the western development region of Nepal than are wage-workers. This likely reflects the fact that short haul porters often work around bus stations and larger markets, which are more prevalent in the central and west regions of Nepal than elsewhere.

Porters seem to come from relatively disadvantaged backgrounds. Parental characteristics of porters are summarized in Table 8. Literacy among both fathers and mothers is lower for porters than wage workers. Porters report higher levels of paternal schooling completion than paternal literacy, so either there is data error on the coding of paternal education or there are lots of illiterate fathers of porters who have completed primary school. The maternal education data is consistent with the observed lower maternal literacy rates for porters than wage workers. Porters are also more likely to report both a father or a mother that is disabled, and to report a mother who is working.

5.4 Attributable Risk Estimates for Porters

Paternal and maternal disability and maternal wage work stand out as strong predictors of selection into portering. The first column of table 9A contains estimates of attributable risk for each listed row characteristic separately. Attributable risk is computed as described in the methodology section, following King and Zeng (2001). Specifically, the census and SRP data are pooled. An indicator that a child is a porter is regressed (using a logit) on age, gender, ethnicity, language, belt, development region, and, in column 1, the variable indicated by the row. The logit is estimated using prior correction (eq. 3.4) with a bias correction for small samples. Attributable risk is then computed by estimating the differences in absolute risk level as computed with equation 3.3. Standard errors are corrected for clustering owing to sample design.

Paternal disability raises the probability a child is observed portering by more than a tenth of a percent. Maternal disability has a similar positive association with portering. The maternal disability pattern is the opposite of what was observed in domestics. Children are less likely to be a domestic when their mother is disabled, but they are more likely to be porters. Another strong indicator factor associated with an elevated risk of being a porter is having a mother working for wages. Female wage work is relatively rare in Nepal, so that this observation might reflect something about the geographic location of the control population relative to the portering population. It is also consistent with the idea that women only enter the labor market when the family's marginal utility of income is very high. Hence, the wage work observation might be consistent with a view that poverty is critical in explaining selection into portering.

Attributable risk estimates in table 9A are not causal estimates of how selection into portering will be affected by changes in any of the listed observable characteristics. Rather, they merely describe how the likelihood of observing a child porter varies with changes in maternal or paternal characteristics. The conditional attributable risk estimates are computed by holding all listed observable characteristics constant (at their mean) except for the variable specified by the row. Paternal disability is the largest predictor of selection into portering.

Interestingly, the findings for porters in table 9A differ than those observed for domestics in table 5A. For domestics, maternal disability diminished the risk of observing a child as a domestic. However, porters are more likely to report maternal disability than other children. Porters are also more likely to report maternal wage employment which is likely a correlate of poverty in Nepal (especially conditional on location and ethnicity). Hence, one interpretation of the porter data is that it is more consistent with additional income concerns alone than is the domestic evidence (where the different responses of domestic service to paternal and maternal disability hinted at the importance of the household's need for the child's labor).

Table 9B contains estimates of attributable risk for becoming a porter associated with changing several of the covariates from Table 9A (right side) simultaneously. For example, a mother who is disabled and not working raises the probability a child is observed as a porter by nearly 0.2 percentage points for a landless household (nearly double the risk observed in a household with land). In general, landless households are more likely to be observed sending children to porter in the context of a paternal or maternal disability or if both mother and father are observed working. A comparison of attributable risk estimates in table 9B to that observed for wage work in table 5C is illustrative. The patterns observed with disability and literacy are similar for portering and other types of wage work. The main difference with portering is that the presence of self employment in the household lowers the risk of portering (while it raises the risk of observing a child in wage work). This is similar to what was observed for domestics in table 5B. Hence, the portering data at least contains some suggestion that the availability of employment within the household may be associated with a diminished risk of seeking work in portering outside of the family. It is important to note, however, that the magnitudes of the observed changes in attributable risk with home enterprises are very small.

6. Analyzing Selection into Worst Forms: Ragpickers

6.1 Data on Ragpickers

Ragpickers collect rags and other used goods to be recycled and reused. As an activity, ragpicking is primarily an urban activity. Adult and child ragpickers collect plastics, polyethylene, bottles, metals, and tins from dumping sites, streets, river banks, etc. These collected materials are sold to junkyards and shops which in turn sell these materials to suppliers for recycling. Ragpicking is nearly universally viewed as a worst form because of the extremely hazardous work environment.

The ragpickers survey (RAG) was conducted in urban areas of Nepal. The original survey design was to sample sites where ragpickers worked. However, researchers found it difficult to interview children in dumping areas, garbage disposal and refuse areas, slums, and river banks and faced additional difficulties associated with the mobility of ragpickers. Thus, while the survey was being fielded, enumerators abandoned the original sample frame and interviewed children in junkyard shops or locations where they spend their leisure time.

The nonrandom nature of the survey and this disconnect between sample design and survey implementation creates an unknowable array of problems for inference and makes it impossible to know whether estimates of the incidence of ragpicking from this data are accurate. If one is willing to treat the RAG data as if it were based on random sampling of job sites, it is possible to make inferences about the scope of ragpicking in Nepal. That said, the survey suggests that there are 3, 695 child ragpickers age 6-18 in Nepal in 2002. 974 of these ragpickers are age 10-14.

6.2 Differences in Child Characteristics

As with porters and child domestics, the population census is source of the control sample, and all of the qualifications discussed in the context of porters are relevant in the analysis of selection into ragpicking as well. Specifically, the sample selection necessary for matching children to parents in the census and the risk of contamination in the control census because of an inability to identify ragpickers in the census data both potentially create substantive biases in the present analysis.

There are a total of 372 ragpickers age 10-14 interviewed in the RAG survey. If population projections are correct, this implies that more than one third of ragpickers 10-14 are interviewed. Various child characteristics of ragpickers are in table 10. Table 10 also summarizes child characteristics for wage workers, children in home enterprises, and children who do not work in the population census for comparison purposes. For each activity category in the census data, the hypothesis that the mean of the row characteristic in the census is different from the mean of the row characteristics in the RAG is tested. A * indicates the difference in means is statistically significant at 10 percent, and ** indicates the difference is significant at 5 percent.

Ragpickers tend to be younger than wage workers, and they are much less likely to be ethnic Tharu. The fact that ragpickers are younger is consistent with a role for employment opportunities in selection into ragpicking as young children have fewer formal wage earning opportunities. Ragpickers also appear to be relatively more educated although it seems likely that this difference with the census might reflect biases owing to who responds to the questionnaire. Ragpickers are less likely to be higher caste than the general population, and less likely to be Tharu. The low incidence of Tharu ragpickers is interesting. Two possible explanations seem obvious. First, ragpicking may be more common in places where the Tharu are less prevalent. Second, desperate Tharu may have better options than ragpicking. Bonded labor is common in the Tharu population, and it could be that debt-bondage is preferable to ragpicking.

6.3 Differences in Background Characteristics

Ragpickers are much more likely to be from hill areas than are wage workers and are more likely to be from central Nepal. Table 11 describes background characteristics of ragpickers from the RAG survey and other children in the census. The concentration of ragpickers is consistent with the location of the large recycling centers which are especially prevalent in the Kathmandu Valley (central-hill). However, this is also where trash is especially concentrated because of the population density. Hence, one should not infer that the presence of the recycling industry is the reason why there are ragpickers in the Valley. Of course, if there was no market for their output, it seems unlikely children would pick through trash except to help meet basic needs.

Ragpickers are also less likely to come from households that own farmland. This observation is consistent with the view that a lack of alternative income generating strategies may play an important role in selection into ragpickers. To some extent this seems obvious as its hard to imagine that picking through trash and debris is ever someone's first choice for income.

However, it is easy to over interpret this correlation between farmland and ragpicking. Children working for wages are less likely to own farmland than children who work in family enterprises (like farms). Moreover, a lack of land may be correlated with fewer at home employment opportunities but it also may be correlated with a lack of income.

Several parental background characteristics suggest that selection into ragpicking is correlated with having a relatively disadvantaged background. Table 12 contains descriptive statistics on parental background for ragpickers, children in wage work, children working in family enterprises, and children that do not work. Maternal literacy is lower than wage workers and both mothers and fathers of ragpickers are less likely to have some post primary education.

Moreover, parental disability is a strong correlate of ragpicking (as has been observed with porters and domestics as well). Four percent of ragpickers have a disabled father, and 1 percent of ragpickers have a disabled mother. For contrast, less than one tenth of one percent of the general population has a disabled father.

Also, ragpickers are less likely to have a parent who owns a small business or is employed in agriculture. While 63 percent of children in wage work have a father who works in agriculture, less than 9 percent of ragpickers do. Forty-eight percent of wage earning children have a mother in agriculture. Less than 8 percent of ragpickers have a mother engaged in agriculture. It is impossible to discern whether this reflects the employment opportunities open to the children, the family's disadvantaged background, or something transitory in the child's family's economic environment. However, the differences in the means are not present in other activities.

6.4 Attributable Risk Estimates for Ragpicking

Table 13A provides estimates of attributable risk by observable background and family characteristic. It is constructed identically to tables 5A and 9A for the domestics and porters respectively. See the discussion of each table in preceding sections for explanation of how to read the table's content.

Paternal disability stands out as the largest predictor of selection into ragpicking. Less than three hundredths of a percent of children 10-14 are engaged in ragpicker, but paternal disability raises the probability that a child is observed in ragpicking by nearly two tenths of a percent. While no other characteristic is as strong a predictor as paternal disability, the observation that the child's family's employment background is an important risk factor persists in the attributable risk estimates. Either owning agricultural land or maternal or paternal work in agriculture substantially lowers the odds of observing a child in ragpicking. This may reflect differences in location rather than the household's employment opportunities, but the fact that maternal self employment also is associated with a diminished risk of observing a child as a ragpicker suggests that at least some part of why these are risk factors may owe to employment opportunities.

Estimates of changes in attributable risk are generally uninformative in the conditional specification. See table 13B. The one exception is with regards to paternal disability, because that is such a large predictor of selection into ragpicking. Recall (table 12) that 4 percent of ragpickers report a disabled father whereas less than a tenth of a percent of children in wage work report a disabled father. In table 13B, observing a disabled father significantly increases the risk that a child is observed ragpicking, and this increased risk of ragpicking is larger for the landless than for children who come from families with land. The larger magnitudes estimated for landless families are consistent with the descriptive data which also suggest a link between selection into ragpicking and employment opportunities. However, in general, there are few observable characteristics other than paternal disability which can predict a risk of ragpicking. This suggests that most of the determinants of selection into ragpicking are outside the scope of the available data.

Another important reason why the attributable risk of ragpicking is so small is that ragpicking is estimated to be extremely rare (less than three hundredths of a percent of children 10-14). In section 3, we discussed how to estimate bounds on attributable risk when the incidence of a worst form is uncertain. In table 13C, we implement this methodology. The incidence of ragpicking is assumed to vary between 0.03 percent and 0.3 percent. Thus, the estimates from table 13B are used for one bound and attributable risks are recalculated assuming an incidence of three tenths of a percent to form the other bound. The data pass the test for positive monotonicity suggested in section 3. Table 13C contains bounds on attributable risk for landless households.

Contrasting table 13C and Table 13B highlights how important estimates of baseline incidence are for computing attributable risk. In very low probability events, it is a challenge to capture covariates that substantially increase the risk of the child entering the worst form simply because the event itself is rare. In general, the patterns recovered by the bounds estimates in table 13C suggest risk factors for entry into ragpicking that are similar to that observed for portering (table 9B) and different with regards to self employment from what was observed in table 5C for wage work.

7. Discussion

This study illustrates an approach to study the correlates of participation in a worst form of child labor. Survey data on the background characteristics of children engaged in worst forms of child labor are combined with nationally representative data on those same background characteristics. With this combination of data, it is possible to calculate what characteristics are associated with an increased risk of engaging in a worst form of child labor. When combined with data on the incidence of the worst form in the population, it is possible to compute how large of an increased risk of involvement in a worst form can be attributed to variation in a characteristic. This simple, descriptive comparison sheds some light on how the background characteristics of children engaged in domestic work, portering, and ragpicking in Nepal differ from the general population of children in Nepal.

Are worst forms different than other more common forms of employment from the perspective of the agent who makes decisions about child time allocation? The data are consistent with the view that worst forms are different. As reviewed in section 2.2, most theoretical treatments of entry into worst forms posit that children are more likely to enter worst forms when their alternative employment opportunities are limited. A child is more likely to participate in a worst form when the net economic return is larger. The data suggest that children are more likely to be involved in wage work when there is a family enterprise. This might be causal effect of the family's business or simply reflect that family's are more apt to own businesses in locations with more active labor markets. However, children are less likely to engage in work as domestics, ragpickers, and porters when there is a family business at home. This association could reflect something about the impact of a family enterprise on entry into worst forms through the value of child time in the family business or the enterprise's correlation with family incomes. Alternatively, the association between family enterprises and entry into worst forms might owe to an association between family enterprises and the overall local labor market (as speculated with regards to wage work). Domestics typically work away from home while most porters and ragpickers are working in the same geographic location as their parents. Thus, if omitted labor market characteristics were driving the finding that home enterprises are associated with a reduced risk of participation in a worst form, it is surprising that the ragpicker and porter patterns would differ from that observed for wage work. The idea that the association between home enterprises and entry is driven by either the potential economic contribution of the child to its household or household living standards is more compelling.

There are some further associations in the data that are consistent with the idea that the child's employment opportunities in their household cast an important influence on entry into worst forms. Child domestics are more likely to be female who are likely to have few other employment opportunities outside their family (relative to boys). Domestics come from areas where wage work is rarer. Owning agricultural land and having a father or mother with self employment also lowers the probability that a child is observed as a domestic. Similarly, households with porters and ragpickers are less likely to own agricultural land, although this association is not particularly robust for these two populations. Portering is most prevalent in areas where there is the most need for porters as ragpickers are most prevalent in areas where there is trash and a recycling industry. Maternal wage work also seems to predict portering, and like with domestics, self-employment is negatively correlated with ragpicking. However, all of these characteristics predict only a small amount of the observed prevalence of each worst form.

Parental, especially paternal, disability stands out as a strong predictor of observing a child in one of these three worst forms in Nepal. Relative to wage working children, domestics are 7 times, porters are 5 times, and ragpickers are 4 times more likely to report that their father is disabled.   This association between paternal disability and entry into worst forms could reflect that children are more vulnerable to victimization when their father is disabled, but their father is still living and there is little correlation between paternal and maternal disability in the data. Paternal disability also does not appear to be strongly associated with some particular source location for the child; it is not likely to be capturing omitted geographic factors. Moreover, the magnitudes are so much larger than what is observed for any individual measure of parental self-employment or other household economic activity, it seems likely that paternal disability reflects more than an association between paternal disability and employment opportunities open to the child within its own household (which are conditioned on in the empirical work). It seems most plausible that the strong association between paternal disability and entry into worst forms reflects that paternal disability is strongly correlated with the child's family being substantially poorer. If this interpretation is correct, then the data support Dessy and Pallage's (2005) model of partially compensated wage differentials for worst forms of child labor.

The methodology used to asses the correlates of selection into worst forms is extremely general, but its data requirements are not trivial. Namely, four conditions must be met:

1. The type of work that qualifies as a worst form is explicitly identified
2. Reasonable estimates of the incidence of that worst form exist in the population
3. There are individual level data on background characteristics of children engaged in the worst form available
4. There are nationally representative data on the same set of background characteristics available for the general population.

Unfortunately, the data on children in worst forms and the representative data used in this study are not perfectly consistent in how they collect information, and there is limited information that is in common in the targeted surveys and the nationally representative data. This problem is easily resolved if future survey work on children in worst forms would merely be attentive to existing data resources, and design their survey work to be in part consistent with nationally representative data. Even better of course, would be to integrate target surveys into a broader national survey program and to combine that effort with scientific evaluation of interventions aimed at children engaged in worst forms of child labor..

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Table 1: Prevelance Rates of Worst Forms of Child Labor in Nepal

	Number	(%)
Children in bonded labour	17,152	13.5
Child ragpickers	3,965	3.1
Child porters	46,029	36.2
Child domestic workers (a)	55,655	43.8
Children in mines	115	0.1
Children in the carpet sector	4,227	3.3
TOTAL	**127,143**	**100**

(a) for urban areas only
source: ILO (2001) using the MES

Table 2: Comparison of Child Characteristics in Domestic Workers Survey and Census

	Domestic Workers Survey		2001 Population and Housing Census								
			Wage Work			Home Enterprise Work			Not Work		
	Mean	SE	Mean	SE		Mean	SE		Mean	SE	
# of observations	486		6,900			25,390			297,506		
Estimated population size	21,659		63,143			254,290			2,592,568		
Age	12.422	0.040	12.419	0.020		12.272	0.010	**	11.823	0.003	**
Female	0.523	0.035	0.370	0.008	**	0.611	0.004	**	0.470	0.001	
Ethnicity											
High Status Hindu Caste	0.416	0.045	0.094	0.005	**	0.253	0.005	**	0.351	0.003	
Tharu	0.287	0.062	0.151	0.007	**	0.062	0.003	**	0.076	0.002	**
Newar	0.020	0.008	0.027	0.003		0.025	0.002		0.057	0.002	**
Dalit	0.084	0.026	0.302	0.009	**	0.202	0.004	**	0.145	0.002	**
Muslim	0.004	0.003	0.100	0.007	**	0.047	0.003	**	0.034	0.001	**
Other	0.189	0.039	0.325	0.008	**	0.411	0.006	**	0.336	0.002	**
Native Language											
Nepali	0.376	0.037	0.222	0.008	**	0.484	0.006	**	0.520	0.003	**
Tharu	0.286	0.062	0.133	0.007	**	0.052	0.003	**	0.058	0.002	**
Other	0.339	0.040	0.644	0.010	**	0.464	0.006	**	0.422	0.003	**
In School	0.467	0.056	0.159	0.006	**	0.271	0.005	**	0.864	0.001	**
Can read and write	0.654	0.039	0.272	0.008	**	0.381	0.005	**	0.875	0.001	**
Completed Some School^	n/a		0.185	0.007		0.291	0.005		0.822	0.002	
Completed Std. 5	0.161	0.024	0.063	0.004	**	0.105	0.003	**	0.346	0.002	**
Completed Post Primary	0.084	0.012	0.025	0.002	**	0.049	0.002	**	0.191	0.002	**

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

^All child domestics report completing grade 1.

Table 3: Comparison of Background Characteristics in Domestic Workers Survey and Census

	Domestic Workers Survey		2001 Population and Housing Census					
			Wage Work		Home Enterprise Work		Not Work	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Belt								
Hill	0.546	0.207	0.191	0.011 *	0.495	0.007	0.462	0.005
Terai	0.454	0.207	0.789	0.011	0.368	0.006	0.478	0.005
Region								
East	0.254	0.173	0.312	0.011	0.192	0.005	0.230	0.004
Central	0.448	0.225	0.406	0.012	0.306	0.006	0.335	0.005
West	0.158	0.118	0.107	0.006	0.155	0.005	0.223	0.004
Mid-West	0.113	0.088	0.112	0.007	0.188	0.005	0.117	0.003
Far-West	0.027	0.023	0.063	0.006	0.158	0.005 **	0.094	0.003 **
Household Background								
Owns Farmland	0.605	0.051	0.508	0.010 *	0.934	0.002 **	0.821	0.005 **

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

Table 4: Comparison of Parental Characteristics in Domestic Workers Survey and Census

	Domestic Workers Survey		2001 Population and Housing Census					
			Wage Work		Home Enterprise Work		Not Work	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Father Characteristics								
Reports Characteristics	0.765	0.040	0.910	0.004 **	0.906	0.002 **	0.888	0.001 **
Age	42.367	0.664	43.855	0.196 **	45.175	0.099 **	44.717	0.040 **
Can Read and Write	0.370	0.038	0.290	0.011 **	0.335	0.004	0.573	0.003 **
Completed Some School	0.151	0.021	0.179	0.010	0.162	0.003	0.334	0.003 **
Completed Std. 5	0.147	0.022	0.148	0.009	0.101	0.003 **	0.269	0.003 **
Completed Post Primary	0.085	0.013	0.124	0.009 **	0.068	0.002	0.214	0.003 **
Disabled	0.007	0.004	0.001	0.001	0.002	0.000	0.001	0.000
Not Work	0.077	0.017	0.057	0.004	0.036	0.002 **	0.066	0.001
Owns Small Business	0.034	0.007	0.108	0.006 **	0.059	0.002 **	0.109	0.002 **
Employed in Agriculture	0.646	0.048	0.629	0.011	0.862	0.003 **	0.682	0.005
Mother Characteristics								
Reports Characteristics	0.797	0.031	0.919	0.004 **	0.928	0.002 **	0.953	0.001 **
Age	36.462	0.507	39.468	0.172 **	40.337	0.084 **	39.484	0.035 **
Can Read and Write	0.173	0.043	0.151	0.010	0.075	0.003 **	0.232	0.003
Completed Some School	0.035	0.009	0.088	0.008 **	0.026	0.001	0.117	0.003 **
Completed Std. 5	0.033	0.009	0.079	0.007 **	0.017	0.001 *	0.090	0.002 **
Completed Post Primary	0.011	0.006	0.072	0.007 **	0.010	0.001	0.068	0.002 **
Disabled	0.002	0.002	0.007	0.002 **	0.006	0.001 *	0.004	0.000
Not Work	0.260	0.043	0.376	0.010 **	0.161	0.004 **	0.366	0.003 **
Owns Small Business	0.019	0.010	0.099	0.006 **	0.098	0.003 **	0.102	0.001 **
Employed in Agriculture	0.575	0.059	0.477	0.011	0.780	0.004 **	0.556	0.004

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

Table 5A: Attributable Risk Estimates for Background Characteristics in Domestic Workers Survey

	Unconditional			Conditional		
	Attributable Risk	95% Confidence Interval		Attributable Risk	95% Confidence Interval	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Household Background						
Owns Farmland	-0.0284	-0.0597	-0.0096	-0.0198	-0.0399	-0.0090
Father Characteristics						
Reports Characteristics	-0.0314	-0.0618	-0.0131			
Can Read and Write	-0.0155	-0.0306	-0.0066	-0.0075	-0.0147	-0.0033
Disabled	0.0753	0.0111	0.1921	0.0497	0.0101	0.1291
Not Working	0.0060	-0.0020	0.0216	-0.0031	-0.0079	0.0015
Owns Small Business	-0.0125	-0.0269	-0.0048	-0.0076	-0.0169	-0.0026
Employed in Agriculture	-0.0036	-0.0165	0.0052	-0.0020	-0.0079	0.0028
Mother Characteristics						
Reports Characteristics	-0.0541	-0.1079	-0.0218			
Can Read and Write	-0.0060	-0.0171	0.0020	-0.0024	-0.0088	0.0042
Disabled	-0.0051	-0.0232	0.0403	-0.0036	-0.0141	0.0186
Not Working	-0.0075	-0.0149	-0.0019	-0.0088	-0.0194	-0.0034
Owns Small Business	-0.0152	-0.0300	-0.0070	-0.0107	-0.0212	-0.0045
Employed in Agriculture	0.0004	-0.0089	0.0067	-0.0057	-0.0168	-0.0009

All regressions include controls for child age, gender, ethnicity, language, belt, and development region. All standard errors corrected for clustering at the block level (primary sampling unit). Estimates computed using King and Zeng's relogit code with prior correction: http://gking.harvard.edu/stats.shtml#relogit. Each estimate of attributable risk in the "unconditional" column is from a separate regression. Each estimate in the "conditional" column is from one regresion, including all of the listed covariates plus additional controls for whether mother and father have completed primary or post primary school. All estimates assume an incidence rate of child domestic service of 0.72 percent. Attributable risks are computed for a change in the row variable from 0 to 1 at the mean of all other covariates except all "conditional" estimates are computed at father and mother reports characteristics =1.

Table 5B: Attributable Risk Estimates for various scenarios in Domestic Workers Survey

	At Mean Landholding Rate			Landless		
	Attributable Risk	95% Confidence Interval		Attributable Risk	95% Confidence Interval	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Disability						
Dad is disabled & cannot work (1)	0.044	0.004	0.131	0.109	0.013	0.273
Mom is disabled & cannot work (2)	-0.004	-0.014	0.019	-0.012	-0.038	0.048
Literacy						
Literate dad (avg sch) & illiterate mom (no sch.) to literate mom (3)	-0.002	-0.006	0.003	-0.005	-0.019	0.008
Illiterate mom & dad to literate dad (no schooling) (4)	-0.007	-0.015	-0.003	-0.020	-0.040	-0.010
Illiterate mom & dad to literate mom & dad (no schooling) (5)	-0.009	-0.020	-0.003	-0.025	-0.056	-0.008
Home Enterprises						
Household without any self employment to mom self employment (6)	-0.010	-0.022	-0.005	-0.029	-0.061	-0.014
Household w/o self emp. to dad self emp. (7)	-0.009	-0.020	-0.004	-0.023	-0.051	-0.010
Household w/o self emp. to mom & dad self emp (8)	-0.012	-0.025	-0.006	-0.035	-0.067	-0.016

Attributable risks computed using results from the "conditional regression" results in table 9a. The first columns compute probabilities for households with mean probability of holding land. The second column computes probabilities for household without landholdings.

(1) - Change in probability that child is a domestic if father moves from not disabled and mean work to disabled and no work (any catagory).

(2) - same as (1) for mother

(3) - change in probability that child is a domestic if dad is literate with average schooling and mom moves from illiterate to literate (with no schooling)

(4) - change in probability that child is a domestic if illiterate mom and dad shifts to a illiterate mom with literate dad (no schooling)

(5) - change in probability that a child is a domestic if illiterate mom and dad shifts to literate mom and dad (no schooling)

(6) - change in probability that child is domestic if household moves from no self employment to mom self employment

(7) - same as (6) only for father

(8) - change in probability that child is a domestic if household moves from no self employment to both mom and dad in self employment

Table 5c: Attributable Risk Estimates for various scenarios, census wage workers

	Average Land Holdings			Landless		
	Attributable Risk	95% Confidence Interval		Attributable Risk	95% Confidence Interval	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Disability						
Dad is disabled & cannot work (1)	0.002	-0.004	0.012	0.003	-0.007	0.021
Mom is disabled & cannot work (2)	0.013	0.004	0.024	0.021	0.008	0.041
Literacy						
Literate dad (avg sch) & illiterate mom (no sch.) to literate mom (3)	-0.001	-0.002	0.000	-0.002	-0.003	0.000
Illiterate mom & dad to literate dad (no schooling) (4)	-0.006	-0.007	-0.005	-0.010	-0.012	-0.008
Illiterate mom & dad to literate mom & dad (no schooling) (5)	-0.008	-0.009	-0.006	-0.013	-0.015	-0.010
Home Enterprises						
Household without any self employment to mom self employment (6)	0.001	0.000	0.002	0.002	0.000	0.004
Household w/o self emp. to dad self emp. (7)	0.007	0.005	0.009	0.011	0.008	0.015
Household w/o self emp. to mom & dad self emp (8)	0.009	0.006	0.012	0.014	0.010	0.020

Attributable risks computed using results from the "conditional regression" results in table 5. The first columns compute probabilities for households with mean landholdings. The second column computes probabilities for household without landholdings.

(1) - Change in probability that child is a wage worker if father moves from not disabled and mean work to disabled and no work.

(2) - same as (1) for mother

(3) - change in probability that child is a wage worker if dad is literate with average schooling and mom moves from illiterate to literate (with no schooling)

(4) - change in probability that child is a wage worker if illiterate mom and dad shifts to a illiterate mom with literate dad (no schooling)

(5) - change in probability that a child is a wage worker if illiterate mom and dad shifts to literate mom and dad (no schooling)

(6) - change in probability that child is wage worker if household moves from no self employment to mom self employment

(7) - same as (6) only for father

(8) - change in probability that child is a wage worker if household moves from no self employment to both mom and dad in self employment

Table 6: Comparison of Child Characteristics in Short Route Porters Survey and Census

	Short Route Porters Survey		2001 Population and Housing Census								
			Wage Work			Home Enterprise Work			Not Work		
	Mean	SE	Mean	SE		Mean	SE		Mean	SE	
# of observations	164		6,900			25,390			297,506		
Estimated population size	1,404		63,143			254,290			2,592,568		
Age	13.044	0.107	12.419	0.020	**	12.272	0.010	**	11.823	0.003	**
Female	0.282	0.058	0.370	0.008		0.612	0.004	**	0.470	0.001	**
Ethnicity											
High Status Hindu Caste	0.192	0.036	0.094	0.005	**	0.253	0.005	*	0.351	0.003	**
Tharu	0.126	0.042	0.151	0.007		0.062	0.003		0.076	0.002	
Newar	0.013	0.008	0.027	0.003	*	0.025	0.002		0.057	0.002	**
Dalit	0.285	0.068	0.302	0.009		0.202	0.004		0.145	0.002	**
Muslim	0.037	0.023	0.100	0.007	**	0.047	0.003		0.034	0.001	
Other	0.348	0.058	0.325	0.008		0.411	0.006		0.336	0.002	
Native Language											
Nepali	0.588	0.067	0.222	0.008	**	0.484	0.006		0.520	0.003	
Tharu	0.109	0.042	0.133	0.007		0.052	0.003		0.058	0.002	
Other	0.303	0.059	0.644	0.010	**	0.464	0.006	**	0.422	0.003	**
In School	0.190	0.054	0.159	0.006		0.271	0.005		0.864	0.001	**
Can read and write	0.687	0.046	0.272	0.008	**	0.381	0.005	**	0.875	0.001	**
Completed Some School	0.869	0.056	0.185	0.007	**	0.291	0.005	**	0.822	0.002	
Completed Std. 5	0.159	0.041	0.063	0.004	**	0.105	0.003		0.346	0.002	**
Completed Post Primary	0.085	0.034	0.025	0.002	*	0.049	0.002		0.191	0.002	**

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

Table 7: Comparison of Background Characteristics in Short Route Porters Survey and Census

	Short Route Porters Survey		2001 Population and Housing Census							
			Wage Work			Home Enterprise Work			Not Work		
	Mean	SE	Mean	SE		Mean	SE		Mean	SE	
Belt											
Hill	0.503	0.086	0.191	0.011	**	0.495	0.007		0.462	0.005	
Terai	0.497	0.086	0.789	0.011	**	0.368	0.006		0.478	0.005	
Region											
East	0.131	0.054	0.312	0.011	**	0.192	0.005		0.230	0.004	*
Central	0.300	0.066	0.406	0.012		0.306	0.006		0.335	0.005	
West	0.363	0.087	0.107	0.006	**	0.155	0.005	**	0.223	0.004	
Mid-West	0.172	0.078	0.112	0.007		0.188	0.005		0.117	0.003	
Far-West	0.034	0.018	0.063	0.006		0.158	0.005	**	0.094	0.003	**
Household Background											
Owns Farmland	0.671	0.075	0.508	0.010	**	0.934	0.002	**	0.821	0.005	**

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

Table 8: Comparison of Parental Characteristics in Short Route Porters Survey and Census

	Short Route Porters Survey		2001 Population and Housing Census								
			Wage Work			Home Enterprise Work			Not Work		
	Mean	SE	Mean	SE		Mean	SE		Mean	SE	
Father Characteristics											
Reports Characteristics	0.847	0.044	0.910	0.004		0.906	0.002		0.888	0.001	
Age	48.779	1.696	43.855	0.196	**	45.175	0.099	**	44.717	0.040	**
Can Read and Write	0.263	0.054	0.290	0.011		0.335	0.004		0.573	0.003	**
Completed Some School^	n/a		0.179	0.010		0.162	0.003		0.334	0.003	
Completed Std. 5	0.342	0.136	0.148	0.009		0.101	0.003	*	0.269	0.003	
Completed Post Primary	0.251	0.120	0.124	0.009		0.068	0.002		0.214	0.003	
Disabled	0.005	0.004	0.001	0.001		0.002	0.000		0.001	0.000	
Not Work	0.059	0.023	0.057	0.004		0.036	0.002		0.066	0.001	
Owns Small Business	0.053	0.021	0.108	0.006	**	0.059	0.002		0.109	0.002	**
Works for Wages	0.425	0.065	0.571	0.009	**	0.095	0.003	**	0.225	0.003	**
Employed in Agriculture	0.545	0.067	0.629	0.011		0.862	0.003	**	0.682	0.005	**
Mother Characteristics											
Reports Characteristics	0.842	0.036	0.919	0.004	**	0.928	0.002	**	0.953	0.001	**
Age	40.512	1.872	39.468	0.172		40.337	0.084		39.484	0.035	
Can Read and Write	0.065	0.025	0.151	0.010	**	0.075	0.003		0.232	0.003	**
Completed Some School^	n/a		0.088	0.008		0.026	0.001		0.117	0.003	
Completed Std. 5	0.042	0.051	0.079	0.007		0.017	0.001		0.090	0.002	
Completed Post Primary	0.042	0.051	0.072	0.007		0.010	0.001		0.068	0.002	
Disabled	0.018	0.017	0.007	0.002		0.006	0.001		0.004	0.000	
Not Work	0.284	0.048	0.376	0.010	*	0.161	0.004	**	0.366	0.003	*
Owns Small Business	0.007	0.004	0.098	0.006	**	0.098	0.003	**	0.102	0.001	**
Works for Wages	0.301	0.057	0.350	0.009		0.027	0.002	**	0.053	0.001	**
Employed in Agriculture	0.503	0.071	0.477	0.011		0.780	0.004	**	0.556	0.004	

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

^All children report parent completing at least grade 1

Table 9A: Attributable Risk Estimates for Background Characteristics in Short Route Porters Survey

	Unconditional Attributable Risk	95% Confidence Interval		Conditional Attributable Risk	95% Confidence Interval	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Household Background						
Owns Farmland	-0.00033	-0.00078	-0.00003	-0.00009	-0.00028	0.00005
Father Characteristics						
Reports Paternal Char.	-0.00009	-0.00036	0.00008			
Can Read and Write	-0.00024	-0.00039	-0.00012	-0.00012	-0.00023	-0.00004
Disabled	0.00118	0.00006	0.00503	0.00065	0.00000	0.00315
Not Working	0.00000	-0.00016	0.00025	-0.00010	-0.00018	-0.00003
Owns Small Business	-0.00012	-0.00024	0.00002	-0.00009	-0.00017	-0.00002
Works for Wages	0.00030	0.00010	0.00065	-0.00003	-0.00011	0.00006
Employed in Agriculture	-0.00018	-0.00043	-0.00003	-0.00017	-0.00038	-0.00004
Mother Characteristics						
Can Read and Write	-0.00020	-0.00031	-0.00009	-0.00010	-0.00016	-0.00004
Disabled	0.00143	-0.00009	0.00773	0.00054	-0.00007	0.00236
Not Working	-0.00006	-0.00016	0.00006	-0.00001	-0.00012	0.00010
Owns Small Business	-0.00025	-0.00039	-0.00015	-0.00014	-0.00025	-0.00007
Works for Wages	0.00127	0.00051	0.00257	0.00042	0.00011	0.00105
Employed in Agriculture	-0.00010	-0.00034	0.00005	-0.00005	-0.00024	0.00004

All regressions include controls for child age, gender, ethnicity, language, belt, and development region. All standard errors corrected for clustering at the block level (primary sampling unit). Estimates computed using King and Zeng's relogit code with prior correction: http://gking.harvard.edu/stats.shtml#relogit. Each estimate of attributable risk in the "unconditional" column is from a separate regression. Each estimate in the "conditional" column is from one regresion, including all of the listed covariates. All estimates assume an incidence of short route porters of 0.05 percent. Attributable risks are computed for a change in the row variable from 0 to 1 at the mean of all other covariates except all "conditional" estimates are computed at father and mother reports characteristics =1.

Table 9B: Attributable Risk Estimates for various scenarios in Short Route Porters Survey

	At Mean Landholding Rate			Landless		
	Attributable Risk	95% Confidence Interval		Attributable Risk	95% Confidence Interval	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Disability						
Dad is disabled & cannot work (1)	0.0004	0.0000	0.0017	0.0006	-0.0001	0.0029
Mom is disabled & cannot work (2)	0.0008	0.0000	0.0043	0.0016	-0.0001	0.0102
Literacy						
Literate dad (avg sch) & illiterate mom (no sch.) to literate mom (3)	-0.0001	-0.0001	0.0000	-0.0001	-0.0003	0.0000
Illiterate mom & dad to literate dad (no schooling) (4)	-0.0001	-0.0003	-0.0001	-0.0002	-0.0005	-0.0001
Illiterate mom & dad to literate mom & dad (no schooling) (5)	-0.0002	-0.0003	-0.0001	-0.0003	-0.0007	-0.0002
Home Enterprises						
Household without any self employment to mom self employment (6)	-0.0002	-0.0003	-0.0001	-0.0003	-0.0006	-0.0001
Household w/o self emp. to dad self emp. (7)	-0.0001	-0.0002	0.0000	-0.0002	-0.0004	0.0000
Household w/o self emp. to mom & dad self emp (8)	-0.0002	-0.0003	-0.0001	-0.0003	-0.0006	-0.0001
Wage Labor						
Household w/ no wage work to dad (9)	0.0000	-0.0001	0.0001	0.0000	-0.0002	0.0001
Household w/ no wage work to mom & dad (10)	0.0003	0.0001	0.0010	0.0005	0.0001	0.0015

Attributable risks computed using results from the "conditional regression" results in table 9a. The first columns compute probabilities for households with mean probability of holding land. The second column computes probabilities for household without landholdings.

(1) - Change in probability that child is a porter if father moves from not disabled and mean work to disabled and no work (any catagory).

(2) - same as (1) for mother

(3) - change in probability that child is a porter if dad is literate with average schooling and mom moves from illiterate to literate (with no schooling)

(4) - change in probability that child is a porter if illiterate mom and dad shifts to a illiterate mom with literate dad (no schooling)

(5) - change in probability that a child is a porter if illiterate mom and dad shifts to literate mom and dad (no schooling)

(6) - change in probability that child is porter if household moves from no self employment to mom self employment

(7) - same as (6) only for father

(8) - change in probability that child is a porter if household moves from no self employment to both mom and dad in self employment

(9) - change in probability that child is a porter if household moves from no wage work to father wage work

(10) - same as (9) except mom & dad in wage work

Table 10: Comparison of Child Characteristics in Ragpickers Survey and Census

	Ragpickers Survey		2001 Population and Housing Census								
			Wage Work			Home Enterprise Work			Not Work		
	Mean	SE	Mean	SE		Mean	SE		Mean	SE	
# of observations	372		6,900			25,390			297,506		
Estimated population size	974		63,143			254,290			2,592,568		
Age	12.024	0.096	12.419	0.020	**	12.272	0.010	**	11.823	0.003	**
Female	0.198	0.043	0.370	0.008	**	0.611	0.004	**	0.470	0.001	**
Ethnicity											
High Status Hindu Caste	0.163	0.049	0.094	0.005		0.253	0.005	*	0.351	0.003	**
Tharu	0.006	0.003	0.151	0.007	**	0.062	0.003	**	0.076	0.002	**
Newar	0.026	0.014	0.027	0.003		0.025	0.002		0.057	0.002	**
Dalit	0.339	0.104	0.302	0.009		0.202	0.004		0.145	0.002	*
Muslim	0.080	0.059	0.100	0.007		0.047	0.003		0.034	0.001	
Other	0.384	0.071	0.325	0.008		0.411	0.006		0.336	0.002	
Native Language											
Nepali	0.394	0.090	0.222	0.008	*	0.484	0.006		0.520	0.003	
Tharu	0.007	0.004	0.133	0.007	**	0.052	0.003	**	0.058	0.002	**
Other	0.599	0.089	0.644	0.010		0.464	0.006		0.422	0.003	**
In School	0.100	0.026	0.159	0.006	**	0.271	0.005	**	0.864	0.001	**
Can read and write	0.450	0.068	0.272	0.008	**	0.381	0.005		0.875	0.001	**
Completed Some School	0.944	0.019	0.185	0.007	**	0.291	0.005	**	0.822	0.002	**
Completed Std. 5	0.067	0.020	0.063	0.004		0.105	0.003	*	0.346	0.002	**
Completed Post Primary	0.011	0.008	0.025	0.002		0.049	0.002	**	0.191	0.002	**

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

Table 11: Comparison of Background Characteristics in Ragpickers Survey and Census

	Ragpickers Survey		2001 Population and Housing Census								
			Wage Work			Home Enterprise Work			Not Work		
	Mean	SE	Mean	SE		Mean	SE		Mean	SE	
Belt											
Hill	0.540	0.190	0.191	0.011	*	0.495	0.007		0.462	0.005	
Terai	0.460	0.190	0.789	0.011	*	0.368	0.006		0.478	0.005	
Region											
East	0.165	0.120	0.312	0.011		0.192	0.005		0.230	0.004	
Central	0.616	0.175	0.406	0.012		0.306	0.006	*	0.335	0.005	
West	0.177	0.122	0.107	0.006		0.155	0.005		0.223	0.004	
Mid-West	n/a		0.112	0.007		0.188	0.005		0.117	0.003	
Far-West	0.041	0.044	0.063	0.006		0.158	0.005	**	0.094	0.003	
Household Background											
Owns Farmland	0.397	0.077	0.508	0.010		0.934	0.002	**	0.821	0.005	**

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

Table 12: Comparison of Parental Characteristics in Ragpickers Survey and Census

	Ragpickers Survey		2001 Population and Housing Census								
			Wage Work			Home Enterprise Work			Not Work		
	Mean	SE	Mean	SE		Mean	SE		Mean	SE	
Father Characteristics											
Reports Characteristics	0.871	0.020	0.910	0.004	*	0.906	0.002	*	0.888	0.001	
Age	44.110	0.735	43.855	0.196		45.175	0.099		44.717	0.040	
Can Read and Write	0.299	0.043	0.290	0.011		0.335	0.004		0.573	0.003	**
Completed Some School	0.166	0.028	0.179	0.010		0.162	0.003		0.334	0.003	**
Completed Std. 5	0.105	0.022	0.148	0.009	*	0.101	0.003		0.269	0.003	**
Completed Post Primary	0.082	0.018	0.124	0.009	**	0.068	0.002		0.214	0.003	**
Disabled	0.035	0.013	0.001	0.001	**	0.002	0.000	**	0.001	0.000	**
Not Work	0.087	0.017	0.057	0.004	*	0.036	0.002	**	0.066	0.001	
Owns Small Business	0.095	0.042	0.108	0.006		0.059	0.002		0.109	0.002	
Employed in Agriculture	0.088	0.024	0.629	0.011	**	0.862	0.003	**	0.682	0.005	**
Mother Characteristics											
Reports Characteristics	0.828	0.026	0.919	0.004	**	0.928	0.002	**	0.953	0.001	**
Age	36.914	0.786	39.468	0.172	**	40.337	0.084	**	39.484	0.035	**
Can Read and Write	0.127	0.036	0.151	0.010		0.075	0.003		0.232	0.003	**
Completed Some School	0.088	0.024	0.088	0.008		0.026	0.001	**	0.117	0.003	
Completed Std. 5	0.042	0.017	0.079	0.007	**	0.017	0.001		0.090	0.002	**
Completed Post Primary	0.021	0.012	0.072	0.007	**	0.010	0.001		0.068	0.002	**
Disabled	0.013	0.007	0.007	0.002		0.006	0.001		0.004	0.000	
Not Work	0.413	0.050	0.376	0.010		0.161	0.004	**	0.366	0.003	
Owns Small Business	0.032	0.013	0.098	0.006	**	0.098	0.003	**	0.102	0.001	**
Employed in Agriculture	0.076	0.023	0.477	0.011	**	0.780	0.004	**	0.556	0.004	**

Sample restricted to children age 10-14. **Difference significant at 5% *Difference significant at 10%

Table 13A: Attributable Risk Estimates for Background Characteristics in Ragpickers Survey

	Unconditional Attributable Risk	95% Confidence Interval		Conditional Attributable Risk	95% Confidence Interval	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Household Background						
Owns Farmland	-0.00017	-0.00031	-0.00008	0.00000	-0.00001	0.00000
Father Characteristics						
Reports Characteristics	-0.00002	-0.00006	0.00000			
Can Read and Write	-0.00004	-0.00008	-0.00002	-0.00001	-0.00002	0.00000
Disabled	0.00154	0.00052	0.00376	0.00024	0.00006	0.00064
Not Working	0.00002	0.00000	0.00006	0.00000	-0.00002	0.00000
Owns Small Business	0.00000	-0.00004	0.00009	0.00000	-0.00001	0.00001
Employed in Agriculture	-0.00016	-0.00030	-0.00007	-0.00003	-0.00009	-0.00001
Mother Characteristics						
Reports Characteristics	-0.00012	-0.00023	-0.00005			
Can Read and Write	-0.00001	-0.00003	0.00002	0.00000	-0.00001	0.00000
Disabled	0.00016	0.00001	0.00057	0.00002	0.00000	0.00015
Not Working	0.00001	-0.00003	0.00008	0.00000	0.00000	0.00001
Owns Small Business	-0.00004	-0.00007	-0.00001	-0.00001	-0.00002	0.00000
Employed in Agriculture	-0.00011	-0.00021	-0.00005	-0.00002	-0.00005	0.00000

All regressions include controls for child age, gender, ethnicity, language, belt, and development region. All standard errors corrected for clustering at the block level (primary sampling unit). Estimates computed using King and Zeng's relogit code with prior correction: http://gking.harvard.edu/stats.shtml#relogit. Each estimate of attributable risk in the "unconditional" column is from a separate regression. Each estimate in the "conditional" column is from one regresion, including all of the listed covariates. All estimates assume an incidence rate of ragpicking of 0.03 percent. Attributable risks are computed for a change in the row variable from 0 to 1 at the mean of all other covariates except all "conditional" estimates are computed at father and mother reports characteristics =1.

Table 13B: Attributable Risk Estimates for various scenarios in Ragpickers Survey

	At Mean Landholding Rate			Landless		
	Attributable Risk	95% Confidence Interval		Attributable Risk	95% Confidence Interval	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Disability						
Dad is disabled & cannot work (1)	0.00046	0.00011	0.00121	0.00075	0.00017	0.00208
Mom is disabled & cannot work (2)	0.00009	0.00001	0.00061	0.00014	0.00001	0.00064
Literacy						
Literate dad (avg sch) & illiterate mom (no sch.) to literate mom (3)	0.00000	-0.00001	0.00000	0.00000	-0.00001	0.00000
Illiterate mom & dad to literate dad (no schooling) (4)	-0.00001	-0.00003	0.00000	-0.00001	-0.00004	0.00000
Illiterate mom & dad to literate mom & dad (no schooling) (5)	-0.00001	-0.00004	0.00000	-0.00001	-0.00005	0.00000
Home Enterprises						
Household without any self employment to mom self employment (6)	0.00000	-0.00002	0.00000	-0.00001	-0.00002	0.00000
Household w/o self emp. to dad self emp. (7)	0.00000	-0.00001	0.00001	0.00000	-0.00001	0.00001
Household w/o self emp. to mom & dad self emp (8)	0.00000	-0.00002	0.00000	-0.00001	-0.00002	0.00000
Wage Labor						
Household w/ no wage work to dad (9)	0.00000	0.00000	0.00002	0.00001	0.00000	0.00002
Household w/ no wage work to mom & dad (10)	0.00005	0.00001	0.00017	0.00008	0.00002	0.00024

Attributable risks computed using results from the "conditional regression" results in table 13a. The first columns compute probabilities for households with mean probability of holding land. The second column computes probabilities for household without landholdings.

(1) - Change in probability that child is a ragpicker if father moves from not disabled and mean work to disabled and no work (any catagory).

(2) - same as (1) for mother

(3) - change in probability that child is a ragpicker if dad is literate with average schooling and mom moves from illiterate to literate (with no schooling)

(4) - change in probability that child is a ragpicker if illiterate mom and dad shifts to a illiterate mom with literate dad (no schooling)

(5) - change in probability that a child is a ragpicker if illiterate mom and dad shifts to literate mom and dad (no schooling)

(6) - change in probability that child is ragpicker if household moves from no self employment to mom self employment

(7) - same as (6) only for father

(8) - change in probability that child is a ragpicker if household moves from no self employment to both mom and dad in self employment

(9) - change in probability that child is a ragpicker if household moves from no wage work to father wage work

(10) - same as (9) except mom & dad in wage work

Table 13C: Bounds on Attributable Risk Estimates for various scenarios in Ragpickers Survey, landless households
Incidence rates bounded between 0.3 and 0.03 percent

	Estimated Bounds		95 % Confidence Intervals for Bounds	
	Upper	Lower	Lower Value	Upper Value
Disability				
Dad is disabled & cannot work (1)	0.00742	0.00075	0.00017	0.01995
Mom is disabled & cannot work (2)	0.00136	0.00014	0.00001	0.00621
Literacy				
Literate dad (avg sch) & illiterate mom (no sch.) to literate mom (3)	0.00000	-0.00003	-0.00009	0.00000
Illiterate mom & dad to literate dad (no schooling) (4)	-0.00001	-0.00010	-0.00039	0.00000
Illiterate mom & dad to literate mom & dad (no schooling) (5)	-0.00001	-0.00013	-0.00047	0.00000
Home Enterprises				
Household without any self employment to mom self employment (6)	-0.00001	-0.00007	-0.00022	0.00000
Household w/o self emp. to dad self emp. (7)	0.00000	-0.00004	-0.00011	0.00001
Household w/o self emp. to mom & dad self emp (8)	-0.00001	-0.00008	-0.00020	0.00000
Wage Labor				
Household w/ no wage work to dad (9)	0.00007	0.00001	0.00000	0.00022
Household w/ no wage work to mom & dad (10)	0.00080	0.00008	0.00002	0.00238

Attributable risks computed using results from the "conditional regression" results in table 13a assuming an incidence of 0.03 percent and unreported regressions assuming an incidence of 0.3 percent.

(1) - Change in probability that child is a ragpicker if father moves from not disabled and mean work to disabled and no work (any catagory).

(2) - same as (1) for mother

(3) - change in probability that child is a ragpicker if dad is literate with average schooling and mom moves from illiterate to literate (with no schooling)

(4) - change in probability that child is a ragpicker if illiterate mom and dad shifts to a illiterate mom with literate dad (no schooling)

(5) - change in probability that a child is a ragpicker if illiterate mom and dad shifts to literate mom and dad (no schooling)

(6) - change in probability that child is ragpicker if household moves from no self employment to mom self employment

(7) - same as (6) only for father

(8) - change in probability that child is a ragpicker if household moves from no self employment to both mom and dad in self employment

(9) - change in probability that child is a ragpicker if household moves from no wage work to father wage work

(10) - same as (9) except mom & dad in wage work