

**Alternative Income Generation and Entry into Worst Forms of Child Labor**  
Theory and evidence from ragpickers, porters, and child domestics in Nepal

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## **Executive Summary**

Alternative income generating activities (IGA) for vulnerable families have the potential to increase or decrease child labor. Rising family incomes may make families less dependent on the child's economic contribution or better able to afford schooling expenses. Rising income may help families avoid sending a child away or the circumstances that lead to child migration or child trafficking. However, they may also be associated with changing employment opportunities to children. Activities in which children can participate may generate increases in the number of working children. While activities that substitute for children may push children out of employment in the household, perhaps into school, unemployment, or other types of work away from their family. In the end, theory cannot predict the impact of IGA on child work or even participation in activities that are considered worst forms. The expected impact of a growth in IGA on perceptions of child welfare then depends on both the type of IGA and how different types of work are viewed in a country.

Article 3 of ILO Convention 182 allows considerable discretion for countries in how they define worst forms of child labor. A worst form of child labor can include any "work that is likely to endanger the health, safety, or morals of children." The accompanying recommendation (190) draws attention to cases where children are exposed to abuse, work in an unhealthy environment, work long hours (including during the night), or face confinement to the employer's premises. Ragpicking, portering, and child domestic service are among the 16 worst forms of child labor in Nepal as identified by the Government of Nepal's National Master Plan, and they are among the 7 worst forms of child labor targeted for elimination under the 2001 Time-Bound Program (TBP) in Nepal.

The original purpose of this study was to analyze how the structure of economic activity in the child's parents' environment is correlated with participation in domestic service, ragpicking, and portering in Nepal. Ultimately, little is found to suggest a clear connection (consistent with the theoretical ambiguity discussed above). Hence, this study's more substantive

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contribution is to show how it is possible to analyze the correlates of selection into worst forms of child labor. With nothing more than data on children in a worst form as might be collected from targeted surveys, it is impossible to infer why children select into a given worst form. This study shows how to estimate the correlates of entry into a worst form when four conditions are 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.

Inference will only be possible over characteristics that are observed in both the targeted survey and the nationally representative data. The primary source of representative data for this study is the 2001 population and housing census of Nepal. The census and the TBP baseline surveys of children in worst forms of child labor have in common questions about location, whether the family owns agricultural land and a household roster with sex, age, ethnicity, mother tongue, employment occupation, and education of each family member. This study illustrates how to draw inference about the relative significance of each of these attributes in explaining selection into worst forms of child labor. Moreover, the census identifies whether children are engaged in market work in the family business or farm and wage work. Hence, with the census, it is possible to compare selection into worst forms of child labor with these other, more prevalent forms of child labor.

Nothing in the data considered herein suggests a pivotal role for alternative income generating activities in influencing selection into worst forms. In theory, it is not obvious how IGA to the household will influence child participation in worst forms, and in practice, at best, the data only hint at a possible, small role for employment opportunities for children in explaining selection into ragpicking, domestic service, or portering. Parental disability (especially paternal disability) stands out as a strong correlate of participation in a worst form, but the role of IGA in helping families cope with something like paternal disability is unclear. However, the data suggest some small correlation between parental self employment and entry into worst forms. While parental self employment is associated with more wage work by children in general, it is associated with a reduced probability of observing a child as a domestic, porter, or ragpicker. Overall, though the diminished risk of selection into these worst forms associated with self employment is tiny compared to the elevated risk associated with paternal disability.

Only a more complete integration of scientific evaluation techniques into existing IGA projects can answer whether there is any scope for IGA to influence entry into worst forms. That said, the analytical approach adopted in this study based on combining population estimates of the worst form, targeted data, and nationally representative data should be useful in other country contexts and may help researcher better target IGA interventions for evaluation purposes.

## **1. Introduction**

Few issues in low income countries draw more popular attention than child labor, and the eradication of the worst forms of child labor has become a goal in development policy. Several different policy instruments are being employed to combat the worst forms of child labor, but alternative income generation strategies are among the most promising because they seek to eliminate the flow of children into these worst forms of child labor. The design of alternative income generation strategies to help marginalized children requires an understanding of why children are marginalized. This study hopes to review and enhance our understanding why children select into some of the worst forms of child labor prevalent in Nepal.

The question of why children are working in worst forms of child labor has received substantial theoretical attention, but empirical evidence suitable to understanding selection into the worst forms of child labor is scarce. The difficulty of capturing the activities with randomized sampling is largely responsible for the paucity of empirical work. Hence, 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 typically respond that they are working because either they or their family need the money. Insights of this sort have led to the conclusion that alternative income generation schemes may be a partial solution to the problem of labor supply in these activities. 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. Thus, this observation is of limited use for the design of policy to ameliorate the supply of labor into these activities, and a better understanding of why children select into worst forms of child labor is of first order importance for policy decisions.

This study has two main objectives. First, this study reviews the existing literature on why there is a link between income and child labor. Though the empirical work in this study focuses on survey data from Nepal, the review component of this study is not limited to Nepal. Rather, it seeks to provide a more comprehensive review of both the theoretical and empirical academic literature on the link between family income and child labor. This academic literature predicts income generating activities (IGA) can influence child time allocation through their impact on family income and their impact on the value of child time inside the household. This later mechanism makes the impact of IGA in the family ambiguous. Rising family incomes may decrease pressures to have children work or not attend school. Rising incomes may help families better support their existing children, reducing the need to send children away and mitigating incentives for child migration. If rising incomes (or the IGA activities themselves) are accompanied by a perceived increase in the return to educating a child, they may draw children away from work into the classroom. Moreover, additional employment opportunities inside the household may draw some children into working in the IGA. If the IGA crowd out existing household activities and the child's relative performance in the IGA is poor, IGA could spur more children to look for work outside of their household. Depending on how different types of activities are viewed, it is theoretically possible that IGA could increase the number of working children or push already working children into situations where they are more vulnerable to worst forms of child labor. Whether this theoretical possibility has any bearing for reality is ultimately an empirical question.

A common issue that will arise in the discussion of existing IGA programs is a general lack of evidence on their impact. This comment will seem inaccurate to practitioners who often have observed and commissioned reports about the impact of IGA programs in the field. An analogy to medical research is appropriate here. For a long time, pharmaceutical products and medical procedures were evaluated by asking subjects whether they felt better after they'd

received a medication or undergone a treatment. However, concerns about placebo effects, sampling, recording and reporting biases, and the interpersonal dynamics of evidence of this nature eventually lead to the adoption of more scientific standards for evaluation based on randomization when feasible and quasi-experimental methods when randomization is not possible. Evaluation is costly, but in the case of medicine, it was deemed worthwhile because of the important role medical treatments can have for individual welfare, and scientific evaluation also has the advantage of advancing knowledge by learning whether and why products work. It is not clear why these welfare concerns and desire to learn are not equally appropriate for the study of IGA. Comments about a general lack of evidence on the impact of IGA programs refer to the absence of this type of experimental or quasi-experimental scientific evidence.

Second, this study combines data on porters, ragpickers, and domestic servants in Nepal and estimates of the incidence of each in the population 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. Often work that qualifies as a worst form is not explicitly identified. However, when it is explicit as in the present case, this combination of population estimates, targeted data on participants, and representative data is often available in low income environments and can be used to develop an understanding of the correlates of selection into worst forms. Only child background characteristics that appear in both the targeted and nationally representative data can be analyzed, and differences in the nature of the data collection process between the worst forms data and the nationally representative data can significantly bias estimation. However, it is striking how unusual it is to analyze participation in worst forms in the context of nationally representative data on children who are not engaged in the worst form. It would be very simple and costless to improve quantitative survey instruments of children in worst forms to substantially improve our ability to analyze why children select into these activities, and this study illustrates how this is possible.

There is no evidence below to suggest a strong connection between type of parental employment or household activity and selection into any of the worst forms considered herein. There are hints in the descriptive work of some role for outside employment opportunities, but the only observable household characteristic that stands out is a strong correlation between parent (especially paternal disability) and selection into a worst form. 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. It seems theoretically possible that IGA could compensate for the loss of a disabled father's contribution to the household, but it is not clear whether the association between paternal disability and participation in a worst form reflects a loss of income, a loss of employment opportunities within the household, a loss of care or attention, or something else that happens to be coincident with paternal disability and selection into a worst form. That said, the data are consistent with a small role for IGA as porters, ragpickers, and domestics are slightly less likely to have parents who are self employed.

The next section reviews the relevant theoretical literature. Section 3 describes how to combine targeted surveys and representative data to draw inferences about the correlates of entry into worst forms. Section 4 presents findings from data on domestics, porters, and ragpickers in Nepal. Section 5 summarizes the findings of this study and discusses their implications for future research.

## **2. Alternative Income Generating Activities (IGA) as a Way to Influence Selection into Worst Forms**

Empirical evidence on why children select into worst forms of child labor is scarce. Unfortunately scientific evaluation of the impact of IGA targeted to disadvantaged families is

still in its infancy. Consequently, there is very little direct evidence on whether or how IGAs might influence entry into worst forms of child labor.

The purpose of this section is to speculate about the possible role for IGAs in influencing selection into child labor. There is a large academic literature exploring the relationship between family income and common forms of child labor. This section begins with a summary of that literature and discusses its relationship to IGAs. The extent to which these findings extend to worst forms depends on whether worst forms are some how fundamentally different for reasons other than working conditions. The second part of this section reviews current academic understanding of the relationship between worst forms and common forms of child labor and contemplates what these theories suggest for how IGAs influence selection into worst forms.

## **2.1 Family Incomes and Child Labor**

Qualitative interviews of children in both common and worst forms of child labor emphasize poverty as a key factor influencing why children work. The idea that children work because of the family's need for income really contains two statements about why children work. First, the family's marginal utility (or extra welfare) gained by additional income from the child is high even if the income earned is small. Second, the return to child time spent working (or in a worst form) is greater for the family than other uses of the child's time. This second point is important, because it implies a role for local schooling institutions as well as cultural norms about how parents internalize the value of child time in child labor decisions. Moreover, this second aspect of the idea that children are working in order to help their families may be especially important for designing alternative income generation to affect worst forms of child labor as will be discussed below.

Several ways in which rising family incomes might influence child labor have been emphasized in the academic literature. First, child labor may be a bad in parental preferences so that as incomes improve, the family chooses to have children work less. In fact, in the seminal child labor paper by Basu and Van (1998), they posit the "luxury axiom": children only work when the family is unable to meet its basic needs. Beyond subsistence, the luxury axiom posits, families always opt to keep children out of work. This extreme characterization of parental preferences presumes that there are always preferred uses for child time outside of some form of work. Hence, it is difficult to reconcile evidence of a correlation between working and returns to education, school quality, employment opportunities, and family living arrangements. Edmonds (2005) applies the Basu and Van model to data from Vietnam, and he needs to assume that the household's perception of its basic needs depends on returns to education, school quality, etc. in order to reconcile the Basu and Van model with the data. However, it seems plausible that the luxury axiom may be applicable to worst forms without additional qualifications. Most narratives of worst forms emphasize that a high share of participants are migrant or trafficked children, and it seems plausible that the luxury axiom might extend to the decision about whether to send a child away without the need for additional qualification.

Second, with diminishing marginal utility of income, the value of the marginal contribution of the child's income decreases. Note that an important part of the child's economic contribution to the family might be through not attending school if direct and indirect schooling costs are high. In fact, Edmonds (2006) documents strong schooling and work responses to anticipated income changes in South Africa that seem to stem in part from schooling related expenses. Edmonds, Pavcnik, and Topalova (2006) observe that the avoidance of school related expenses appears to be a significant factor in why there is a (relative) increase in the share of

children who work without attending school in Indian districts where there is a rise in poverty (relative to the national trend) attributable to Indian trade reforms in the early 1990s.

Nonetheless, the economic contribution of working children can be substantial. Psacharopoulos (1997) observes that income earned by working Bolivian 13 year olds amounted to 13% of total household income on average. Menon et al (2004) attempt to compute the value of child's own farm labor to largely subsistence farm households in rural Nepal. They estimate that children contribute roughly 11 percent of the value of total agriculture production in Nepal or about 9 percent of GDP. If moving children out of work entails giving up such a significant contribution to income, it is hard to imagine that preferences do not play a role.

Third, rising incomes may facilitate improved credit access or more effective insurance. The idea that access to credit is important for child labor supply has recently been formalized in theoretical work by Baland and Robinson (2000) and Ranjan (2000) with empirical support at the macro level in Dehejia and Gatti (2005) and in microdata in Edmonds (2006). In addition to leveraging credit to make productive investments, credit may facilitate the intertemporal reallocation of resources so that current investment decisions such as education need not depend solely on contemporaneous considerations. The return for the child's future can be balanced against current considerations. Better informal insurance associated with rising incomes may also reduce the import of contemporaneous economic circumstances for child schooling decisions. Evidence on the importance of insurance failures for child labor appears in Beegle et al (2006).

The empirical evidence on the link between family incomes and child labor typically finds improvements in income associated with declining child labor. Using cross-country estimates of child labor supply, Edmonds and Pavcnik (2005a) note that 73 percent of the cross-

country variation in child labor can be attributed to variation in national income. Econometric attempts to address the endogeneity of national income and child labor do not diminish this strong correlation (Edmonds and Pavcnik 2006a). Within countries, studies that track children or families over time also tend to find a similarly strong, robust negative association between child labor supply and family incomes (for example: Beegle et al. 2006, Duryea, Lam, and Levison 2003, and Edmonds 2005).

An important fourth way in which income may be related to child labor is highlighted by the considerable confusion that exists over how to interpret some of the evidence on the family income – child labor correlation. Within country, cross-sectional studies of the relationship between child labor and family income typically find a less robust relationship. An intrinsic problem in studies of the link between economic status and child labor is that poor households differ from rich households in many ways that might be associated with child labor. Disentangling these omitted factors from the underlying causal relationship is difficult, but the association between family incomes, the employment opportunities open to children, and perceived returns to education is perhaps the most important of these omitted factors in the cross-sectional evidence.

Specifically, the economic opportunities available to children are typically positively associated with family income. Everything else equal, better employment opportunities should mean that more children work. Several recent studies note that child labor is higher in households with more self employment activities (Edmonds and Turk 2004 in Vietnam, Parikh and Sadoulet 2005 in Brazil) and Wydick (1999) notes a correlation between work and household involvement in a microcredit program. In fact, using detailed time use data from Botswana, Mueller (1984) documents that the more productive capital the household has, the

more productive work its children perform. She estimates that the positive productivity effect of productive capital outweighs its association with family income in its effects on child time allocation. Households must balance these rising returns to child labor against a desire to have the child work less or devote more time to schooling, and theory cannot predict which of these two factors will dominate. In fact, one should assume that the relative importance of rising incomes and rising employment opportunities in child labor should be location specific.

Edmonds and Pavcnik (2005b) illustrates this point. Vietnam liberalized its rice markets in the mid-1990s and concurrent with this liberalization are increases in employment opportunities in rice related activities and increased family income. In the Vietnam context where schooling is accessible and of relatively high quality, Edmonds and Pavcnik find a large decline in child labor with rising incomes despite increasing employment opportunities.

Moreover, decisions about child labor depend not on the absolute return to child time in work but on labor's relative return, and it is not obvious theoretically that higher income will be associated with higher relative returns to work. Higher family incomes may facilitate the purchase of substitutes for child labor that lower the return to child labor within the household. For example, a washboard, fertilizer spreader, livestock, or a combine harvester may replace child labor within the home. Edmonds and Pavcnik (2006b) document some suggestive evidence that this replacement of child labor with market inputs was important in the decline in child labor discussed in the preceding paragraph. Alternatively, the child's productivity in other activities such as schooling might improve because the family might be able to afford better inputs to schooling such as nutrition, textbooks, or uniforms. Higher income might also raise the family's perceived returns to education, especially when raising incomes are associated with other changes in the family's environment that might reward education.

In fact, the empirical evidence suggests that the association between the relative return to work and rising family incomes will be extremely sensitive to local circumstances. For example, Bhalotra and Heady (2003) find that the additional within household employment opportunities open to girls associated with greater landholdings in Pakistan and Ghana are sufficiently larger than households with greater land wealth are more apt to have their child work. Chernichovsky (1985) uses the same Botswana data as Mueller to point out that when substitutes for child labor are available inside the household, children tend to attend school rather than work even in the presence of productive capital. Interestingly, Psacharopoulos and Arriagada (1989) document similar patterns in Brazil. As an important substitute for child labor, they emphasize a piped water supply. Cockburn (2002) goes into further detail in Ethiopian data. He notes that small livestock and land appear to be market work increasing whereas oxen, bulls, ploughs, land quality, and again, proximity to water are child labor decreasing. These patterns make sense in that the factors Cockburn identifies as child labor decreasing all substitute for children and are difficult for children to manage.

These studies have an interesting implication for the present context. The impact of IGA on child labor will depend on how it affects household income and the employment opportunities available to children within the household. Our prior should be that rising household incomes will put downward pressure on child labor. However, children are most likely to work within their own homes. Rising income through alternative, household based, income generating activities may affect these preferred employment opportunities.

IGA could both increase or decrease child employment opportunities within the household. This will depend both on the type of activity and the specific country context. For example, Free the Children – India has been active in distributing gem polishers and sewing

machines to marginalized women in India as part of its "Adopt a village" campaign. This additional productive capital in the household might displace some of the work children performed. What might displaced children do? Perhaps they would go to school if there was affordable, accessible schooling of sufficient quality to make it worthwhile. They might turn instead to other work, perhaps even work outside of the household. Alternatively, the additional income may allow families the luxury of not having their children work, or the additional productive capital may induce children to work more inside the household in the IGA activity (from school or from other work outside of or away from the household).

One solution to this ambiguity is to target IGA to give children work. For example, "YES Nigeria" has been active in targeting microcredit loans to youths in order to help them start small businesses and accumulate savings that might be used to finance schooling. Hieffer International and the Maasai Association in Kenya have been active in giving children small livestock such as goats or chickens whose care demands are compatible with schooling. The goal of these organizations is to mitigate the family's incentive to have the child seek other forms of employment that might be less compatible with schooling. However, in turn, they may induce more children to work as might IGA targeted at parents. If the alternative to this involvement in the families IGA is working in a worst form, it may be the case that the way IGA can deter entry into worst forms in part entails an increase in overall levels of child labor. Hence, it is important to set national policy priorities about what types of work need to be deterred.

## **2.2 Are worst forms different than more common activities?**

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. 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 active 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 workers 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. Eighty-eight percent 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 percent 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 (because debts are inherited, many argue that the children are implicitly bonded in the system). 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 worst forms 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 something other than a form of work.

Three views about differences in the selection process into common forms and worst forms of child labor seem to dominate the academic literature. 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. In this case, the link between worst forms and income will be the same as that of more common forms of child labor, and the resulting policy prescriptions will be the same. Thus, the reasons why there is a strong connection between income and child labor will be important for understanding whether success of alternative income strategies will simply be a function of providing more income to the families of targeted children or whether some income-generating strategies might be more appropriate than others for helping families where children work. Moreover, to the extent that insurance markets are incomplete, the stability of IGA income will also be important in how it affects entry into worst forms. Thus, alternative sources of income that help families cope with insurance and credit market failures will help ameliorate the need for children to work.

In a second view, worst forms of child labor are partially compensated so that they pay more (Dessy and Pallage 2005). 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. Policy to reach the most disadvantaged may need to be considerably more aggressive than in the fully compensated case. Moreover,

policies that increase employment opportunities for children within their family or home community may be particularly effective at decreasing worst forms even if they lead to higher levels of more common forms of child labor. For example, employment in worst forms is typically urban and a common anecdote is that these children come from rural areas. Hence, policies that help increase employment opportunities and economic activity in rural areas may be effective at mitigating the flow of children into worst forms even if they increase child labor overall.

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. 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 role that alternative income generation can play here is more mixed. On the one hand, increased income or perhaps perceived returns to schooling may mitigate the parent's willingness to send children into work, and therefore the effect of increased, stable sources of income may be similar as in the fully compensated case. However, poor information or the willingness to send a child to work in the context of uncertainty may function in the same way as pay differentials that are not fully compensated so that the policy prescriptions discussed in the previous case may be more relevant. Empirically, the information explanation will be hard to identify in data, and qualitative data may be the most productive avenue to assess information

problems. Moreover, to the extent that information appears to be a fundamental issue in some worst forms, education and other services might be an important companion to income generation activities.

In reality, because of inference problems with rare events, we have little evidence on why children select into worst forms and whether selection is driven by characteristics that differ from those discussed above. Until scientific evaluation of IGAs is conducted with attention to entry into worst forms, we can only speculate whether family income effects associated with IGAs will be important or whether IGAs influence the employment opportunities open to children in ways that discourage activities associated with selection into worst forms.

An important issue is omitted from the above discussion. Who decides whether children work, how they work, and where they work? Reports of child abuse at home are commonplace in qualitative interviews, and interviews of older migrant children often emphasize a desire to have greater autonomy. To the extent that autonomy is important, the impact of IGA on child residency patterns and time allocation may depend on who captures the income from these activities. In particular, it seems plausible that income in the hands of a child, especially an older child, may be a powerful influence on how the child spends his time. Could increasing the employment opportunities available to older children be a way to increase schooling and prevent entry into worst forms? Unfortunately, the answer to this question is not known at present, and this study will not shed any additional light on this important question. However, in policy discussions, it is often impossible to do anything that might encourage children to work even though this might be a useful channel to prevent participation in worst forms.

### 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 statistic 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  $Y$ . The researcher is interested in knowing how factor  $D$  increases the probability that a child with other characteristics  $X$  enters into activity  $Y$ . When  $D$  is discrete, this is:

$$P[Y = 1|D = 1, X] - P[Y = 1|D = 0, X].$$
 Neither probability can be computed in the set of  $Y=1$ .

Put another way; let's say a child in an interview remarks that they are engaged in activity  $Y$  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  $Y$  (lots of children have a parent loose a job without becoming a ragpicker), but without data on children not in  $Y$  there is no way to compute the increased chance of engaging in  $Y$  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  $Y_i$  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  $Y_i$  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:

$$\pi_i = \Pr(Y = 1|D_i). \quad (\text{eq. 1})$$

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

$$R = \frac{\Pr(Y = 1|D = 1)}{\Pr(Y = 1|D = 0)}. \quad (\text{eq. 2})$$

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

$$A = \Pr(Y = 1|D = 1) - \Pr(Y = 1|D = 0). \quad (\text{eq. 3})$$

Each of these outcomes is potential 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  $Y=1$ ) and controls ( $Y=0$ ). 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 that 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  $\lambda$  denote the incidence of the worst form in the population, and let

$\bar{Y}$  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  $\lambda$  and  $\bar{Y}$ . Specifically, the regression's intercept in the logit  $\beta_0$  needs to be adjusted as :

$$\beta_0 - \ln \left[ \left( \frac{1-\lambda}{\lambda} \right) \left( \frac{\bar{Y}}{1-\bar{Y}} \right) \right] \quad (\text{eq. 4})$$

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  $\lambda$ . However, at a minimum, researchers will have some idea of a plausible range of values for incidence in the population. Let  $\lambda_L$  and  $\lambda_H$  indicate the lower and upper values of the plausible range of  $\lambda$ . King and Zeng (1999) suggest computing bounds on possible values of absolute and relative risk by estimating either at both  $\lambda_L$  and  $\lambda_H$ . Because absolute and relative risk are positive monotone functions of  $\lambda$ , computing either at the lower and upper values of  $\lambda$  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  $\lambda$ . Define  $A(\lambda_k)$  as the estimate of attributable risk associated with an estimated incidence of  $\lambda_k$ .

King and Zeng (1999) suggest checking for whether  $\lambda_L$  and  $\lambda_H$  are in a monotone region of attributable risk by evaluating whether attributable risk appears to have the same derivative with respect to  $\lambda$  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  $\lambda_L$  and  $\lambda_H$  are in a monotone region of A, then bounds can be calculated as:

$$A \in \left\{ \min(A(\lambda_L), A(\lambda_H)), \max(A(\lambda_L), A(\lambda_H)) \right\}. \quad (\text{eq. 5})$$

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:

$$A \in \left\{ \min(A(\lambda_L), A(\lambda_0), A(\lambda_H)), \max(A(\lambda_L), A(\lambda_0), A(\lambda_H)) \right\}. \quad (\text{eq. 6})$$

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

$$\omega = \frac{\Pr(Y = 1|D = 1)\Pr(Y = 0|D = 0)}{\Pr(Y = 0|D = 1)\Pr(Y = 1|D = 0)}. \quad (\text{eq. 7}).$$

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. 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. Findings from Child Domestic Workers, Child Porters, and Child Ragpickers in Nepal**

### **4.1 Domestic Workers**

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. Domestic workers often live in isolation as it is unusual for households to employ multiple domestic workers, and domestic workers are often confined to their employer's premises. Domestic workers 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 domestic workers.

Interestingly, there is little popular stigma against employing a domestic worker. This permits precise estimates of the incidence of domestic workers from the population census. The 2001 population and housing census captured 29,556 domestic workers age 6-18. This corresponds to roughly 0.4 percent of children in Nepal. Forty-nine percent of all domestic workers are in Kathmandu. Fostered domestic workers are primarily urban phenomena. These 29.6 thousand domestic workers 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 worker's background, work conditions, etc. were administered to sampled domestic workers. 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.

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.

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 bring income from outside their family. Domestic workers 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.

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.

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. 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). 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 they react to changes in the family's environment.

#### **4.2 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.

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.

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.

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. 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. 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 domestic 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.

### **4.3 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.

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 as there a population where debt-bondage is especially prevalent.

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 it is 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.

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 ragpicking, 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.

## **5. Conclusion**

There are no strong theoretical predictions about how alternative income generation strategies will impact selection into worst forms of child labor. Rising family incomes may decrease pressures to have children work or not attend school. Rising income may mitigate the incentives for child fostering and child migration. Additional employment opportunities inside the household may draw some children into working in the IGA. If the IGA crowd out existing household activities and the child's relative performance in the IGA is poor, IGAs could spur

more children to look for work outside of their household. Depending on how different types of activities are viewed, it is theoretically possible that IGAs could increase the number of working children or edge already working children into situations where they are more vulnerable to worst forms of child labor. Of course, by providing additional income, alternative forms of employment, or raising perceived returns to staying at home or getting education, IGAs might also deter entry into worst forms.

The data do not present any compelling evidence of a strong role for income generating activities in influencing selection into worst forms of child labor. This observation is driven by the fact that the available type of parental employment is not a strong predictor of selection into any of the activities studied here. However, the data are consistent with a small role for IGA as porters, ragpickers, and domestics are less likely than other types of children to report parental self employment.

There are some further associations in the data that are consistent with some role for child employment opportunities in influencing entry into worst forms. Child domestics are more likely to be female, and, thus, have fewer other employment opportunities outside their family (relative to boys). Domestics are more prevalent in areas where wage work is rarer. Owning agricultural land and having a father or mother who is self employed 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. Of course, employment opportunities in general are important. Porterage is most prevalent in areas where there is the most need for porters just 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. It seems theoretically possible that IGA could compensate for the loss of a disabled father's contribution to the household, but it is not clear whether the association between paternal disability and participation in a worst form reflects a loss of income, a loss of employment opportunities within the household, a loss of care or attention, or something else that happens to be coincident with paternal disability and selection into a worst form. One interesting side note on the correlation between parental disability and selection into worst forms is that for domestics, maternal disability decreases the probability a child works as a domestic. This hints at a role for own household labor demand (in this case for domestic services) that may have some influence on entry into worst forms.

A challenge in interpreting these findings is that they reflect correlations in the data and not the causal impact of owning land or a family business on entry into a worst form. In fact, it is straightforward to explain most of these characteristics as being correlates of poverty. So that the results above could mean nothing more than children in these worst forms are more likely to come from a disadvantage background than children in other types of activities. Put another way, perhaps all ragpickers come from an extremely poor household, whereas some wage working children also do but some do not. This might generate all of the patterns above. However, the present evidence is consistent with the view that insurance mechanisms and better

social infrastructure for coping with family troubles might be a more direct approach to mitigate entry into worst forms.

Two important cautions deserve special emphasis. First, the empirical methods used herein are not causal and are only useful for estimating the correlates of selection into worst forms in the data. They cannot be used to extrapolate how exogenously changing family earning opportunities through IGAs would impact children. Causal inference about the impact of IGAs can most effectively be accomplished by embedding scientific evaluation into IGA programs at their inception.

Second, while the methodology used to assess the correlates of selection into worst forms is extremely general, 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 IGAs.

## Works Cited

- Baland, Jean-Marie, and James A. Robinson. 2000. "Is Child Labor Inefficient?" *Journal of Political Economy*. August, 108(4), 663-79.
- Basu, Kaushik, and Pham Hoang Van. 1998. "The Economics of Child Labor." *American Economic Review*, 88(3), 412-27.
- Beegle, Kathleen, Rajeev H. Dehejia, and Roberta Gatti. 2003. "Child Labor, Crop Shocks, and Credit Constraints." NBER Working Paper 10088. Cambridge, Mass.: National Bureau of Economic Research.
- Bhalotra, S. and Heady, C. (2003): "Child Farm Labor: The Wealth Paradox", *The World Bank Economic Review* 17: 197-227.
- CDPS (Central Department of Population Studies, Tribhuvan University) / ILO, 1998. *Child Labour Situation in Nepal: Facts and Figures*. ILO-IPEC, Kathmandu
- Central Department of Population Studies (CDPS), 2003. *Labour Market Dynamics and Child Porters: The Nepalese Context*. CDPS / Tribhuvan University, Kathmandu.
- Chernichovsky, D (1985), "Socioeconomic and Demographic Aspects of School Enrollment and Attendance in Rural Botswana," *Economic Development and Cultural Change*, 33(2), 319-332.
- Cockburn, J., (2002): "Child Labour Versus Education: Poverty Constraints or Income Opportunities?" Centre for Study of African Economies and Nuffield College Manuscript.
- Dehejia, Rajeev and Gatti, Roberta. 2005. "Child Labor: The Role of Income Variability and Credit Constraints across Countries." *Economic Development and Cultural Change*
- Dessy, Sylvain E. and Stephane Pallage. 2003. "A Theory of the Worst Forms of Child Labour." *Economic Journal*, forthcoming.
- Duryea, Suzanne, Hoek, Jasper, Lam, David, and Levison, Deborah. 2004. "Dynamics of Child Labor: Labor Force Entry and Exit in Urban Brazil" *Child Labor and Education in Latin America*. Peter Orazem and Guilherme Sadlacek, eds. Washington, D.C.: Inter American Development Bank.
- Duryea, Suzanne, Lam, David, and Levison, Deborah. 2003. "Effects of Economic Shocks on Children's Employment and Schooling in Brazil." *Population Studies Center Research Report 03-541*, December. Ann Arbor, MI: University of Michigan.
- Edmonds, E. 2005. "Does Child Labor Decline with Improving Economic Status?" *The Journal of Human Resources*, Winter 2005.
- Edmonds, E. 2006. Schooling and Child Labor Responses to Anticipated Cash Transfers. *Journal of Development Economics*, forthcoming.
- Edmonds, E. and Pavcnik, N. (2005a). Child Labor in the Global Economy, *Journal of Economic Perspectives* 18(1), Winter 2005, 199-220.
- Edmonds, E. and Pavcnik, N. (2005b). The Effect of Trade Liberalization on Child Labor, *Journal of International Economics* 65(2), March 2005, 401-419.
- Edmonds, E. and Pavcnik, N. (2006a). International Trade and Child Labor: Cross-Country Evidence, *Journal of International Economics*, forthcoming.
- Edmonds, E. and Pavcnik, N. (2006b). Trade Liberalization and the Allocation of Labor between Households and Markets in a Poor Country, *Journal of International Economics*, forthcoming.

- Edmonds, E. and Sharma S. (2006). Investments in Children Vulnerable to Bondage. Dartmouth Manuscript.
- Edmonds, E. and Turk, C. (2004). Child Labor in Transition in Vietnam, in P. Glewwe, N. Agrawal and D. Dollar (eds), *Economic Growth, Poverty and Household Welfare in Vietnam*. Washington DC: World Bank, 2004, pp. 505-550
- Edmonds, E., Pavcnik N., and Topalova P. (2005). Trade Policy, Child Labor, and Schooling: Evidence from Indian Districts. Dartmouth Manuscript.
- Gurung, H. *et al.*, 1983, *Internal and International Migration in Nepal*, Summary and Recommendations, Task Force on Migration. Tanka P Acharya Memorial Foundation, Kathmandu
- ILO (2001), *The Time Bound Program in Nepal*, Kathmandu: ILO.
- ILO-IPEC, 1995. *Child labour in Nepal. An Overview and A Proposed Plan of Action Vol. II*, Kathmandu
- ILO-IPEC, 2001. *Country Profile: Nepal*. Geneva
- KC, B.K., Adhikari, K.P, Subedi, G. and Gurun, Y.B., 2001. *Situation of Child Porters: A Rapid Assessment*. Investigating the Worst Forms of Child Labour Series, No.6. ILO-IPEC, Geneva
- KC, B.K., Suwal, B.R., Adhikari, K.P. and Gurung, Y.B., 1997. *Migration of Working Children in Nepal* (Report from Migration and Employment Survey, 1995/96 Data). ILO-IPEC, Kathmandu
- KC, Bal Kumar, 1998. *Trends, Patterns and Implications of Rural-to-Urban Migration in Nepal*. CDPS, Tribhuvan University, Kathmandu
- KC, Bal Kumar, Gurung, Y.B., Adhikari, K.P. and Subedi,G., 2001<sup>a</sup>. *Nepal, Situation of Child Ragpickers: A Rapid Assessment*, Investigating the Worst Forms of Child Labour, No.4. ILO-IPEC, Geneva
- King, Gary and Langche Zeng. Logistic Regression in Rare Events Data, *Political Analysis*, Vol. 9, No. 2 (Spring, 2001): Pp. 137-163
- Lancaster, Tony and Guido Imbens. 1996. "Case Control Studies with Contaminated Controls." *Journal of Econometrics*, 71, 145-160.
- Manski, Charles F. 1999. "Nonparametric Identification Under Response-Based Sampling." In *Nonlinear Statistical Inference: Essays in Honor of Takeshi Amemiya*, eds. C. Hsiao, K. Morimune, and J. Powell. New York: Cambridge University Press (in press).
- Menon, M, Pareli, F., and Rosati, F (2004), "Estimation of the Contribution of Child Labour to the Formation of Rural Incomes: An Application to Nepal," *Understanding Children's Work Working paper* , April 2004.
- Mhukherjee, Sanjukta, 2003. *Child Ragpickers in Nepal: A Report on the 2002-2003 Baseline Survey*. ILO-IPEC: Kathmandu.
- MOLT (Ministry of Labor and Transport Management, HMG), 2001. *A National Master Plan on Child Labor in Nepal (2001-2010)*. Kathmandu
- Mueller, Eva. 1984. "The Value and Allocation of Time in Rural Botswana," *Journal of Development Economics* 15: 329-360.
- Mueller, Eva. 1984. "The Value and Allocation of Time in Rural Botswana," *Journal of Development Economics* 15: 329-360.
- National Labour Association, 2004. *Child Domestic Workers in Nepal: A Report on the 2003 Baseline Survey*. ILO-IPEC, Kathmandu

- Parikh, A. and Sadoulet E (2005). "The Effect of Parents' Occupation on Child Labor and School Attendance in Brazil," *UC Berkeley Manuscript*.
- Pradhan, G., 1995. *Urban Domestic Child Labour in Nepal*. Child Workers in Nepal Concerned Group (CWIN), Kathmandu.
- Prentice, R. L., and R. Pyke. 1979. "Logistic Disease Incidence Models and Case-Control Studies." *Biometrika* 66:403–411.
- Psacharopoulos, G. (1997): "Child Labour Versus Educational Attainment: Some Evidence from Latin America", *Journal of Population Economics* 10: 377-386.
- Psacharopoulos, G. and Arriagada, AM (1989), "The Determinants of Early Age Human Capital Formation: Evidence from Brazil," *Economic Development and Cultural Change* 37(4):683–708.
- Ranjan, Priya. 2001. "Credit Constraints and the Phenomenon of Child Labor." *Journal of Development Economics*. 64(1): 81-102.
- Rogers, Carol A. and Kenneth A. Swinnerton. 2002. "A Theory of Exploitative Child Labor." Georgetown University Manuscript.
- Sharma, S., Thakurathi, M., Sapkota, K., Devkota, B., Rimal. B., 2001. *Situation of Domestic Child Labourers in Kathmandu: A Rapid Assessment*. ILO/IPEC, Geneva
- Tomz, Michael; Gary King; and Langche Zeng. ReLogit: Rare Events Logistic Regression, *Journal of Statistical Software*, Vol. 8, Issue 2 (2003).
- Wydick, B. 1999. "The Effect of Microenterprise Lending on Child Schooling in Guatemala", *Economic Development and Cultural Change*, 47(4), 853-69.

**Table 1: Prevalence Rates of Worst Forms of Child Labor in Nepal**

	<b>Number</b>	<b>(%)</b>
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
<b>TOTAL</b>	<b>127,143</b>	<b>100</b>

*(a) for urban areas only*

*source: ILO (2001) using the MES*

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

	<u>Domestic Workers Survey</u>		<u>2001 Population and Housing Census</u>								
	Mean	SE	<u>Wage Work</u>			<u>Home Enterprise Work</u>			<u>Not Work</u>		
			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

		<u>Domestic Workers Survey</u>		<u>2001 Population and Housing Census</u>					
		Mean	SE	<u>Wage Work</u>		<u>Home Enterprise Work</u>		<u>Not Work</u>	
				Mean	SE	Mean	SE	Mean	SE
<b>Belt</b>									
	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
<b>Region</b>									
	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 **
<b>Household Background</b>									
	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

	<u>Domestic Workers Survey</u>		<u>2001 Population and Housing Census</u>						
	Mean	SE	<u>Wage Work</u>		<u>Home Enterprise Work</u>		<u>Not Work</u>		
			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

	<u>Unconditional</u>			<u>Conditional</u>		
	<u>Attributable Risk</u>	<u>95% Confidence Interval</u>		<u>Attributable Risk</u>	<u>95% Confidence Interval</u>	
	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 regression, 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

	<u>At Mean Landholding Rate</u>			<u>Landless</u>		
	<u>Attributable Risk</u>	<u>95% Confidence Interval</u>		<u>Attributable Risk</u>	<u>95% Confidence Interval</u>	
	Estimate	Lower	Upper	Estimate	Lower	Upper
<b>Disability</b>						
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
<b>Literacy</b>						
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
<b>Home Enterprises</b>						
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 category).
- (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

	<u>Average Land Holdings</u>			<u>Landless</u>		
	<u>Attributable Risk</u>	<u>95% Confidence Interval</u>		<u>Attributable Risk</u>	<u>95% Confidence Interval</u>	
	Estimate	Lower	Upper	Estimate	Lower	Upper
<b>Disability</b>						
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
<b>Literacy</b>						
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
<b>Home Enterprises</b>						
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					
	Mean	SE	Wage Work		Home Enterprise Work		Not Work	
			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

		<u>Short Route Porters Survey</u>		<u>2001 Population and Housing Census</u>							
		Mean	SE	<u>Wage Work</u>		<u>Home Enterprise Work</u>			<u>Not Work</u>		
				Mean	SE		Mean	SE		Mean	SE
<b>Belt</b>											
	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
<b>Region</b>											
	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 **
<b>Household Background</b>											
	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

	<u>Short Route Porters Survey</u>		<u>2001 Population and Housing Census</u>								
	Mean	SE	<u>Wage Work</u>			<u>Home Enterprise Work</u>			<u>Not Work</u>		
			Mean	SE		Mean	SE		Mean	SE	
<b>Father Characteristics</b>											
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 <sup>^</sup>	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	**
<b>Mother Characteristics</b>											
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 <sup>^</sup>	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%

<sup>^</sup>All children report parent completing at least grade 1

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

	<u>Unconditional</u>			<u>Conditional</u>		
	<u>Attributable Risk</u>	<u>95% Confidence Interval</u>		<u>Attributable Risk</u>	<u>95% Confidence Interval</u>	
	Estimate	Lower	Upper	Estimate	Lower	Upper
<b>Household Background</b>						
Owns Farmland	-0.00033	-0.00078	-0.00003	-0.00009	-0.00028	0.00005
<b>Father Characteristics</b>						
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
<b>Mother Characteristics</b>						
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 regression, 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

	<u>At Mean Landholding Rate</u>			<u>Landless</u>		
	<u>Attributable Risk Estimate</u>	<u>95% Confidence Interval</u>		<u>Attributable Risk Estimate</u>	<u>95% Confidence Interval</u>	
		Lower	Upper		Lower	Upper
<b>Disability</b>						
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
<b>Literacy</b>						
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
<b>Home Enterprises</b>						
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
<b>Wage Labor</b>						
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 category).
- (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

	<u>Ragpickers Survey</u>		<u>2001 Population and Housing Census</u>							
	Mean	SE	<u>Wage Work</u>		<u>Home Enterprise Work</u>		<u>Not Work</u>		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

		<u>Ragpickers Survey</u>		<u>2001 Population and Housing Census</u>					
		Mean	SE	<u>Wage Work</u>		<u>Home Enterprise Work</u>		<u>Not Work</u>	
				Mean	SE	Mean	SE	Mean	SE
<b>Belt</b>									
	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
<b>Region</b>									
	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
<b>Household Background</b>									
	Owens 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

	<u>Ragpickers Survey</u>		<u>2001 Population and Housing Census</u>					
	Mean	SE	<u>Wage Work</u>		<u>Home Enterprise Work</u>		<u>Not Work</u>	
			Mean	SE	Mean	SE	Mean	SE
<b>Father Characteristics</b>								
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 **
<b>Mother Characteristics</b>								
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

	<u>Unconditional</u>			<u>Conditional</u>		
	<u>Attributable Risk</u>	<u>95% Confidence Interval</u>		<u>Attributable Risk</u>	<u>95% Confidence Interval</u>	
	Estimate	Lower	Upper	Estimate	Lower	Upper
<b>Household Background</b>						
Owns Farmland	-0.00017	-0.00031	-0.00008	0.00000	-0.00001	0.00000
<b>Father Characteristics</b>						
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
<b>Mother Characteristics</b>						
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 regression, 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

	<u>At Mean Landholding Rate</u>			<u>Landless</u>		
	<u>Attributable Risk Estimate</u>	<u>95% Confidence Interval</u>		<u>Attributable Risk Estimate</u>	<u>95% Confidence Interval</u>	
		Lower	Upper		Lower	Upper
<b>Disability</b>						
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
<b>Literacy</b>						
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
<b>Home Enterprises</b>						
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
<b>Wage Labor</b>						
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 category).
- (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
<b>Disability</b>				
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
<b>Literacy</b>				
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
<b>Home Enterprises</b>				
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
<b>Wage Labor</b>				
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 category).
- (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