Child Labor Variation by Type of Respondent: Evidence from a Large-Scale Study

Ana C. Dammert*
Carleton University and IZA

Jose C. Galdo
Carleton University and IZA

Abstract

Child labor has increasingly been a topic of interest in development economics. The empirical literature has focused on assessing the relative importance of factors that influence child labor and schooling decisions without considering a key survey design decision: self-reporting versus proxy interviewing. This study uses a controlled self/proxy design implemented in a large-scale, nationally representative survey in Peru. The child/proxy disagreement affects 20 percent of the sample, which translates in a 17.1 percentage points difference in the rate of national child labor by type of respondent. As a result, the marginal effects from standard child labor supply functions show large child/proxy differences, particularly when the household experienced adverse income shocks. Moreover, we find that attitudes and social perceptions toward child labor are not related to the likelihood of disagreement. A modified bivariate choice model with misclassification errors reports statistically significant probabilities of misclassification for both child and proxy reports.

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Contacts: A. Dammert, Department of Economics and Norman Paterson School of International Affairs, Carleton University, 1125 Colonel by Drive, Ottawa, ON K1S5B6, Canada. E-mail: ana_dammert@carleton.ca. J. Galdo, Department of Economics and School of Public Policy and Administration, Carleton University, 1125 Colonel by Drive, Ottawa, ON K1S5B6, Canada. E-mail: jose_galdo@carleton.ca.

1. Introduction

Child labor is widespread in developing countries. According to the International Labor Organization, in 2001 at least 211 million children were working around the world, mostly in developing countries, with over 8 million engaged in hazardous and exploitative forms of child labor (ILO 2002). Many authors argue that child labor deserves attention because it has long-lasting consequences for the economic development of countries through its interaction with education. Not surprisingly, an extensive empirical literature, invigorated by the increasing availability of household surveys in developing countries, has focused on the determinants of child labor in order to assess the relative importance of factors that influence decisions about child labor and education (see Bhalotra and Tzannatos 2002; Brown et al. 2003, Edmonds 2008).

Yet little is known about how child labor information should be collected or how survey designs affect the measurement of child labor. The literature has focused on the conceptual and operational definitions of child labor, working children, and economically active children (e.g., ILO 2004), without attending to the measurement of child labor itself. Although estimates of child labor vary depending on the definition of a child and market/domestic work, there is considerable unexplained inconsistency in child labor statistics across and within countries (Guarcello et al. 2009).

This study investigates the role of survey design and type of respondent in explaining variations in child labor statistics. We exploit a controlled self/proxy survey design implemented in a large-scale, nationally representative survey that targets child labor in Peru. The question concerning whom to ask about the child labor supply is particularly important in this setting because of the inherent tradeoffs between children’s and proxy’s responses. In most surveys, information about children’s schooling and work are collected from the most informed household member (often the household head) or the primary caretaker. Much less frequently, the measures come from the children themselves.

The literature on adult labor markets has emphasized the challenges of measuring irregular and marginal labor activities because of the seasonality of the jobs and the absence of steady work schedules and wage rates (e.g., Campanelli et al. 1989; Martin and Polivka 1995; Bardasi et al. 2010). The propensity to error in child labor settings is even more significant if one considers social desirability and normative values on one hand, and children's cognitive processes on the other. If child labor is viewed as "bad" for social, institutional, or cultural reasons, proxy underreporting of the true status is more likely to happen. For example, in most developing countries, including Peru, child labor is considered illegal for children younger than 14 years of age, although enforcement is far from strict. At the same time, child-based measures do not necessarily provide the "true" information on children's labor participation since cognitive processes may be an important source of misreporting (Bound et al. 2001; Borgers 2000). Therefore, this study does not claim that one method of data collection is better quality than the other, rather it assumes that both children's and proxies' reports are affected by error[1].

We investigate how the self/proxy distinction affects the determinants of child labor supply functions, as changes in these coefficients may alter the way we understand the economic forces that are behind child labor decisions. This study uses a rich dataset on child, proxy, and household attributes deemed important in the literature. Most important, this study provides evidence on the relationship between household income shocks and child labor, and analyzes how this relationship varies by type of respondent. A recent stream of the child literature has highlighted that child labor is used to buffer income shocks (Yang 2008, Duryea et al. 2007,

[1] Administrative information, a validation study, or a respondent debriefing study would be required to know the true classification of children's work. As the next section shows, however, this data does not exist.

Beegle et al. 2006). It is possible that exposure to adverse shocks affects the way how proxy (or child) respondents answer child labor survey questionnaires, either because they are more aware of the child involvement in market activities, or because attitudes and social perceptions toward child labor might change in times of crisis. The survey design allows us to identify several shocks experienced by the household in the 12 months prior to the survey including weather (e.g., floods, drought), economic (e.g., broken family business), and personal shocks (e.g., head of household abandons the house).

Furthermore, this study also analyzes the factors that explain the child/proxy disagreement in child labor measures. A rich set of attributes from both the child and proxy respondents are considered. While there is general agreement that child labor is responsive to the household's economic and social environment, it is less clear how this responsiveness is shaped by parental attitudes and social perceptions toward child labor (Parsons and Goldin 1989, Edmonds 2008). We then exploit a module on parental attitudes and social perceptions toward child labor that includes questions about the parents' own experiences as child laborers, along with subjective (normative) statements regarding child labor. How this set of variables affects the probability of child/proxy disagreement is an empirical question that, to the best of our knowledge, has not yet been addressed in the context of child labor statistics.

Given that validation data is non-existent in child labor studies, and inspired by the work of Hausman, Abrevaya and Scott-Morton (1998), we implement a modified maximum likelihood parametric model to assess the extent of misclassification error in child labor measures for both child-based and proxy-based reports. This adjusted probit model, which allows for the estimation of false positive and false negative participation probabilities, has been applied in topics as diverse as smoking (Kenkel, Lillard and Mathios 2004), education (Caudill and Mixon 2005), patents (Palangkaraya et. al 2010), and electoral voting (Flores 2009).

Several findings emerge from this analysis. First, we uncover substantial disagreement between child-based and proxy-based responses of child labor participation, disagreement that affects 20 percent of the sample, regardless of the number of hours the child works. As a result, there is a 17.1 percentage point difference in the rate of national child labor by type of respondent. This result holds across children's age, gender, and rural/urban residence.

Second, the estimation of standard child labor supply functions reveals sizable child/proxy differences in the magnitude, sign, and statistical significance of common attributes considered important in the literature. While this study supports recent evidence regarding the role of child labor supply as part of the household's self-insurance strategy against adverse shocks (i.e., Beegle et al. 2006), the effects on child labor are dependent on the type of respondent. For instance, exposure to some income shocks seems to be a significant predictor of child labor according to proxy respondents but not to self-based reports.

Third, contrary to the conventional wisdom, a multinomial analysis of the determinants of child/proxy disagreement shows that neither child's age nor schooling has sizable impacts on the likelihood of disagreement. Neither subjective attitudes nor social norms regarding child labor. Only a few handful of attributes have some sizable impacts on the likelihood of disagreement: rural/urban residence, ethnicity, and the proxy's own experience as child laborer.

Fourth, the implementation of the adjusted probit model in the context of misclassification in the dependent variable shows statistical significant false positive and false negative probabilities for both child- and proxy-based reports. In particular, proxy respondents are prone to underreport the labor status of children, independently of the hours worked; while child self-respondents tend to overreport (underreport) when working few (large) number of hours per week.

The remainder of the paper proceeds as follows: section 2 presents an overview of misclassification in child labor statistics. Section 3 describes the study design and data used in the empirical section. Section 4 presents a statistical analysis of child labor variation by type of respondent, investigates the determinants of child labor allocation by type of respondent, and analyzes the determinants of disagreement between child and proxy respondents. Section 5 presents the modified maximum likelihood approach to estimate the extent of misclassification in child labor statistics. Finally, Section 6 offers some concluding comments.

2. The Noisy Nature of Child Labor Statistics

There is a substantial recognition that child labor statistics are particularly prone to error (ILO 2008). Information on child labor is collected primarily using standard household surveys that target adult work rather than child work, and formal jobs rather than unpaid, informal, and seasonal jobs. The broader literature on adult work has shown the inherent difficulty in capturing reliable information on employment, working hours, and salaries of individuals who work in the marginal ranks of the economy (e.g., Campanelli et al. 1989). As a result, underreporting of labor market status is common, particularly when researchers use short survey design sequences (Anker 1983, Bardasi et al. 2010). In this type of settings, the use of detailed screening questions, at the expense of higher costs and effort feasibility, has been shown to ameliorate the problem of underreporting for adult workers (Martin and Polivka 1995).

Due to budgetary constraints in developing countries, collecting information for each individual living in the same household entails an additional key survey design decision: self-reporting versus proxy interviewing. Survey design studies have shown that self-reporting respondents, rather than proxies, provide more accurate information on topics as diverse as adult labor markets (Hussmanns et al. 1990), schooling (Ashenfelter and Krueger 1994), and health (Mathiowetz and Groves 1985)[2]. While this evidence comes from the analysis of adult markets, it has direct implications for child labor statistics because of the intrinsic tradeoffs in the accuracy of the information provided by children and proxy respondents.

In the context of child labor surveys, the advantages of using children-based rather than proxy-based reports are not quite obvious. Child-reported information may be more accurate than proxy responses, given that a child knows best how he or she allocates his or her time. This point is relevant, especially for children who work outside the family farm or business. At the same time, the cognitive development of children, particularly those aged 9 and younger, may affect the quality of the information provided. Calculations on weekly hours worked, for example, could be an issue for younger children. Similarly, the head of household may be familiar with the children's activities since many child laborers in developing countries work in the family farm or enterprise. Yet, the proxy respondent may tend to underreport the true rate of participation if child labor is viewed as "bad" because of social norms and cultural values. In fact, it is widely documented in the measurement error literature that questions regarding socially undesirable behavior and attitudes result in patterns of underreporting because sensitive questions entail strong positive or negative normative responses (Bound et al. 2001; Tourangeau et al. 1999).

In this regard, the ILO's guidelines for the measurement of child labor suggest that children aged 9 and older should respond to the questionnaires by themselves, while younger

[2] There are also several studies that shown no differences in response bias between self- and proxy respondents (see for instance the review in Moore 1988)

children should be assisted by their parents only when they have cognitive difficulties that impede their ability to understand the questions and communicate the answers (ILO 2004). These recommendations are based on evidence drawn from the discipline of cognitive and social psychology, which shows that children aged 9 and older are able to comprehend questions, retrieve the information from memory, and assess the correspondence between the retrieved information and the requested information (Borgers et al. 2000; Schaeffer 2000). So far, the standard practice in developing countries is to use proxy respondents—generally, the head of household—to elicit information on children's activities due to budgetary constraints and under the assumption that proxy respondents are familiar with the children's time schedules.

Evidence on the magnitude, impact, and potential solutions of measurement error in child labor statistics constitutes a gap in the literature. Little is known, for instance, about whether the type of respondent, question sequencing, or the use of screening questions has an effect on child labor statistics or about how these factors might affect the estimated parameters of standard child labor supply functions. At the macro level, one exception is the work of Guarcello et al. (2009), who documents large discrepancies in child labor statistics between independent national surveys within the same country. The magnitude of these discrepancies is compelling, ranging in the order of 20 to 30 percentage points, even after accounting for differences in sample design.

On the micro data level, the absence of studies addressing measurement error in child labor statistics is also apparent. A potential explanation for this vacuum is the absence of validation data in developing countries[3]. One of the main restrictions in comparing survey-based estimates of children's work with administrative data is that most developing countries,

[3] Some exceptions are Akee (2010) and Escobal and Laszlo (2008). The former analyzes measurement error in adult wages in Micronesia. The latter compares self-reported travel time to the nearest populated center to the "true" travel time estimated using Global Position System (GPS) in Peru.

including Peru, have ratified the ILO Convention 138 on the minimum age and the ILO Convention 182 on the worst forms of child labor. According to these laws, there is a minimum legal age for employment based on economic sector. For example, in Peru the minimum age for employment in non-industrial jobs is 15, while the minimum age in the industrial sector of the economy is 16. Children aged 12 to 14 may work only if they obtain permission from the Ministry of Labor after certifying that they are attending school[4]. In 2009, the Ministry of Labor issued 1,078 work permits for children aged 12 to 17, the large majority of which (85 percent) were issued for children aged 16 to 17 (MINTRA 2009). Matched administrative information and self-reported employment for this small non-random sample could provide insights about differences in labor market outcomes. However, as far as we know, no such matched data exists. Furthermore, selection issues may bias the results since only a small fraction of child laborers apply for a permit.

To the best of our knowledge, only two recent micro empirical studies have addressed the role of survey design in child labor statistics. Dillon (2010) compares two different modules of child labor in the same survey for a sample of 1445 children aged 10 to 17 in five districts of northern Mali. The first module was completed by proxy respondents, the children's parents, through standard questions on labor market outcomes. The second module elicited subjective information from the children. The main finding suggests that parents systematically underreport child labor statistics relative to child-based measures. This result cannot disentangle the proxy effects from those of survey design because children's responses are based on subjective measures of child labor elicited from a subjective card game.

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[4] National laws are available at:
http://www.mintra.gob.pe/archivos/file/cpeti/marco_normatico/CODIGO_NINOS_ADOLESCENTES.pdf

Dillon et al. (2010) also address measurement error in child labor statistics based on a randomized survey experiment of 566 children aged 10 to 15 in seven districts across Tanzania. By comparing short questionnaires with detailed questionnaires and child-based responses with proxy-based responses, the authors find that short questionnaires yield statistically significant lower incidence of child labor than detailed questionnaires do, but they find no significant differences between child-based and proxy-based responses. Yet, as the authors acknowledge, the study design does not capture a pure proxy effect because the lack of data on the same person from both proxy and child respondents.

3. The Survey Design and Data

This study uses a large-scale, nationally representative survey that targets child labor activities from 11,739 children aged 6 to 17 in Peru in 2007. The Peruvian National Child Labor Survey (hereafter PNCLS) was conducted by Peru's national statistical agency, the Instituto Nacional de Estadistica e Informatica, with the support of the International Labor Organization as part of its International Programme on the Elimination of Child Labor. The questionnaires used in the PNLCS strictly follow the ILO's guidelines for Statistical Information and Monitoring Programme on Child Labour *(*SIMPOC) surveys[5].

This unique database allows us to investigate the effects of survey design on child labor statistics by focusing on the type of respondent (child-based versus proxy-based reports) across alternative definitions of child labor. The child/proxy distinction is significant because it unambiguously refers to the same individual. The proxy respondent offered demographic,

[5] The survey was taken in September, October, and November of 2007. It was conducted as a standalone survey, with the aim of gathering information on child labor statistics. The sampling framework was based on the 2005 Population Census and the sample was comprised by households with at least one child in the 5 to 17 age range.

schooling, employment, and other household information for all household members. At the same time, using the same objective questions, the survey asks children directly to self-report their employment, demographic, and schooling information.

Unlike uncontrolled self/proxy approaches, this research design systematically draws information from two sources for every child in the sample, which allows us to estimate proxy impacts by comparing two standard labor modules on the same person. The PNLCS survey instructions state that the person selected to be a proxy respondent should be the head of household, the spouse of the head, or another household member older than age 18. A potential criticism of child/proxy observational studies is the non-random nature of the proxy respondents. It may be the case that the results would change depending on whether the proxy respondent is the father, the mother, an aunt, a grandparent or a sibling, whose responses could be influenced by other factors. However, since the PNCLS followed a controlled research design that purposely targets parents as respondents, there was no room for self-selection as parents accounted for 91 percent of the proxy responses. In only 7.5 percent of cases older siblings answered the questions. Therefore, the results presented in this paper follow a valid child/proxy design for children's and parents' responses[6].

The distinction between proxy interviewing and collecting the information from an individual directly is not always a sharp one. For instance, a child could ask for parental help while answering questions if he or she does not know the answer or does not feel comfortable answering it. In this regard, the survey protocol states that private interviews for children are preferable whenever possible. Only in those cases where this was not possible, the field

[6] Nonetheless, we analyze the possible differences introduced by the type of respondent by restricting the sample estimation to children and their parents and by analyzing fathers' and mothers' responses separately. Unreported results are similar to the estimates presented in this study and all qualitative findings hold when we restrict the proxy sample to parents, independently of their gender.

enumerator was authorized to collect information on the presence of another household member. It turns out that no other household member assisted the child in responding the survey questionnaire in 98 percent of cases.

We consider two different age groups, children 6 to 9 and children 10 to 14. By comparing measures of child labor across age groups, we investigate, for instance, whether child/proxy disagreements on labor market activities are higher for children with lower cognitive development. At the same time, we exclude from the analysis the work of teenagers since they are not considered as child laborers, resulting in a final sample of 8,194 children aged 6 to 14. As Table 1 shows, children in this age group are, on average, 10 years old and 98 percent are enrolled in school, with an average of 3.6 years of completed schooling. Moreover, proxy respondents are, on average, 40 years old, with 7.7 years of completed schooling, and who had worked themselves as child laborers in 77 percent of the cases.

Both the proxy and the child respondent were asked a series of questions about employment and schooling using the same standard survey instruments and questions. Children answered one of two types of standard questionnaires based on their age. The 5-to-9 age group questionnaire was comprised of 43 questions about schooling, employment during the preceding week and the preceding twelve months, domestic work, and health and safety issues. The 10-to-17 age group questionnaire was comprised of 63 questions about schooling, employment during the preceding week and the preceding twelve months in principal and secondary jobs, domestic work, and health and safety issues.

The first question in the labor module is the standard “During the past week, from (date) to (date), did (name) work for at least one hour?” This type of question is commonly used in short questionnaires to generate statistics with a high frequency. As child labor is an activity that can be subject to misinterpretation because of the complexity of the behavioral experience, detailed subsequent questions target those respondents –both children and proxy- who answered “no” to the first question. Several questions about specific economic activities were asked in order to learn whether children were indeed not engaged in labor activities. A typical question asks, for instance, “During the past week, from (date) to (date), did (name) help in growing farm produce or looking after animals for the household?”[7].

Based on the sequencing of these questions, a child laborer is defined as an economically active child if he or she is engaged in market activities for at least one hour in the week prior to the survey. This standard definition (hereafter CLS) includes paid and unpaid work, work in the family enterprise and family farm, among others, and is consistent with the ILO’s Statistical Information and Monitoring Program on Child Labor (SIMPOC) definition. The CLS definition does not include domestic work performed inside the child’s own household, as non-economic housework is the subject of a separate module in the survey, module that differs between the proxy and child questionnaires.

Furthermore, since there is no consensus on the literature on the definition of child labor, we also investigate the sensitivity of the child/proxy disagreement to alternative measures of child labor. A common approach is to consider an arbitrary cutoff in the number of hours worked, approach that would let us know, for instance, whether proxies are more likely to report the child as working when the child reports working several hours per week rather than only a

[7] These follow-up questions also aimed at capturing the work activities of children older than 12 years old who were not engaged in any economic activity during the week of reference but who had a job attachment to a permanent job or business to which the child plans to return. As expected, no child or proxy respondent reported a single individual who had a permanent job or his/her own business.

few hours. A second definition, namely CLH, is therefore implemented and considers child laborers to children who are engaged in market activities at least nine hours per week[8].

4. Quantifying Child Labor Reports

4.1 Descriptive Statistics

Table 2 presents the means and standard deviations for both child-based and proxy-based measures of children's participation in the labor market. Panel A shows the results for the full sample, that is, children aged 6 to 14, while panels B and C consider children aged 6 to 9 and children aged 10 to 14, respectively. Within each panel two definitions of child labor participation are implemented, CLS and CLH, for boys and girls and urban and rural subsamples. Statistical analysis of mean differences between child-based and proxy-based measures is implemented following standard t-tests.

By looking at the first row in panel A, we observe significant differences between child-based and proxy-based mean responses in the full sample. While 59.9 percent of children declared to work according to the standard CLS definition of labor participation, only 42.8 percent of proxy respondents answer the same, yielding a 17.1 percentage points difference between child and proxy responses, difference that is statistically significant at the 1 percent level. One observes the same qualitative result when splitting the sample by gender and geographic location. The magnitude of the child/proxy difference is comparatively stable in all subsamples, although it affects more boys than girls (18.3 versus 15.9 percentage points), and more urban than rural children (18.4 versus 15.1). By turning our attention to children's age in the first row of panels B and C, we observe, as expected, higher rates of participation for children

[8] Economically active children in our sample report working in market activities an average (median) of seven (nine) hours per week.

aged 10 to 14 relative to those aged 6 to 9, according to both type of respondents. A higher rate of child/proxy disagreement for children aged 6 to 9, relative to the older ones (19.6 versus 15.3), particularly for the rural subsample (19.2 versus 11.9), is also observed.

The second row in Table 2 shows mean differences when using the alternative definition of child labor, CLH. As expected, the national estimates of child labor drop almost in half for both child- and proxy-based reports after imposing a cutoff for weekly hours worked. As a result, the child/proxy mean difference decreases 2.5 times in the full sample, from 17 to 7 percentage points. This outcome is mainly explained by a large fall in the child/proxy disagreement in the urban subsample (from 18 to 4), whereas the rural one shows only a modest change (from 15 to 11). Similar to the differences found for the CLS definition, higher rates of disagreement are reported for children aged 6 to 9, relative to the older ones, particularly in the rural subsample.

The last row within each panel in Table 2 shows the mean and standard deviation for the (unconditional) weekly hours of work according to both the self- and proxy-based responses. There is evidence of significant underreporting of weekly hours worked by proxy measures, relative to child-based measures. The difference reaches 1.62 hours of work, which represents 25 percent of the (child-based) children's average number of working hours. Children may perceive time differently than adults do, or the differences in the reports may be due to activities carried out by children in the family farm or business that are not viewed as labor by the proxy. The magnitude of the proxy underreporting is stable across age groups, as the disagreement reaches 1.59 and 1.65 hours for children aged 6 to 9 and 10 to 14, respectively. For boys and girls, the underreporting for hours worked is around 1.60 hours, while the rural subsample shows the highest proxy underreporting, at 2.20.

The descriptive analysis presented in Table 2 suggests that child labor statistics are highly sensitive to the type of respondent. In particular, the proxy-based reports underscore significant underreporting, relative to self-based measures. This result is consistent with Dillon et al.'s (2010) findings for child labor in Tanzania and with the broader literature on adult labor markets (Anker 1983). Among children whose proxies report them as not working or not engaged in any economic activity, child-reported information shows that 29.8 percent helped parents in looking after livestock, 27.4 percent helped parents in growing or harvesting produce, and 11 percent helped or worked in commerce or selling products.

Table 2 also suggest that variation in child labor statistics is greatly exacerbated when the child works only a few hours as one observes a better match up in the rate of national child labor between child- and proxy-based measures after imposing an arbitrary cutoff for hours worked. Yet, a complementary statistical analysis shows a different story. Table 3 reports cross tabulations between child- and proxy-based measures for the CLS and CLH definitions for the full sample and by age groups. Two features emerge from this table. First, the likelihood of disagreement is quite similar for both definitions of child labor. The off-diagonal numbers shows that around 20 percent of the cases, child-based and proxy-based measures diverge. Second, imposing a cutoff in hours worked only changes the incidence on the type of disagreement but not the overall disagreement. Taking the child-based measure as the reference response, for instance, one observes that 90 percent of the total disagreement in CLS is explained by the proxy 'false negatives', while only 10 percent of the disagreement is due to 'false positives'. On the other hand, when the measurement of child labor is based on a cutoff value for hours worked, two-thirds of the disagreement in CLH is explained by the proxy 'false negatives', while a sizable one-third of the disagreement is due to 'false positives'. This result highlights that self/proxy disagreement in child labor statistics is large and it is not tempered by the number of hours the child works.

For comparison purposes, Table 4 depicts child/proxy responses for two schooling variables: whether the child is attending school and years of education completed. The results show marginal differences on schooling outcomes for children aged 6 to 14. While 97.7 percent of children reported attending school the week prior to the survey, 99.9 percent of proxy respondents reported that children had attended school. In regards to number of years of completed schooling, the difference between the two reports is also very small (-0.002) and statistically not significant.[9] This result reinforces the evidence that child labor statistics is particularly prone to be reported with error because of the complex nature of child labor relationships in developing countries.

4.2 Child/Proxy Effects on Child Labor Allocation

One contribution arising from the growth of empirical studies on child labor over the last decade has been a better understanding of the role of individual, household, and market characteristics to explain child labor allocation (Edmonds 2008, Basu 1999). Child labor elasticities with respect to covariates of interest are estimated by standard parametric models under the assumption that one observes the true response variable. Let y_i^* be a latent variable representing the net benefits of child labor as a function of observable determinants x_i and a disturbance term ε_i,

$$y_i^* = x_i'\beta + \varepsilon_i \qquad (1)$$

[9] Unreported results show no differences in reported age between children and proxy respondents as well.

As the child works when the net benefits (to the household) are positive (Basu and Van 1998), the true child labor status, $\overline{y}_i$, is defined by

$$\overline{y}_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

In the absence of misclassification, the observed survey response on child labor status, y_i, is identical to the true status $\overline{y}_i$, and one consistently estimates β by

$$y_i = x_i'\beta + \varepsilon_i \qquad (2)$$

Yet, it is possible that the magnitude and statistical significance of β would be sensitive to the type of respondent, which in turn may alter the way we understand the economic forces that help determine child labor rates in Peru. We therefore estimate equation (2) separately for child- and proxy-based reports by using a rich set of attributes that are deemed important in the literature (see Edmonds 2008, Bhalotra and Tzannatos 2002, and Brown et al. 2003). In addition to having information on children and household attributes, the Peruvian PNCLS survey is particularly rich in capturing information on a variety of adverse shocks that affected households in the last 12 months to the interview date, as a recent stream of studies has highlighted that child labor is part of the household's self-insurance strategy against crop (Beegle et al. 2006), employment (Duryea et al. 2007), financial (Yang 2008), and weather shocks (Jacoby and Skoufias 1997). One wonders whether exposure to weather or economic shocks affects the way how proxy or self respondents answer child labor survey surveys either because they are more aware of the child involvement in market activities or because attitudes and social perceptions toward child labor change in times of crisis.

Unlike the mentioned studies that focus on a single shock, the PNCLS survey allows us to capture information on multiple adverse shocks, which we group in three categories:

(i) weather shocks: drought, floods due to rainfall, freezing conditions, epidemics;

(ii) economic shocks: employment loss of family member, broken family business, crop loss, price drop in agriculture output, price drop in family business;

(iii) family shocks: death or serious accident/illness of family member, head abandons the house.

Testing which shocks are unanticipated/anticipated or transitory/permanent is out of the scope of this study, although it is apparent that some type of shocks are arguably exogenous and unanticipated either because of the randomness of the weather (e.g., floods) or because choices that are taken outside the family influence (e.g., drop in agricultural prices). Rather, we focus on analyzing the magnitude and significance of diverse type of shocks in child labor supply functions by type of respondent.

Table 5 reports the marginal effects, along with their standard errors, from labor supply functions estimated by standard parametric probit models. Columns 1 and 2 show the results for the CLS measure whereas columns 3 and 4 show the corresponding estimates for the CLH measure. Overall, one observes sizable differences between child- and proxy-based marginal effects for most attributes considered in the child labor supply model. By focusing on panel A, one observes that common child attributes like age, gender, and ethnicity, are the least sensitive parameters to the type of respondent in child labor supply functions, while household attributes are quite sensitive. In particular, the sign and statistical significance of household composition (family size) and household budget constraints (expenditures per capita), change depending on the type of respondent. By looking at the CLS definition in columns 1 and 2, one observes that larger families and higher expenditures per capita attributes are (statistically) associated to lower child labor participation according to the proxy-based measure, while these attributes are not statistically related according to the child-based report. Moreover, when turning our attention to the CLH definition in columns 3 and 4, we observe that family size is statistically significant at the 1 percent level but have opposite signs for child-based (positive) and proxy-based (negative) reports. As a result, a researcher armed only with the child-based information would have concluded that, as larger households tend to be poorer, the marginal utility of consumption will be higher (everything else equal) in large households, which explains the positive sign. On the contrary, a researcher armed with only the proxy-based report would have concluded that the value of child time in household production is higher in large households and dominates the marginal utility of consumption effect, which explains the negative sign.

Panel B shows the corresponding marginal effects for weather shocks. Without ambiguity the estimates show that the occurrence of weather shocks increases significantly child labor participation. The magnitude of the estimates are large and statistically significant at 1 percent level for all type of shocks, CLS and CLH definitions, and for both child- and proxy-based reports. These new results for Peru support recent evidence from other developing countries that highlight the role of child labor supply as part of the household's self-insurance strategies against adverse shocks (Beegle et al. 2006). With respect to the comparison between child-based and proxy-based reports, we observe sizable differences in the marginal effects, particularly for the CLH definition. In this case, columns 3 and 4 show almost a two-fold difference in the magnitude of the marginal effects by type of respondent.

Panel C show the marginal effects associate to several economic/business shocks. Unlike weather shocks, there is more heterogeneity in the child labor supply responsiveness depending on the type of economic shock and the type of respondent. The estimates suggest that child labor supply is used to buffer economic shocks in Peru. This result is particularly observed for 'broken family business', 'harvest loss', and 'agriculture price drop' covariates. Moreover, 'loss of employment for the head of household' is the only attribute that shows statistically significant negative impacts on child labor supply, which suggests that adult and child work are complementary rather than substitute activities in Peru.

When comparing the marginal effects for CLS by type of respondent in columns 1 and 2, one notices that for most economic shocks the size of the marginal effects are larger for the proxy-based report, relative to the child-based report. For example, the marginal effects of 'broken family business', 'crop loss', and 'agriculture price drop', are almost two times bigger for proxy-based reports than that for child-based reports. As a result, all economic shocks are statistically significant according to the proxy-based report, while only three out of five economic shocks are statistically significant determinants of child labor supply according to the self-based report. These results suggest that, ceteris paribus, proxy respondents have higher propensity to report the child as working, relative to child respondents, when the household is hit by economic shocks.

When the definition of child labor is based on an arbitrary cutoff of hours worked, on the other hand, columns 3 and 4 show one noticeable difference: the higher responsiveness of child labor to economic shocks according to the proxy respondent is lost given the lack of statistical significance of 'family business price drop' for both child-based and proxy-based marginal effects.

Finally, Panel D in Table 5 reports the marginal effects of two family shocks experienced in the last 12 months: 'death or serious accident/illness' (of a family member) and 'head of household abandons the house'. It is quite striking to observe how child labor supply decisions are affected by this second attribute. The magnitude of the coefficients is only comparable to rural-urban differences or Quechua-Spanish differences, making this particular shock an important determinant of child labor in Peru. When turning our attention to the child/proxy differences for the standard child labor definition, CLS, we observe in columns 1 and 2 large differences in the marginal effects for both family shocks. For instance, the magnitude of the estimates for ‘death or serious accident/illness’ is three times higher for the proxy-based report, relative to the child-based report, albeit statistically significant only in the former case. These differences, however, disappear after imposing a cutoff for hours worked, as shown in columns 3 and 4.

All in all, this analysis has shown evidence that the type of respondent matters for child labor statistics. The child/proxy discrepancies are striking and have sizable effects when estimating the determinants of child labor in Peru. In particular, the magnitude and statistically significance of expenditures per capita, household composition, and economic shocks are sensitive to the type of respondent, particularly for the standard CLS definition. It is worth noticing that these results only indicate that the biases associated with child and proxy reports of child labor are different, and not that one measure elicits better information than the other.

4.3 Determinants of Child/Proxy Disagreement

In this section, we shed light on the variables that explain the child/proxy disagreements by considering a rich set of children, proxy, household, and economic attributes. In addition to common socio-demographic variables related to the child and proxy respondents, we also consider whether the household was subject to weather, economic, or personal shocks, as evidence presented in the previous section suggest that adverse shocks have a disproportional effect on proxy responses, relative to the child ones. Moreover, while there is a general agreement in the empirical literature that child labor is responsive to the household’s economic and social environment, it is less clear how this responsiveness is shaped by parental attitudes towards child work (Edmonds 2008)[10]. We therefore consider an additional set of determinants of child/proxy disagreement related to parental attitudes and social perceptions toward child labor. It is important to recall that information from the proxy respondent corresponds in 90 percent of the cases to the information provided from one of the parents of the child.

The first variable considered is the parents' own experiences as child laborers, information that is important in studies addressing the intergenerational persistence of child labor (e.g., Barham et al. 1995; Emerson and Souza 2003). Parents' work experiences at a young age can shape their attitudes toward child labor later on: such experiences may cause parents to feel that there is nothing wrong with child work, giving them no incentive to hide it, or bad experiences at a young age can lead parents to misreport the true information about their own children's work. How this variable affects the probability of disagreement is an empirical question that, to the best of our knowledge, has not been addressed in the context of measurement error in child labor statistics.

Furthermore, we consider three additional variables that capture subjective information on attitudes and perceptions about child labor. Specifically, proxy respondents were asked the following questions: Do you agree or disagree with child labor? Do you agree or disagree with the following statement: "child labor is hurtful for children"? Do you agree or disagree with the following statement: "child labor should be eliminated"?[11] We incorporate this information in a multivariate regression that looks at correlations between the proxy's attitudes toward child labor and the divergence between the reports from children and proxy respondents. We acknowledge

[10] An exception is the work Parsons and Goldin (1989), which addressed the role of social norms and attitudes toward child labor in the United States.

[11] There is also a question about the preference for schooling over child labor that we do not use because there was not much variation in the answers.

that disentangling the causal relationship between child labor and parental attitudes toward child labor is difficult because of the confounded relationship between parents' attitudes and other factors influencing child labor.

To make a distinction between the two possible directions of the difference between the child and proxy reports, the analysis is based on a multinomial probit model. The empirical implementation considers three possible outcomes for each child: (1) proxy reports the child as working but the child reports himself as not working, (2) proxy reports the child as not working but the child reports himself as working, and (3) both child and proxy agreed on their reports, which is the base category in the estimation model. All these outcome variables are created separately for each definition of child labor, CLS and CLH.

Table 6 presents the marginal effects, along with their standard errors. Each column represents a different outcome variable. By focusing first on the standard CLS definition in columns 1 and 2, one observes that the first outcome i.e., proxy reports the child as working but the child reports himself as not working, seems to be random given the fact that all but two attributes are not statistically related to this outcome. The gender of the child and whether the parent worked as child laborer are the only two significant determinants of this type of disagreement, although the magnitudes of their marginal effects are negligible (-0.7 and 1.0 percentage points, respectively).

When moving to the second outcome in column 2 (proxy reports the child as not working but the child reports himself as working), we observe a different pattern: several demographic variables related to the child and proxy respondents, as well as household exposure to adverse shocks, are statistically significant determinants of child/proxy disagreement. In particular, the disagreement reduces by 6 percentage points for aboriginal children, 2.4 for rural children, and

3.5 for households that were exposed to economic shocks. On the other hand, it increases by 3 percentage points when the proxy worked as child laborer and 2.7 when the household was hit by family shocks in the last 12 months. Interestingly, and contrary to our priors, neither the age nor the schooling of the child or proxy respondents have sizable impacts on the likelihood of disagreement. Likewise, attitudes and social perceptions toward child labor are not related to the likelihood of divergence between the child's and proxies' reports. The resulting likelihood of disagreement is negligible and statistically not significant whenever proxy respondents are against child labor, or they believe that child labor is harmful for children, or that child labor should be eliminated.

Columns 3 and 4 of Table 6 show the determinants of disagreement when the definition of child labor is based on a threshold of the number of hours worked. The determinants of the first outcome i.e., proxy reports the child as working but the child reports himself as not working, are mainly related to the characteristics of the child, although the magnitude of the coefficients is negligible. Indeed, only the rural attribute have somewhat sizable impacts on this type of disagreement (3 percentage points). The rest of attributes, including economic shocks or proxy attitudes toward child labor, do not play, again, a role in explaining this type of disagreement. In column 4, on the other hand, we show the marginal effects for the most common type of disagreement i.e., proxy reports the child as not working but the child reports himself as working. Four variables emerge as the main determinants of disagreement: whether the child lives in rural area (8 percentage points), whether the child is Quechua or Aymara (-3.4 percentage points), whether the proxy respondent speaks an aboriginal language (4.6 percentage points), and whether the proxy worked as child laborer (1.6 percentage points). All other attributes have a negligible or no statistical relationship with the outcome of interest.

Overall, and contrary to the conventional wisdom, neither child's age nor schooling has sizable impacts on the likelihood of disagreement. Likewise, subjective attitudes and social norms regarding child labor does not play any role in explaining divergences in child's and parents' reports. Only a small number of attributes have sizable impacts on the likelihood of disagreement: rural/urban residence, ethnicity, and the proxy's own experience as child laborer. In particular, the rural and ethnic background attributes emerge as the most important predictor of divergence when one imposes a cutoff for the number of hours worked. These results may be related to the type of activities in which children engage in urban and rural areas. Rural children, most of whom are Quechua or Aymara descendents, engage primarily in helping their parents in agricultural activities (58 percent), taking care of the animals (51 percent), and selling things in the market (7 percent). Urban children, on the other hand, show a more diversified engagement in the labor market, with the share of urban workers distributed more evenly across twenty or so different economic activities.

5. Accounting for Misreporting in Child Labor Estimates

In the absence of misclassification, equation (2) yields consistent estimates for β and thus the conditional expectation of the observed measure, $E(y_i \mid x_i)$, equals $F(x'_i \beta)$, the cumulative distribution function of $-\varepsilon_i$ (e.g., normal or logistic). Yet, when the child labor survey response is an imperfect measure of the true status, as it is suggested in the previous sections, two misclassification probabilities emerge: the probability of classifying a child as working when she did not (α_0) and the probability of classifying a child as not working when she did work (α_1). The former is defined as $\alpha_0 = \Pr(y_i = 1 \mid \bar{y}_i = 0)$, a false positive, while the latter is defined as

$\alpha_1 = \Pr(y_i = 0 \mid \overline{y}_i = 1)$, a false negative. In this case, the conditional expectation of the observed child labor measure can be derived straightforwardly from equation (2) as

$$
\begin{aligned}
E(y_i \mid x_i) &= \Pr(y_i = 1 \mid x_i) \\
&= \Pr(\overline{y}_i = 1 \mid x_i)\Pr(y_i = 1 \mid \overline{y}_i = 1) + \Pr(\overline{y}_i = 0 \mid x_i)\Pr(y_i = 1 \mid \overline{y}_i = 0) \\
&= F(x_i'\beta)(1-\alpha_1) + (1 - F(x_i'\beta))(\alpha_0) \\
&= \alpha_0 + (1-\alpha_0-\alpha_1)F(x_i'\beta) \qquad (3)
\end{aligned}
$$

Equation (3) collapses to the usual $F(x'_i\beta)$ when both misclassification probabilities, α_0 and α_1, equal zero[12].

Given that both child- and proxy-based reports are measured with error, this section implements the estimator developed by Hausman, Abrevaya, and Scott-Morton (1998), to explore, in the absence of validation data, the magnitude of false positive and false negative participation probabilities in the context of misclassification in the dependant variable of a binary choice model. This adjusted probit model has been applied in a variety of empirical settings including smoking (Kenkel, Lillard and Mathios 2004), education (Caudill and Mixon 2005), patents (Palangkaraya et. al 2010), electoral voting (Flores 2009), among others.

In particular, Hausman et al. (1998) provided conditions for identification of the parameters $[\alpha_0, \alpha_1, \beta]$ under the assumption that $F(x'_i\beta)$ is known. Because equation (3) provides a moment condition, one can estimate the parameters of a binary choice model with misclassification by maximum likelihood (MLE) through a modified log likelihood function:

[12] At the extensive margin, the dependent variable is, by definition, a dichotomous variable representing whether the child works during a specific period of time (usually the week prior to the survey). A dichotomous variable can be misclassified in only one of two ways, so the probabilities of introducing positive or negative errors are, by construction, correlated to the true value of the variable. Thus, the assumption of classical measurement error is violated. The estimated parameters in the child labor supply equation will be biased and inconsistent with the magnitude of the bias proportional to the coefficient from a regression of the measurement error on the explanatory variables (Griliches 1986; Bound and Krueger 1991).

$$\ell(\hat{\alpha}_0, \hat{\alpha}_1, \hat{\beta}) = n^{-1} \sum \begin{Bmatrix} y_i \ln(\hat{\alpha}_0 + (1-\hat{\alpha}_0 - \hat{\alpha}_1) F(x_i ' \hat{\beta}) \\ +(1-y_i) \ln(1-\hat{\alpha}_0 - (1-\hat{\alpha}_0 - \hat{\alpha}_1) F(x_i ' \hat{\beta})) \end{Bmatrix} \qquad (4)$$

By maximizing equation (4) with respect to $[\hat{\alpha}_0, \hat{\alpha}_1, \hat{\beta}]$, we recover consistent and efficient $\hat{\beta}$ parameters, along with the estimated probabilities of misclassification, $\hat{\alpha}_0$ and $\hat{\alpha}_0$, probabilities that provide a specification test for misclassification error.

The identification conditions are similar to those for the traditional binary choice model and are based entirely on the nonlinearity of $F(x'_i \beta)$. This approach involves only one child measure at a time. That is, it does not attempt to derive insights about reporting errors from the comparison of child and proxy responses. The only additional condition, for estimation purposes, is that $\alpha_0 + \alpha_1 < 1$, a monotonicity condition that requires no substantial misclassification error. When this condition fails, the resulting β-estimates have the wrong sign (Hausman et al. 1998).

Identification of α_0 and α_1 requires that the estimated single index $x'_i \beta$ be close to zero or one for some individuals. The intuition comes from the semiparametric identification of the misclassification probabilities. If the distribution of ε_i is unknown, one can identify α_0 and α_1 by estimating the conditional expectation $E(y_i \mid x_i)$ at the limit because the probabilities of misclassification depend only on a child's true labor status and are otherwise independent of *x*,

$$\lim_{x_i ' \beta \to -\infty} E(y_i \mid x_i) = \alpha_0 \quad \text{and} \quad \lim_{x_i ' \beta \to +\infty} E(y_i \mid x_i) = 1 - \alpha_1$$

Therefore, α_0 is identified from the group of children who are very unlikely to work ($x_i ' \beta \to -\infty$) but whose survey response classified them as working, while α_1 is identified from the group of children who most likely work ($x_i ' \beta \to +\infty$) but whose survey response classified them as non-working. Put differently, the probability of false positive reports is identified by looking for unusually high rates of positive reports among children for which the probit index is low, and identifies the rate of false negatives by looking for unusually high negative reports among children for which the probit index is high.

Because both child and proxy responses are measured with error, we estimate α_0 and α_1 for both responses separately. The estimation model uses the same set of attributes used in section 3 given our interest in comparing the sensitiveness of the marginal effects of child labor supply functions to misclassification error. Following equation (3), the marginal effect for a particular attribute *k* is estimated in the adjusted MLE model by

$$\frac{\partial E(y_i \mid x_i)}{\partial x_{ik}} = \frac{\partial \Pr(y_i = 1 \mid x_i)}{\partial x_{ik}} = (1 - \alpha_0 - \alpha_1) f(x_i^{'}\beta)\beta_k$$

where $f(x_i^{'}\beta)$ is the normal density function of $-\varepsilon_i$ in the probit model. This marginal effect converges to the standard formula $f(x_i^{'}\beta)\beta_k$ in the absence of misclassification error[13].

Table 7 reports the estimate probabilities of misclassification, along with the adjusted marginal effects. Columns 1 and 2 report the child and proxy estimates for the standard CLS definition of child labor, while columns 3 and 4 show the corresponding estimates for the CLH definition. Standard errors are shown in parenthesis. By looking at the CLS definition, one observes that the estimated probability that a non-working child is classified as working, α_0, is

[13] To see the intuition consider the following example: suppose one has a sample of 120 children, 60 of whom have a high value of some characteristic that makes them more likely to work (group 1) and the remaining 60 children have a low value of this characteristic that makes them less likely to work (group 2). Further, suppose that 48 children from the group 1 and 24 from the group 2 are identified as child laborers. Then the true marginal effect on the characteristic is [48/60-24/60]=0.40. Now we introduce misclassification that does not depend on the particular characteristic. Suppose that α_0=0.25, i.e., 12 out of the 48 true non child workers are misclassified, and α_1=0.50, i.e., 36 out of the 72 true child workers are misclassified. As the misclassification probabilities are assumed not to depend on the characteristic, this implies that 3 non child worker from the group 1 and 9 from the group 2 are misclassified as child workers, while 24 workers from the group 1 and 12 from the group 2 are misclassified as non child workers. Thus, the marginal effect on the characteristic is [(3-24+48)/60]-[(9-12+24)/60]=0.10, which equals (1- α_0- α_1) times the true marginal effect.

16.1 percent and statistically significant at the 1 percent level, while the probability that a working child is classified as not working, α_1, is 2 percent and statistically significant at the 5 percent level. The difference ($\alpha_0 - \alpha_1$) is 14.1 and statistically significant, which indicates that child respondents tend to overreport their true labor market condition, rather than to underreport it. For proxy-based reports, on the other hand, the corresponding probabilities reach 3.1 and 5.6 percent, respectively, both statistically significant at the 5 and 1 percent level.

When looking at the CLH definition, on the other hand, one observes that both types of respondents underreport the child labor market status. The estimated ‘false positive’ probabilities are 2.3 and 1.4 percent for child and proxy respondents, while the ‘false negative’ probabilities are 21.7 and 30 percent, all statistically significant at the 1 percent level. It is plausible that both respondents underreport the number of hours worked, and as a result, the children status ended up coded as ‘not working’ even when the true status is ‘working’.

Taking together all estimated probabilities of misclassification, one clear pattern emerges: proxy respondents are prone to underreport the labor status of children, independently of the definition of child labor; while child self-respondents tend to overreport (underreport) when working few (large) number of hours per week.

The resulting marginal effects for the adjusted probit models show, again, considerable differences depending on the type of respondent, and are particularly noticeable when the household is exposed to adverse income shocks. While ‘household size’, ‘harvest losses’, ‘price drop in household business’, and ‘accident/serious illness’ attributes are not statistically related to child labor supply according to the child-based responses, they are relevant determinants according to the proxy reports. This evidence is striking because it entails different policy recommendations. For example, taking ‘harvest losses’ as reference, a researcher armed only with the proxy report would suggest that the crop losses have strong welfare impacts for children and point out the role of insurance to mitigate the extent of child labor in Peru. A researcher armed only with the child-based report would have concluded that the loss of income due to harvest losses seems to be an insignificant driver of child labor in Peru.

When comparing the marginal effects from standard and adjusted probit models in Tables 5 and 7, two general patterns emerge. First, accounting for misclassification errors in child labor measures leads to an increase in the absolute values of most estimated coefficients in the child labor supply function for both child-based and proxy-based reports. Second, the most sensitive attribute is per capita expenditures, a key variable in the child labor literature. The marginal effect increases substantially and becomes a significant predictor of child labor participation only after accounting for misclassification. While this variable is unresponsive according to the standard probit model for both child-based and proxy-based reports, a $100 soles increase in per capita expenditures, leads to 6.3 (1.6) percentage points reduction in child labor participation when the adjusted probit implemented according to the children (proxy) report, and it is statistically significant at the 1 percent level. This result shows that the effect of ignoring misclassification error in child labor statistics may mislead police interventions.

Finally, to assess the degree of sensitivity of the results to parametric functional assumptions, we re-estimate the adjusted models using a logit approach rather than a probit one since the logit distribution has fatter tails and it is in the tails that the misreporting probabilities are identified. The estimated probabilities of misclassification along with the resulting marginal effects are similar to the results presented in Table 7. For instance, the estimated probabilities of misclassification are α_0 =15.4 and α_1 =1.10 for the child-based report using the standard CLS definition of child labor, while the corresponding estimates for the proxy-based report are α_0 =2.5 and α_1 =4.5, both statistically significant at the 5 percent level.

6. Conclusions

This paper used a controlled self/proxy design, implemented in a nationally representative survey, to examine the magnitude and consequences of survey design on child labor measures. Overall, our findings highlight the intrinsic challenges in collecting child labor statistics in developing countries. The most striking result is the substantial difference in the rate of national child labor depending on the type of respondent, difference that reach 17.1 percentage points for the standard definition of child labor. This self/proxy difference hold regardless of the children's age, gender, or urban/rural residence. Moreover, estimated probabilities of misclassification, emerging from adjusted probit models, shows that proxy respondents are prone to underreport the labor status of children, while child self-respondents tend to overreport (underreport) when working few (large) number of hours per week.

The magnitude, sign, and statistically significance of standard attributes used in studies of the supply-side determinants of child labor are shown to be sensitive to the type of respondent. While standard demographic variables are the least sensitive, we observe large variations on attributes related to household composition (family size), household budget constraints (expenditures per capita), and several variables related to household exposure to income shocks. If the available information on child labor is reported by the child himself, child labor will be considered unresponsive to income shocks including 'harvest loss', and 'price drop in family business' in Peru. On the other hand, these particular adverse shocks are relevant determinants of child labor according to the proxy report. This result is important since previous studies based on proxy reports have highlighted the role of child labor as part of the household's self-insurance strategy against income shocks (Beegle et al. 2006, Duryea et al. 2007, Yang 2008, Jacoby and Skoufias 1997).

From a policy perspective, understanding what factors explain the child/proxy disagreement would allow the improvement of child labor survey design by focusing on those factors identified as relevant determinants of disagreement. Yet, the coefficients from the multinomial probit show that a substantial portion of the disagreement is left unexplained. In fact, "prime suspect" variables such as children's age and schooling are not related to the likelihood of disagreement. Neither parents' subjective attitudes nor social norms regarding child labor. Only a small number of variables including rural/urban residence, ethnicity, and the parents' own experiences as child laborers seems to affect the probability of disagreement, although the magnitude of their marginal effects is rather modest. This evidence suggests that more research effort should be devoted to address the role of survey design in child labor statistics.

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Table 1: Household and Demographic Characteristics of Children 6-14 years old

	Mean	St. Dev
Child respondent		
Male	50.73	0.49
Age	10.10	2.56
Years of completed schooling	3.61	2.46
School Attendance	97.72	0.15
Weekly Hours Worked (child reported)	6.93	9.14
Weekly Hours Worked (proxy reported)	5.40	8.76
Household size	5.76	2.12
Quechua or Aymara	18.15	0.38
Urban	61.00	0.48
Per capita Household Expenditures (soles)	169.22	594.63
Proxy Respondent		
Years of schooling	7.72	4.38
Age	39.59	10.85
Quechua or Aymara	32.36	0.47
Male	35.12	0.48
Worked as child laborer	77.07	0.42
Against child labor	68.69	0.46
Child labor hurts children	62.61	0.48
Child labor should be eliminated	66.49	0.47

Source: 2007 PNCLS. N=8194.

Table 2: Means and Standard Deviations of Child Labor Measures

	All			Differences by Gender		Differences by Area	
	Self-Reported	Proxy	Diff (self-proxy)	Boys (self-proxy)	Girls (self-proxy)	Urban (self-proxy)	Rural (self-proxy)
<u>Panel A: 6-14 years</u>							
CLS	0.599	0.428	0.171	0.183	0.159	0.184	0.151
	(0.490)	(0.494)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
CLH	0.313	0.241	0.071	0.067	0.076	0.044	0.114
	(0.464)	(0.428)	[0.000]	[0.00]	[0.000]	[0.000]	[0.000]
Weekly hours	6.951	5.329	1.622	1.538	1.526	1.145	2.135
	(0.102)	(0.096)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
<u>Panel B: 6 – 9 years</u>							
CLS	0.530	0.334	0.196	0.208	0.182	0.197	0.192
	(0. 499)	(0.471)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
CLH	0.240	0.159	0.080	0.071	0.090	0.043	0.137
	(0.427)	(0.366)	[0.00]	[0.000]	[0.000]	[0.000]	[0.000]
Weekly hours	5.144	3.556	1.589	1.586	1.583	1.158	2.234
	(0.122)	(0.114)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
<u>Panel C: 10-14 years</u>							
CLS	0.650	0.497	0.153	0.164	0.141	0.175	0.119
	(0. 476)	(0.500)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
CLH	0.367	0.302	0.065	0.064	0.066	0.044	0.097
	(0.482)	(0.459)	[0.00]	[0.000]	[0.000]	[0.000]	[0.000]
Weekly Hours	8.283	6.637	1.646	1.502	1.483	1.136	2.061
	(0.150)	(0.140)	[0.00]	[0.000]	[0.000]	[0.000]	[0.000]

<u>Notes:</u> Standard deviation in parentheses, P-values for the test of equality of means in brackets.
N=8,194. CLS refers to the standard definition of child labor: economically active children who are engaged in market activities for at least one hour in the week prior to the survey. CLH refers to an alternative definition of child labor based on a cutoff value of hours worked: economically active children who are engaged in market activities for at least nine hours in the week prior to the survey.

Table 3: Cross tabulations of Self-Reported and Proxy Measures of Child Labor

Panel A: 6-14 years old

	CLS	**Self-Reported**		**CLH**	**Self-Reported**	
		Don't work	Work		Don't work	Work
Proxy	Don't work	3,083	1,604	Don't work	5058	1,155
		(37.62)	(19.57)		(61.72)	(14.09)
	Work	201	3,306	Work	566	1,415
		(2.45)	(40.34)		(6.90)	(17.26)

Panel B: 6-9 years old

	CLS	**Self-Reported**		**CLH**	**Self-Reported**	
		Don't work	Work		Don't work	Work
Proxy	Don't work	1,561	753	Don't work	2451	471
		(44.89)	(21.65)		(70.49)	(13.54)
	Work	73	1,090	Work	190	365
		(2.09)	(31.36)		(5.46)	(10.49)

Panel C: 10-14 years old

	CLS	**Self-Reported**		**CLH**	**Self-Reported**	
		Don't work	Work		Don't work	Work
Proxy	Don't work	1,522	851	Don't work	2607	684
		(32.26)	(18.04)		(55.26)	(14.50)
	Work	128	2,216	Work	376	1050
		(2.71)	(46.97)		(7.97)	(22.25)

Notes: Percent in parentheses. N=8,194. CLS refers to the standard definition of child labor: economically active children who are engaged in market activities for at least one hour in the week prior to the survey. CLH refers to an alternative definition of child labor based on a cutoff value of hours worked: economically active children who are engaged in market activities for at least nine hours in the week prior to the survey.

Table 4: Means and Variances of Schooling Indicators

	Self-Reported		Proxy		Diff (self-proxy)	
	Mean	Std. deviation	Mean	Std. deviation	Mean	Std. Error
School Attendance N=8,142	0.977	0.149	0.999	0.024	-0.022	[0.002]
Years of Completed Schooling N=8,137	3.612	2.463	3.614	2.466	-0.002	[0.003]

Notes: School attendance is defined by a dummy variable that takes the value 1 for those attending school, 0 otherwise.

Table 5: Child Labor Participation, Probit Estimation (marginal effects)

	CLS		CLH	
A. Socio-demographics	**child report**	**proxy report**	**child report**	**proxy report**
age	0.030***	0.043***	0.029***	0.033***
	(0.002)	(0.002)	(0.002)	(0.001)
gender	0.085***	0.061***	0.035***	0.040***
	(0.011)	(0.012)	(0.010)	(0.009)
schooling head	-0.020***	-0.018***	-0.011	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
ethnicity head	0.182***	0.214***	0.170***	0.151 ***
	(0.016)	(0.018)	(0.016)	(0.015)
household size	0.004	-0.007***	0.006***	-0.005***
	(0.003)	(0.002)	(0.002)	(0.002)
urban	-0.256***	-0.284***	-0.173****	-0.117***
	(0.013)	(0.014)	(0.013)	(0.012)
expenditures per capita	-0.0003	-0.0018**	-0.002**	0.0000
	(0.0010)	(0.0009)	(0.001)	(0.0006)
B. Geographic Shocks				
Drought/flood	0.094***	0.110***	0.047***	0.080***
	(0.018)	(0.018)	(0.015)	(0.014)
Freezing conditions	0.110***	0.080***	0.103***	0.043***
	(0.022)	(0.022)	(0.018)	(0.015)
Epidemics	0.082***	0.105***	0.058**	0.088***
	(0.031)	(0.031)	(0.024)	(0.023)
C. Business Shocks				
loss employment	-0.063**	-0.051**	-0.090***	-0.062***
	(0.022)	(0.023)	(0.018)	(0.016)
broken family business	0.072**	0.135***	0.101***	0.063**
	(0.030)	(0.035)	(0.033)	(0.030)
price drop (agriculture)	0.055**	0.090***	0.038**	-0.004
	(0.023)	(0.023)	(0.018)	(0.015)
harvest losses (agriculture)	0.032	0.061***	0.024	0.046***
	(0.021)	(0.021)	(0.016)	(0.015)
price drop (family business)	0.029	0.038*	0.0007	0.028
	(0.024)	(0.022)	(0.0200)	(0.018)
D. Personal shocks				
death/serious illness	-0.011	-0.045***	-0.002	-0.002
	(0.017)	(0.017)	(0.014)	(0.012)
head leaves the house	0.138***	0.201***	0.102***	0.111***
	(0.036)	(0.045)	(0.045)	(0.042)

Notes: Standard error in parentheses. The estimated model follows a standard parametric probit specification.
* indicates statistical significance at 10%; **at 5%; *** at 1%.. N=8,194.
CLS refers to economically active children who are engaged in market activities for at least one hour in the week prior to the survey. CLH refers to economically active children who are engaged in market activities for at least nine hours in the week prior to the survey.

Table 6: Determinants of the Disagreements in the Reports (marginal effects)

	CLS		CLH	
	proxy=1 & child=0	proxy=0 & child=1	proxy=1 & child=0	proxy=0 & child=1
A. Characteristics of the Child				
Age	-0.0005	-0.010**	0.002	-0.004
	(0.001)	(0.004)	(0.002)	(0.003)
Male	-0.007**	0.016*	0.009*	-0.002
	(0.003)	(0.008)	(0.005)	(0.007)
Years of schooling	0.002	0.004	0.005*	-0.004
	(0.002)	(0.004)	(0.003)	(0.003)
Rural	-0.005	-0.024**	0.030***	0.082***
	(0.004)	(0.011)	(0.007)	(0.010)
Household Size	-0.001	0.008***	-0.004***	0.007***
	(0.001)	(0.002)	(0.001)	(0.001)
Quechua or Aymara	-0.001	-0.060***	0.006	-0.034***
	(0.006)	(0.014)	(0.010)	(0.011)
Household Expenditure Per Capita	-0.000	0.001	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
B. Characteristics of the Proxy				
Years of schooling	-0.000	-0.003***	-0.002***	-0.004***
	(0.001)	(0.001)	(0.000)	(0.001)
Age	0.000	-0.001***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Quechua or Aymara	-0.007	0.002	-0.012	0.046***
	(0.004)	(0.012)	(0.008)	(0.011)
Male	-0.003	0.003	-0.010	0.010
	(0.003)	(0.009)	(0.005)	(0.008)
Worked as child laborer	0.010***	0.030***	-0.006	0.016*
	(0.003)	(0.010)	(0.006)	(0.009)
C. Shocks in the last 12 months				
Weather shocks	0.005	-0.012	0.019**	0.019*
	(0.005)	(0.012)	(0.008)	(0.010)
Economic shocks	0.001	-0.035***	0.009	0.001
	(0.003)	(0.010)	(0.006)	(0.009)
Family shocks	0.004	0.027**	0.008	0.003
	(0.004)	(0.012)	(0.007)	(0.010)
D. Proxy Attitudes				
Against child labor	0.002	0.016	-0.012*	-0.004
	(0.004)	(0.013)	(0.007)	(0.009)
Child labor hurts children	-0.002	0.005	-0.010	-0.015*
	(0.004)	(0.012)	(0.006)	(0.009)
Child labor should be eliminated	-0.003	-0.006	0.000	0.000
	(0.004)	(0.013)	(0.006)	(0.009)

Notes: Standard error in parentheses. The estimated model follows a parametric multinomial probit specification. Base category: Agreement in the report. * indicates statistical significance at 10%; **at 5%; *** at 1%. N=8,078.

Table 7: Hausman et.al. (1989) estimator for child labor participation (marginal effects)

	CLS- child	CLS-proxy	CLH- child	CLH-proxy
$\alpha_0 = \Pr(y_i = 1 \mid \bar{y}_i = 0)$	0.161***	0.031**	0.023***	0.014***
	(0.024)	(0.013)	(0.008)	(0.006)
$\alpha_1 = \Pr(y_i = 0 \mid \bar{y}_i = 1)$	0.020**	0.056***	0.217***	0.300***
	(0.009)	(0.018)	(0.029)	(0.047)
A. Socio-demographics				
age	0.034***	0.047***	0.036***	0.043***
	(0.003)	(0.003)	(0.003)	(0.004)
gender	0.100***	0.061***	0.031***	0.050***
	(0.015)	(0.013)	(0.012)	(0.012)
schooling head	-0.017***	-0.018***	-0.010***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.002)
ethnicity head	0.202***	0.234***	0.194***	0.196***
	(0.026)	(0.024)	(0.022)	(0.022)
household size	-0.003	-0.009***	0.002	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
urban	-0.264***	-0.287***	-0.175***	-0.133***
	(0.019)	(0.018)	(0.016)	(0.015)
expenditures per capita	-0.063***	-0.016***	-0.048***	-0.007**
	(0.011)	(0.005)	(0.008)	(0.003)
B. Geographic Shocks				
Drought/flood	0.099***	0.114***	0.067***	0.089***
	(0.023)	(0.021)	(0.019)	(0.018)
Freezing conditions	0.138***	0.094***	0.122***	0.052**
	(0.031)	(0.026)	(0.026)	(0.021)
Epidemics	0.080**	0.120***	0.062**	0.159***
	(0.040)	(0.038)	(0.034)	(0.036)
C. Business Shocks				
loss employment	-0.076***	-0.054**	-0.095***	-0.058**
	(0.027)	(0.026)	(0.026)	(0.024)
broken family business	0.077**	0.128***	0.096***	0.046
	(0.037)	(0.036)	(0.033)	(0.031)
price drop (agriculture)	0.065**	0.110***	0.054**	-0.011
	(0.029)	(0.028)	(0.024)	(0.022)
harvest losses (agriculture)	0.019	0.058**	0.030	0.080***
	(0.024)	(0.023)	(0.021)	(0.021)
price drop (family business)	0.039	0.041**	0.018	0.056**
	(0.029)	(0.019)	(0.026)	(0.024)
D. Personal shocks				
death/accident/illness	-0.011	-0.038**	-0.012	-0.003
	(0.020)	(0.017)	(0.018)	(0.017)
head leaves the house	0.153***	0.202***	0.073	0.146***
	(0.052)	(0.050)	(0.046)	(0.045)

Notes: Standard error in parentheses. The modified maximum likelihood model follows a parametric probit specification. * indicates statistical significance at 10%; ** at 5%; *** at 1%. N=8,194. CLS refers to economically active children who are engaged in market activities for at least one hour in the week prior to the survey. CLH refers to economically active children who are engaged in market activities for at least nine hours in the week prior to the survey