Do wages compensate for harmful child labor?
Evidence from the Philippines

Dhushyanth Raju
Department of Economics
Cornell University

Draft date: August 2005

WORK IN PROGRESS
PRELIMINARY RESULTS

Extended abstract

Harmful child labor is clearly a phenomenon of major proportions in the developing world. In recent years, there has been a growing interest among policymakers in gaining a better understanding of the causes behind, conditions underlying, and consequences of harmful child labor, with the goal of formulating appropriate measures to address the problem. This study aims to contribute to the body of knowledge on harmful child labor by investigating the existence and magnitude of positive compensating wages for harmful child labor using individual-level perception data on workplace harm gathered through a recent household survey in the Philippines. This question is important as it indicates the extent to which market mechanisms operate to compensate child workers for the disutility of experiencing occupational harm. In particular, it also provides indirect evidence of the extent to which child workers (or their parents as economic decision-makers on their behalf) are informed about occupational harm, and whether they have the market power to extract compensation. While there is extensive research on the *ceteris paribus* relationship between occupational harm and earnings for adult workers, this study is the first to examine this relationship for child workers.

The study uses a few complementary empirical strategies to investigate the extent of the earnings-occupational harm trade-off. First, mainly for purpose of obtaining some suggestive evidence, it explores the unconditional or bivariate relationship between earnings and occupational harm by comparing the earnings distributions and summary measures of the earnings distributions between child workers who reported experiencing occupational harm (along various dimensions), and those who reported not to have. Second, it examines the conditional relationship between occupational harm and earnings evaluated at the conditional mean (*via* ordinary least squares) and at the conditional median (*via* least absolute deviations), the latter largely as a robust alternative. Third, it examines the conditional relationship between earnings and occupational harm at various quantiles of the conditional earnings distribution (*via* quantile regression) in order to determine if and how the earnings-occupational harm trade-off changes along the conditional earnings distribution. The conditional analysis provides the more compelling evidence on the nature of the relationship between earnings and occupational harm for child workers.

The study finds strong evidence of an unconditional positive relationship between earnings and occupational harm as represented by psychologically stressful work, physically

strenuous work, and hazardous work. However, these results are mostly invalidated after controlling for various relevant demographic and employment characteristics of the child worker in a multiple regression framework. The only consistent finding across alternative model specifications is a significant earnings premium for physically strenuous labor. The earnings premia for physically strenuous work evaluated at the conditional mean and conditional median are roughly 14 and 11 percent, respectively. The earnings premia for physically strenuous work estimated at various conditional quantiles suggest that the conditional mean result is largely driven by substantial and increasing premia as one moves down the lower half of the conditional earnings distribution. The premia in the upper half of the conditional earnings distribution are largely modest and not significantly different from zero. The study does not find any evidence to suggest that children receive higher earnings for high levels of occupational harm as represented by the frequency of the event, as well as for experiencing multiple forms of occupational harm. Furthermore, the study does not find any evidence to suggest that compensating wages for occupational harm differ by gender, age, or between child workers in urban and rural areas.

The results thus far seem to suggest the presence of positive compensating wages for immediate, transparent, and certain occupational harm as represented by physically strenuous work, particularly for children working in relatively low-wage economic activities. The results also suggest the absence of compensating wages for probabilistic harm or for a state that is relatively intangible such as psychological stress. The results could be cautiously interpreted as reflecting a tendency on the part of child labor-supplying households to discount occupational harm that is psychological and/or probabilistic relative to occupation harm that is physical and deterministic.

I. Introduction

It is fairly well known that child labor remains a mass phenomenon in much of the developing world, particularly in poorer parts such as sub-Saharan Africa and South Asia. The International Labor Organization (ILO), the major source of statistics on the extent of child labor worldwide, estimates that 352 million children (or about one-fifth of the total global population between the age of 5 and 17) were economically active, of which, 246 million child workers were categorized as child laborers in 2000.[1] More disconcertingly, 171 million of these 246 child workers (or over two-thirds) were considered to be employed in harmful or exploitative situations or conditions, of which, roughly 8 million children were deemed to be in what are termed as unconditional worst forms of child labor (ILO 2002).[2]

In attempting to gain some insight into the reasons behind harmful child labor and the economic conditions underlying its existence, this paper examines whether child workers in harmful employment settings are compensated in the form of higher wages. This is an important question, especially from a policy perspective, as it indicates the extent to which market mechanisms operate to compensate child workers for the disutility of experiencing occupational harm. In particular, it also provides indirect evidence of the extent to which child workers (or their parents) are informed about occupational harm, and whether they have the market power to extract compensation for experiencing occupational harm.

The theoretical literature on harmful child labor has proceeded in two distinct directions: one in which labor markets are characterized more or less along standard textbook lines where poor households possess some information about the occupational harm associated with different employment opportunities for their children and maintain the right to exit from an employment relationship (Raju 2005 and Dessy and Pallage 2005), and the other in which households effectively relinquish the child's right to exit from an employment relationship such as under child servitude or child trafficking (Rogers and Swinnerton 2003 and Dessy and Pallage 2003).

[1] Economic activity covers all market production (paid work) and certain types of non-market production (unpaid work), including production of goods for own use. Child labor consists of all children under 15 years of age who are economically active excluding (i) those who are under five years of age and (ii) those between 12-14 years of age who spend less than 14 hours a week on their jobs, unless their activities or occupations are hazardous by nature or circumstance. Added to this are 15-17 year old children in the worst forms of child labor (ILO 2002).

[2] The worst forms of child labor refers to child labor in the context of slavery or slave-like conditions, in prostitution or pornography, in illicit activities such as drug trafficking, or in conditions that are likely to affect the health or safety of the children involved. Unconditional worst forms of child labor exclude the last type. Source: http://www.ilo.org/public/english/standards/ipec/ratification/convention/text.htm.

The predictions regarding the relationship between child wages and child occupational harm between the two characterizations of the labor market differ. Under the first characterization, positive compensating wages arise for child occupational harm, while under the second characterization, *negative* compensating wages arise, that is, poor working conditions are accompanied by low wages.

To date, there has been no research on estimating compensating wages for child occupational harm. In fact, there has been very little work on estimating earnings equations for child workers in general, as the bulk of the empirical literature on child labor has focused on estimating child labor force participation equations in order to identify the key determinants of child labor and, to a lesser extent, the effects of child labor force participation and wages on household and child socioeconomic outcomes such as nutrition, fertility, and education (see, Brown *et al* 2003 for an extensive survey of the empirical literature on child labor).

In recent years, there has been some empirical work on harmful child labor. However, the focus has been on estimating the adverse health effects of child labor both in the short-term and long-term (Beegle *et al* 2004, Emerson and Souza 2004, O'Donnell *et al* 2003, and Rosati and Straub 2004). The rest of the empirical research on harmful child labor essentially consists of descriptive statistics on child work-related injury or illness rates. For example, Ashagrie 1998 provides information on the incidence of workplace injuries and illnesses among child workers disaggregated by industry and gender from household survey data collected in 4 countries.

The empirical research on compensating wage differentials with respect to occupational harm or hazards is extensive, finding substantial wage-occupational risk trade-offs (see Viscusi 1993 and Viscusi and Aldy 2004 for surveys of the literature). In contrast to most of the literature which uses work-related injury or illness data at various levels of aggregation – typically either at the industry or occupation level, and where individual workers are assigned the average injury rate in estimating compensating wage differentials – this study uses individual-level perception data on various types of occupational harm, such as physically strenuous or psychologically stressful labor or hazardous work, collected through a dedicated household survey of working children. Individual-level injury and illness data are also available through the household survey but is not used in the study as such data represent the overt and immediate manifestation of occupational harm and would as a result probably grossly understate the true extent of occupational harm across the sample of child workers as there would conceivably be large number of cases where child workers would not have suffered a workplace injury or illness in the survey reference period but may nevertheless be employed under harmful work conditions.

This research benefits greatly from the discussions on methodological issues and various empirical approaches undertaken to estimate compensating wages in general, and these lessons are reflected in the design of the empirical framework. This paper attempts to estimate the earnings-occupational harm trade-off for child workers using both parametric (ordinary least squares) and semi-parametric methods (quantile regression). The research first presents results from an unconditional analysis where the simple bivariate relationship between occupational harm and earnings among child workers is explored. This serves as a starting point for the conditional analysis in which a (log) earnings equation is estimated via ordinary least squares and quantile regression, the latter method allowing the characterization of the earnings-occupational harm trade-off at different points along the (conditional) earnings distribution.

The remaining sections of the paper are organized as follows. Section II presents the data used in the study. Section III presents the various empirical strategies employed to determine the relationship between occupational harm and earnings for child workers. Section IV describes the incidence and composition of occupational harm among child workers who received labor earnings as well as presents the results from both the unconditional and conditional analysis of the earnings-occupational harm trade-off. Section V summarizes the main results and discusses them.

II. Data

The study uses observational individual- and household-level data from the Filipino *2001 Survey on Children: 5 to 17 Years Old* (2001 SOC). The 2001 SOC is a nationally-representative sample survey conducted by the National Statistics Office (NSO), the Philippines, in collaboration with the International Labor Organization's International Program on the Elimination of Child Labor (ILO-IPEC), with the purpose of gathering a wide range of information on child work activities.

The 2001 SOC adopted the same multi-stage sample design as the NSO Labor Force Survey, using listings from the 1995 Population Census. The first stage consisted of the systematic selection of *barangys*, the smallest political division in the country, with probability proportional to size. In order to ensure broad geographic coverage, prior to their selection, the *barangys* were stratified explicitly along urban-rural lines as well as implicitly by, *inter alia*, municipal district affiliation and groupings based on accessibility and similarities in socio-economic characteristics and religious composition.[3] The second stage consisted of the systematic selection of enumeration areas, geographic divisions within *barangys*, with probability proportional to size. These enumeration areas serve as the primary sampling units (PSUs) in the sample. The master sample consisted of 3,416 PSUs, out of which, a subsample of 2,247 PSUs, designated as the core sample, was used for the 2001 SOC. From each PSU in the core sample, a total of 12 households were selected systematically, providing a total of 26,964 private households for the 2001 SOC.[4] For more detail on the sample design, see NSO (2003). The sample design features of stratification and clustering are incorporated into the empirical analysis as it now well-documented that failing to do so can result in improper estimation of the standard errors for various parameters of interest and thus impair statistical inference (see Deaton 1997).

Two separate survey instruments were fielded as part of the 2001 SOC: a household questionnaire and a child questionnaire. All households with household members between the ages of 5 and 17 were interviewed using the household questionnaire, where the respondent was either the parent or guardian. The main purpose of the household questionnaire was to identify eligible respondents for the child questionnaire, that is, children between the ages of 5 and 17 who engaged in any economic activity for at least one hour in the 12 months preceding the interview date. Information for both survey instruments was collected through personal interviews conducted by field enumerators.

Out of the sample of 26,964 households, 17,454 households had members between 5 and 17 years old; 17,444 of these households were successfully interviewed. Among the interviewed households, 6,523 children indicated that they worked during the reference period, of which, 6,351 children (97.4 percent) were successfully interviewed.

In order to arrive at the appropriate sample for the study, the survey sample was pared down in stages. A problem with data collection was responsible for the first round of eliminations. The child questionnaire asks the first few questions on the two longest employment activities undertaken by the child by referring to them separately. However, the

[3] Information for the explicit and implicit stratification was obtained from the 1990 Census of Population and Housing as well as other administrative reports produced by the NSO.
[4] Individuals who reside in institutions or establishments were not covered as part of the 2001 SOC.

subsequent majority of questions, including the key questions on earnings and occupational harm, were asked without explicitly specifying the employment activity of concern. Clearly, this issue poses a problem only in the cases in which children reported two employment activities during the reference period. Fortunately, this occurs only in 9 percent of the sample. These cases were excluded yielding a sample of 5,791 children.

The second round of eliminations targeted certain categories of child workers either due to their negligible shares in the sample or their incompatibility with the proposed research topic. Given that the aim of the study is to estimate the earnings-occupational harm trade-off for working children, all child workers in the sample who did not work for pay were excluded. These cases accounted for roughly 60 percent of the sample. Almost all of these children were employed in own household-operated enterprises. Children who reported that they were self-employed, which accounted for about 7 percent of the sample, were excluded as these children probably, at least in principle, determine working conditions themselves. Children who reported working as paid workers in own household-operated enterprises, which accounted for slightly over 1 percent of the sample, were also excluded as the wage determination process is probably not (fully) subject to market forces. Finally, two other categories of workers, namely home-based workers and public sector or parastatal workers, were excluded as they jointly accounted for less than 1 percent of the sample. Collectively, these exclusions resulted in a sample of 1,677 child workers with labor earnings, which is roughly 29 percent of the sample of children with only one employment activity in the reference period. These 1,677 child workers were employed in either private households (31 percent) or private enterprises (69 percent).

The third and final round of eliminations was conducted in order to restrict a subset of the variables to be included in the regression analysis to certain values or ranges. The justification remains the same as with the second round of eliminations, namely, to omit values with small numbers of observations or to ensure compatibility of the data with the proposed research. The restriction that has the largest impact on the sample relates to educational attainment. Among the remaining 1,677 child workers, about 12 percent of them reported that they completed at least secondary school. It would probably be safe to infer that the labor market opportunities of these child workers are significantly different from those of child workers with lower levels of schooling. Thus, secondary school graduates were excluded from the sample. This restriction combined with others related to age (8-17 years of age), basis of payment (time-rate or piece-rate) and form of payment (monetary) yielded in an eventual sample size of 1,297 children. This sample of 1,297 child workers is hereinafter referred to as the *study sample*.

In addition to the *study sample*, in order to examine how the incidence of occupational harm differs between children who work for pay and children who work without pay, a sample of non-earners was constructed. This sample, hereinafter referred to as the *non-earners sample*, comprises of all children who reported to have engaged in only one employment activity during the reference period as an unpaid worker in an own household-operated enterprise. In addition, similar to the *study sample*, the *non-earners sample* was further restricted to children who had not completed their secondary schooling and were between the ages of 8 and 17, yielding a final sample size of 3,206 children.

Occupational harm variables

The variables that are used in the study to signify child occupational harm were constructed from responses to the following three questions (provided verbatim): 1. Did you or do you find your work mentally or emotionally stressful, 2. Did you or do you perform heavy physical labor, and 3. Did you or do you consider some aspects of your work risky or dangerous? The available response options for questions 1 and 2 were frequently, sometimes, seldom, and never, while the available response options for question 3 were yes and no. In the instructions provided in the enumerators' manual, frequently was defined as occurring daily or 3-6 times per week, while sometimes was defined as occurring 1-2 times per week or 2-3 times per month (NSO 2001).

Five separate dichotomous variables, denoted by *STRESSFUL*, *STRENUOUS*, *HAZARDOUS*, *OFTEN STRESSFUL*, and *OFTEN STRENUOUS*, were constructed based on the responses to the above questions regarding occupational harm. The first three variables essentially reflect whether or not the child reported experiencing occupational harm, while the latter two variables reflect whether or not the child reported experiencing *regular* occupational harm. Referring first to the occurrence-related occupational harm variables, the variable *STRESSFUL* was set equal to 1 if the respondent indicated that the work activity was frequently or sometimes psychologically stressful, and 0 otherwise. The variable *STRENUOUS* was constructed analogously. The variable *HAZARDOUS* was set equal to 1 if the respondent indicated the work activity was hazardous, and 0 otherwise. Referring next to the magnitude-related occupational harm variables, the variable *OFTEN STRESSFUL* was set equal to 1 if the respondent indicated to have engaged in work that was frequently psychologically stressful, and

0 otherwise. Similarly, *OFTEN STRENUOUS* was set equal to 1 if the respondent indicated to have engaged in work that involved frequent physically strenuous work, and 0 otherwise.

III. Empirical framework

In order to test for the presence of compensating wage differentials for child occupational harm, a semi-logarithmic child earnings equation of the form

$$\ln y_i = h_i'\beta + x_i'\gamma + \varepsilon_i$$

is estimated, where y_i is the average weekly gross cash earnings reported by child worker i; h_i is a vector of occupational harm responses by child worker i; x_i is a vector of socio-demographic characteristics such as age, gender, whether urban or rural, region, and education as well as employment characteristics such as hours of work per day, number of days of work per week, location of work, type of employer, work benefits, and years of potential work experience of child worker i; β and γ are parameters to be estimated; and ε_i is a random error term associated with child worker i.[5]

The vector h_i is specified in three alternative ways, thereby permitting a fuller characterization of the relationship between earnings and occupational harm for child workers. In specification 1, the occurrence-related occupational harm variables *STRENUOUS*, *HAZARDOUS*, and *STRESSFUL* enter together but additively. This specification allows us to examine the partial effect of each form of occupational harm on earnings. In specification 2, the magnitude-related occupational harm variables *OFTEN STRENUOUS* and *OFTEN STRESSFUL* are also included additively. This latter specification allows us to examine not only the partial effect of experiencing occupational harm on earnings but also the partial effect of experiencing regular occupational harm on earnings. Finally, in specification 3, the magnitude-related occupational harm variables are replaced by the three occurrence-related occupational harm entered multiplicatively. This last specification allows us to examine the partial effects of

[5] A large portion of the literature on estimating compensating wage differentials uses the hourly wage as the dependent variable in hedonic wage regressions. However, given the available data, only a crude measure of hourly wage can be constructed as the information on usual hours of work per day was collected in categorical rather than continuous fashion. Consequently, reported weekly earnings is used as the dependent variable in the estimations but usual days of work per week and hours of work per day are included as covariates. This alternative approach is not uncommon in the literature (see Viscusi and Aldy 2003).

experiencing various combinations of occupational harm simultaneously on earnings. Denote the parameter vectors associated with specifications 1, 2, and 3 as β_1, β_2 and β_3, respectively. Hedonic wage theory predicts that $\beta_1 >> 0$, $\beta_2 >> 0$, and $\beta_3 >> 0$.

All three specifications of the child earnings equation are estimated *via* ordinary least squares. However, the classical assumption of identically and independently distributed errors is likely to be violated due to the use of stratification and clustering in drawing the survey sample. This is because individuals found within a specific cluster are likely to possess characteristics that are more similar to each other than individuals found in other clusters. The upshot of this is that the amount of intra-cluster variation in the residuals is likely to be significantly different from the amount of inter-cluster variation. Tests of the hedonic wage function estimated *via* ordinary least squares strongly suggest the presence of heteroskedasticity.[6] Consequently, the standard errors are estimated by using a formula which corrects for the survey design effects (see Deaton 1997).

All three model specifications of the child earnings equation are also estimated *via* quantile regression. The quantile regression estimator has several beneficial features. First, quantile regression provides a robust measure of location as it minimizes a weighted sum of absolute deviations of errors. Thus, the estimation results are much less susceptible to *y*-outliers as compared to those from ordinary least squares. Second, when the error term is non-normally distributed, quantile regression may be more efficient than ordinary least squares. Diagnostic tests after estimating the three model specifications *via* ordinary least squares strongly suggest the presence of *y*-outliers and non-normal residuals, making quantile regression a particularly suitable alternative estimation method.[7] Third, as will be elaborated further below, quantile regression, unlike with ordinary least squares, allows the parameters to vary across the entire distribution of the dependent variable.

The basic quantile regression model specifies the conditional quantile in linear form. Following the notation of Buckinsky 1998, for the θth quantile, the model is as follows.

---

[6] The Breusch-Pagan test was implemented to test whether the OLS residuals exhibited heteroskedasticity. The test strongly rejected the null hypothesis of homoskedastic residuals. The *p*-values from the test were 0.0020, 0.0019 and 0.0012 for specifications 1, 2, and 3, respectively.

[7] The Kolmogorov-Smirnov and Shapiro-Wilks tests were implemented to test whether the OLS residuals were distributed normally or not. Both tests strongly rejected the null hypothesis of normally-distributed residuals.

$$\ln y_i = h_i'\beta_\theta + x_i'\gamma_\theta + \varepsilon_{\theta i}, \qquad Quant(\ln y_i \mid h_i,\ x_i) = h_i'\beta_\theta + x_i'\gamma_\theta \qquad \theta \in (0,1)$$

where $Quant(\ln y_i \mid h_i,\ x_i) = h_i'\beta_\theta + x_i'\gamma_\theta$ denotes the quantile of $\ln y_i$ conditional on the vectors of covariates h_i and x_i. The distribution of the error term, $\varepsilon_{\theta i}$, is left unspecified. The only assumption made is that $\varepsilon_{\theta i}$ satisfies the quantile restriction $Quant(\varepsilon_{\theta i} \mid h_i,\ x_i) = 0$. The θth sample quantile $(0 < \theta < 1)$ of $\ln y$ solves

$$\min_{\beta,\gamma} \frac{1}{n} \left\{ \sum_{i:\ln y_i \ge h_i'\beta + x_i'\gamma} \theta \left| \ln y_i - h_i'\beta - x_i'\gamma \right| + \sum_{i:\ln y_i < h_i'\beta + x_i'\gamma} (1-\theta) \left| \ln y_i - h_i'\beta - x_i'\gamma \right| \right\}$$

An important feature of the framework is that the marginal effects of the covariates, given by β_θ, may differ across quantiles (different values of θ). As is well known, under ordinary least squares, the marginal effects of the covariates are only estimated at the conditional mean of $\ln y$, and hence are constant across the distribution of $\ln y$. Quantile regressions relax this restriction, permitting the researcher to characterize the entire conditional distribution of $\ln y$, given h and x.

Of interest in this study is to estimate the marginal effects of the three forms of occupational harm on log earnings at various distinct quantiles, and to investigate whether there are important differences in the estimated effects across the conditional distribution of $\ln y$. The earnings equation is estimated at quantiles $\theta \in [0.25, 0.75]$.[8] Quantile regressions for $\theta < 0.25$ or $\theta > 0.75$ are not estimated due to concerns that the sample size for the study may not be adequate for standard inference methods to operate properly in the tails of the distribution.

In implementing the quantile regression, the standard errors are estimated by bootstrapping as the formula for obtaining analytical standard errors proposed by Koenker and Bassett (1982) underestimates the standard errors in the presence of heteroskedasticity. Bootstrapping as a valid alternative for estimating the variance-covariance matrix is suggested by

[8] The different quantiles are estimated by weighting the residuals differently. For the median regression ($\theta = 0.5$), all residuals receive equal weight. However, when estimating say the 75th percentile, negative residuals are weighted by 0.25 and positive residuals by 0.75. The criterion is minimized when 75 percent of the residuals are negative. This is set up as a linear programming model and solved.

Deaton (1997). The standard bootstrap method corrects for heteroskedasticity but fails to address the problem of correlated errors. This is because the method resamples observations from the original sample by assuming that each observation has an equal probability of being selected into the bootstrap sample, that is, it assumes a simple random sample. Given that the sample was instead generated from a complex survey design involving both stratification and clustering, the standard bootstrap method needs to be modified to reflect these important survey design elements.

The bootstrap method used in the study is implemented in two steps. In the first step, clusters are randomly selected with replacement from each stratum. The number of clusters selected from each stratum is equal to the total number of clusters found in that particular stratum. In the second step, individuals are randomly selected with replacement from each of the selected clusters from the first step. The number of individuals selected from each cluster is equal to the total number of individuals found in that particular cluster. In this way, each individual in the original sample does not have an equal probability of being selected into the bootstrap sample. Rather, the probability of an individual being selected into the bootstrap sample increases if it already includes an individual from the same cluster. Thus, the bootstrapped standard errors from the two-step method are robust to violations in both homoskedasticity and independence.

IV. Findings

Occupational harm profile

As background, before examining the relationship between earnings and occupational harm, a profile of occupational harm in the *study sample* is constructed. This occupational harm profile is then contrasted against that of the *non-earners sample*. This exercise is conducted principally in order to gain additional insights from a comparative perspective into the incidence and composition of occupational harm experienced by child workers in paid employment.

To begin, focusing solely on the *study sample*, roughly 62 percent of the children indicated that they experienced at least one of the three forms of occupational harm under examination. Table 1 reports the incidence of occupational harm separately by the three forms of occupational harm. Psychologically stressful work is the most commonly reported form of occupational harm (47 percent) followed in descending order by physically strenuous work (38 percent) and hazardous work (28 percent). Table 2 provides a finer disaggregation of the data by distinguishing between various distinct combinations of the three forms of occupational harm. The most commonly reported combinations of occupational harm are: (*i*). all three forms, (*ii*). physically strenuous and psychologically stressful work, and (*iii*). psychologically stressful work only. Each of these three combinations are more or less equally prevalent in the sample, each of them accounting for around 14 percent of the sample.

In terms of the degree of occupational harm, around 1 in 4 children (29 percent) who reported to have engaged in physically strenuous work indicated such work was a frequent occurrence. Likewise, around 1 in 6 children (18 percent) who reported their work to be psychologically stressful indicated that such feelings were frequent (see Table 3). As mentioned previously, the available response options to the hazardous work question precluded the construction of a severity-related measure. However, a follow-up question to children who considered their workplace to be hazardous provided information on the types of hazards they encountered at work. Table 4 shows that among the children who reported their workplace to be hazardous, vehicular accidents was the most frequently cited hazard (23 percent) followed closely by disease and sickness (22 percent).

Turning now to a comparison of the profile of occupational harm between the *study sample* and the *non-earners* sample, Tables 1 and 2 reveal that the incidence of occupational harm differs in important ways between the two samples. First, Table 1 shows that the incidence of all three forms of occupational harm is substantially lower in the *non-earners sample* relative to the *study sample*. To be specific, the share of children reporting psychologically stressful work is 36 percent lower in the *non-earners sample* while the shares of children reporting hazardous or physically strenuous work are 48 percent lower. Furthermore, the difference in the incidence of occupational harm between the two samples is highly statistically significant for all three forms. Table 3 provides a similar picture with respect to regular occupational harm: the shares of children reporting frequent strenuous work or frequent stressful work are 44 and 50 percent lower in the *non-earners sample*, respectively. Second, the more disaggregated picture provided in Table 2 reveals that the pattern of findings in Table 1 is driven almost entirely by substantially smaller shares of children reporting multiple forms of occupational harm in the *non-earners sample* relative to the *study sample*. In particular, the share of children reporting experiencing *all* three forms of occupational harm was around 70 percent lower in the *non-earners sample*. Except in one case, these inter-sample differences in the shares of children reporting multiple forms of occupational harm are highly statistically significant.

Unconditional analysis: comparing distributions, means, and medians

In this subsection, the findings regarding the unconditional bivariate relationship between child earnings and occupational harm are reported. Figure 1 depicts the cumulative distribution functions of earnings separately by whether the child reported the work activity to be hazardous or not. Figures 2 and 3 depict similar cumulative distribution functions for psychologically stressful work and physically strenuous work, respectively. For each of the three occupational harm variables, until at least about the 80th percentile of earnings, the cumulative distribution function of earnings for child workers who reported no occupational harm generally lies above the cumulative distribution function of earnings for children who reported occupational harm, indicating that the latter group of child workers earn more than the former group of child workers. Both Kolmogorov-Smirnov and Wilcoxon Mann-Whitney tests strongly reject the null hypothesis of equality of distributions. The means and medians of earnings also indicate that children who reported occupational harm earn more than those who reported no occupational harm. Except in the case of psychologically stressful work, where the difference in mean earnings was not statistically significant, the differences in mean and median earnings between child workers who reported occupational harm and those who did not are highly statistically significant for both physically strenuous work and hazardous work. To summarize, by and large, the unconditional results strongly suggest that child workers tend to earn more when they engage in work they consider to be hazardous, psychologically stressful, or physically strenuous. The following subsection examines whether these findings remain intact qualitatively when the relationship between earnings and occupational harm among child workers is scrutinized in a multiple regression framework.

Conditional analysis: Ordinary least squares and quantile regression estimation results

In this subsection, the estimation results from ordinary least squares and quantile regression are presented. Table 5 reports the ordinary least square and least absolute deviations ($\theta = 0.5$) estimates for the child earnings equation. The first and second columns of the table provide the estimation results for model specification 1 – where the occurrence-related occupational harm variables only enter separately – from OLS and LAD regression, respectively. The third and fourth columns of the table provide the estimation results for model specification 2 – which includes the magnitude-related occupational harm variables – from OLS and LAD regression, respectively. Finally, the fifth and sixth columns of the table provide the estimation results for model specification 3 – where the occurrence-related occupational harm variables also enter multiplicatively – from OLS and LAD regression, respectively.

Referring first to the OLS regression, which provides estimates evaluated at the conditional mean, as expected *a priori*, evidence that child age and school enrollment status are important determinants of child earnings is found. An additional year in age provides an increase in weekly earnings by 31-32 percent. Children attending school at the time of the survey earn approximately 28 percent less than those who did not. Gender does not appear to affect earnings – we find that males earn approximately 10 percent more than females across the specifications but the finding is not statistically different from zero. The LAD estimations however provide evidence of a gender effect on earnings, bearing in mind that the effect is evaluated at the conditional median instead of the conditional mean. Interestingly, compelling evidence suggesting child workers with some secondary schooling earn more than children who do not have any schooling or only have elementary schooling is not found. Evidence suggesting that longer potential work experience is associated with higher earnings is also not found, where potential work experience is defined as the difference between the age of the child at the time of the survey and the age at which the child first started working. These results seem to suggest that the types of work activities that children typically undertake do not really reward school-based learning or accumulated work experience. However, it is quite possible that the lack of statistical significance associated with potential work experience may be attributable to the limited variation in the potential work experience measure as the median number of years of work experience was 1 and about two-thirds of the *study sample* had less than roughly 4 years of potential work experience (see Table 5). It is also possible that the measure is far too crude an indicator of actual work experience as it does not allow for discontinuous work histories which probably typify most child work.

The findings with respect to direction for the employment-related variables are also for the most part consistent with what is expected *a priori*. Children who work 1-4 hours per day earn approximately 45 percent less than children who work 5-8 hours per day. Child earnings are increasing in the number of workdays per week, but at a decreasing rate, peaking outside the range of the data. Child workers who receive meals at work earn 15 percent less than child workers who do not. Children working for private households receive approximately 16-17 percent less than children working for private establishments. Lastly, child workers who receive piece-rate pay earn approximately 16-17 percent less than those who receive time-rate pay – this finding is surprising as standard theory suggests that piece-rate pay should be associated with higher earnings as it promotes the self-selection of more productive workers into work activities with piece-rate pay systems and/or it induces greater work effort.

The LAD estimates evaluated at the conditional median of earnings are generally consistent with the OLS estimates in terms of statistical significance. The LAD estimates however tend to be larger in magnitude, the only exception being the effect of school enrollment status: children who indicated attending school at the time of the survey earn about 15-16 percent less than those who did not (the magnitude of the LAD estimate is slightly less than half the size of the OLS estimate). The evidence on the gender effect is stronger under LAD both in terms of statistical and practical significance: males earn approximately 16-20 percent more than females, depending on the model specification.[9] Unlike with the OLS estimates which suggest a linear

[9] The partial derivative of the conditional quantile of *y* with respect to *x* should be interpreted as the marginal change in the θth conditional quantile due to a marginal change in *x*. However, some caution should be exercised in the interpretation of results – especially in the case of dummy independent variables where a marginal change may actually represent a dramatic change in the state or circumstances of the individual – as it does not necessarily imply that an individual initially located in the θth quantile of one conditional distribution will continue to remain at the same location given the change in *x* (Buckinsky 1998).

relationship between age and earnings, the LAD estimates suggest the age is increasing but a decreasing rate, peaking outside the range of the data.

We now turn to the evidence on compensating wages for child occupational harm, the variables of primary interest in the study. Across the estimators and model specifications, the only robust finding is the existence of compensating wages for physically strenuous work. For specification 1, the OLS and LAD estimates for the earnings premium for physically strenuous work are 13 and 11 percent, respectively. The evidence from model specification 2 suggests that children do not receive additional compensation for experiencing regular occupational harm. Lastly, the evidence for model specification 3 suggests that strenuous physical work accompanied by either hazardous or psychologically stressful work alone, or both together, do not provide the child worker with any additional earnings premium. The OLS estimates seem to suggest that child workers who report both heavy physical labor and psychologically stressful work obtain a substantially lower earnings premium than child workers who report strenuous physical labor only – this finding is however not robust across estimators as the corresponding LAD estimates are not statistically different from zero. Although the interaction terms of physically strenuous work with psychologically stressful and hazardous work are by themselves statistically insignificant, the main and interacted effects of physically strenuous work are jointly statistically significant, suggesting that the main effect should be adjusted by the interacted effects. This adjustment brings the earnings premium for physically strenuous work from specification 3 in line with the premia from specifications 1 and 2.

Although not reported in the paper, model specifications with interactions between the occupational harm variables and gender, age, and whether urban or rural are also estimated. No evidence that compensating wages for the various occupational harm variables differ by these particular demographic characteristics is found.

As mentioned before, OLS estimates are evaluated at the conditional mean of earnings. By using quantile regression, the effects of occupational harm variables at different quantiles along the conditional distribution of earnings can be estimated. Table 7 reports the estimated slope coefficients for the three occupational harm variables at the 25th, 50th and 75th conditional percentiles. Figures 4, 5, and 6 plot the estimated slope coefficients for the three occupational harm variables between the 25th and 75th conditional percentiles along with their respective 95 percent confidence intervals. The dashed and dotted lines in the figures represent the OLS estimates and their 95 percent confidence intervals, respectively. Both Table 7 and Figures 4 and 5 suggest that the estimated marginal effects for hazardous or psychologically stressful work are not significantly different from zero within the range of the conditional distribution of earnings under examination. There also does not appear to be much variation in the magnitude of the estimated slope coefficients along the conditional distribution – by and large, the earnings premia for hazardous and psychologically stressful work estimated *via* quantile regression lie between -5 and 5 percent.

A uniform marginal effect along the conditional distribution of earnings would imply that it is possible to draw a horizontal line through the estimated slope coefficients at different quantiles. However, the pattern in Figure 6 suggests that the estimated earnings premia for physically strenuous work are larger in magnitude at the lower quantiles than at the higher quantiles. Moreover, the estimated premia cease to be statistically significant slightly above the conditional median of earnings. The decreasing pattern over the distribution and the loss of statistical significance at the higher quantiles suggest that the earnings premium for physically strenuous work is present only for those at the bottom half of the conditional distribution of earnings, and is larger for child workers with lower earnings. Table 7 shows that the estimated earnings premium for physically strenuous work is 28 percent at the 25th conditional percentile and declines more or less monotonically to 11 percent at the 50th conditional percentile, and further to 7 percent at the 75th percentile, though the last result is not significantly different from zero. Tests of the equality of the estimated slope coefficients at the 25th and 75th percentiles as well as the 25th and 50th percentiles suggest that the marginal effects for physically strenuous work at these conditional percentiles are significantly different. Thus, the OLS estimate of a 14 percent earnings premium for physically strenuous work appears to be driven largely by the lower half of the conditional distribution. In light of this fact, the conventional location shift model would have provided a somewhat misleading picture of the marginal effect of physically strenuous work on child earnings.

V. Summary and discussion

In this section, the main findings regarding the earnings-occupational harm trade-off from the empirical strategies implemented in the paper are summarized. First, the unconditional analysis reveals that there is a positive bivariate relationship between earnings and occupational harm for child workers. This finding holds for all three forms of occupational harm examined, namely psychologically stressful work, physically strenuous work, and hazardous work. Second, the conditional analysis reveals a strong positive *ceteris paribus* relationship between earnings and occupational harm only in the case of physically strenuous work – the earnings premium, evaluated at the conditional mean, is roughly 14 percent. On the other hand, the earnings premia for psychologically stressful work and hazardous work are much smaller than for physically strenuous work, apart from being statistically insignificant. Although children receive compensation for physically strenuous work, there is no evidence to suggest that they receive additional compensation for engaging in regular strenuous work. An examination of the interactions between the three forms of occupational harm reveals that child workers do not receive any additional compensation for engaging in work they consider as psychologically stressful or hazardous on top of performing physically strenuous work. The results from quantile regressions at various quantiles between the 25^{th} and 75^{th} percentiles of the conditional distribution more or less concur with the conditional mean results. An additional interesting finding relates to the pattern of earnings premia for physically strenuous work across conditional quantiles. The quantile regression evidence seems to suggest that the higher the conditional quantile, the lower the earnings premia for physically strenuous work. For example, the earnings premia calculated at the 25^{th}, 50^{th} and 75^{th} percentiles are 28, 11, and 7 percent, respectively. The estimate at the 75^{th} percentile is not significantly different from zero. Thus, the earnings premium result at the conditional mean is largely driven by the estimated earnings premia in the lower half of the conditional distribution. In light of this finding, the result for physically strenuous work needs to be qualified: the earnings premia for physically strenuous work is mainly found in relatively lower wage employment activities.

A straightforward interpretation of the above findings is that there appears to be compensating wages for immediate, transparent, and certain occupational harm as represented by physically strenuous work, especially for relatively lower-wage employment activities. The findings also suggest the absence of compensating wages for probabilistic harm or for harm that takes the relatively intangible form of psychological stress. The differing results across types of occupational harm could indicate perceptional differences over the types of harm. For example, households may tend to discount harm when it is uncertain such as with hazardous work or when it is psychological relative to harm when it is physical and deterministic.

References

Ashagrie, K. 1998. *Statistics on Child labor and hazardous child labor in brief*. Geneva: International Labor Organization. http://www.ilo.org/public/english/standards/ipec/simpoc/stats/child/stats.htm

Beegle, Kathleen, Rajeev Dehejia, and Robert Gatti. 2004. Why Should We Care About Child Labor? The Education, Labor Market, and Health Consequences. NBER Working Paper No. 10980.

Brown, Drusilla K., A Deardorff, and R. Stern. 2003. Child Labor: Theory, Evidence, Policy. In K. Basu, H. Horn, L. Roman, J. Shapiro (eds.), *International Labour Standards- Issues, Theories and Policy*, Basil Blackwell, 2003.

Buchinsky, Moshe. 1998. Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research. *Journal of Human Resources* 33(1 Winter): 88-126.

Deaton, Angus. 1997. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. Baltimore: Johns Hopkins University Press.

Dessy, S. E., and S. Pallage. 2003. "A theory of the worst forms of child labor." Manuscript.

Emerson, Patrick and Andre Portela Souza. 2004. Is Child Labor Harmful? The Impact of Starting to Work as a Child on Adult Earnings. Manuscript.

Greene, William H. 1993. *Econometric Analysis*. 2nd edition. New York: Macmillan Publishing Company.

Guarcello, Lorenzo, Scott Lyon, Furio C. Rosati. 2004. Impact of Working Time on Children's Health. Understanding Children's Work (UCW) Working Paper.

Gunderson, M. and D. Hyatt. 2001. Workplace Risks and Wages: Canadian Evidence from Alternative Models. *Canadian Journal of Economics* 34(2 May): 377-395.

ILO 2002. *Every Child Counts: New Global Estimates of Child Labour*. Geneva: International Labour Office.

Koenker, R. and K. F. Hallock. 2001. Quantile Regression. *Journal of Economic Perspectives* 15(4 Autumn): 143-156.

Koenker R. and G. Bassett. 1978. Regression Quantiles. *Econometrica* 46(1 January): 33-50.

Moretti, Enrico. 2000. Do Wages Compensate for Risk of Unemployment? Parametric and semiparametric evidence for seasonal jobs. *Journal of Risk and Uncertainty* 20(1 January): 45-

Raju, D. 2005. "Banning harmful child labor: A labor market and welfare analysis." Manuscript.

Rangvid, Beatrice S. 2003. Educational Peer Effects: Quantile Regression Evidence from Denmark with PISA 2000 data. Chapter 3, Ph.D. dissertation.

Rogers, C. A. and K. A. Swinnerton. 2002. A theory of exploitative child labor. U.S. Department of Labor. Manuscript.

Rosati, Furio C., and Roland Straub. 2004. Does Work During Childhood Affect Adult's Health? An Analysis for Guatemala. Understanding Children's Work (UCW) Working Paper.

O'Donnell, Owen, Furio C. Rosati, and Eddy Van Doorslaer. 2003. Health Effects of Child Labor: Evidence from rural Vietnam. Understanding Children's Work (UCW) Working Paper.

Viscusi, W. Kip and Joseph E. Aldy. 2003. The Value of a Statistical Life: A Critical Review of Market Estimates throughout the World. *Journal of Risk and Uncertainty* 27(1): 5-76.

Viscusi, W. Kip. 1993. The Value of Risks to Life and Health. *Journal of Economic Literature* 31(4 December): 1912-46.

Appendix

Table 1: Incidence of occupational harm by type of harm

Type	*Study sample* (percent)	*Non-earners sample* (percent)	Inter-sample difference in proportions
HAZARDOUS	27.8	14.5	***
STRESSFUL	46.7	30.0	***
STRENUOUS	38.2	19.8	***
Sample size	1,297	3,206	

Notes: The occupational harm categories are not mutually exclusive.
* statistically significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 2: Incidence of occupational harm by various combinations of occupational harm

Combination	*Study sample* (percent)	*Non-earners sample* (percent)	Inter-sample difference in proportions
None	38.1	57.0	***
HAZARDOUS only	5.7	5.3	
STRESSFUL only	13.8	14.6	
STRENUOUS only	6.1	5.9	
STRESSFUL and *HAZARDOUS* only	4.2	3.3	
STRESSFUL and *STRENUOUS* only	14.3	8.0	***
HAZARDOUS and *STRENUOUS* only	3.4	1.7	**
All three types	14.4	4.2	***
Total	100.00	100.00	
Sample size	1,297	3,206	

Notes: * statistically significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 3: Incidence of *frequent* occupational harm among children who reported experiencing occupational harm of that particular type

	Study sample	*Non-earners sample*	Inter-sample difference in proportions
OFTEN STRENUOUS	28.7	14.5	***
OFTEN STRESSFUL	17.7	10.0	**

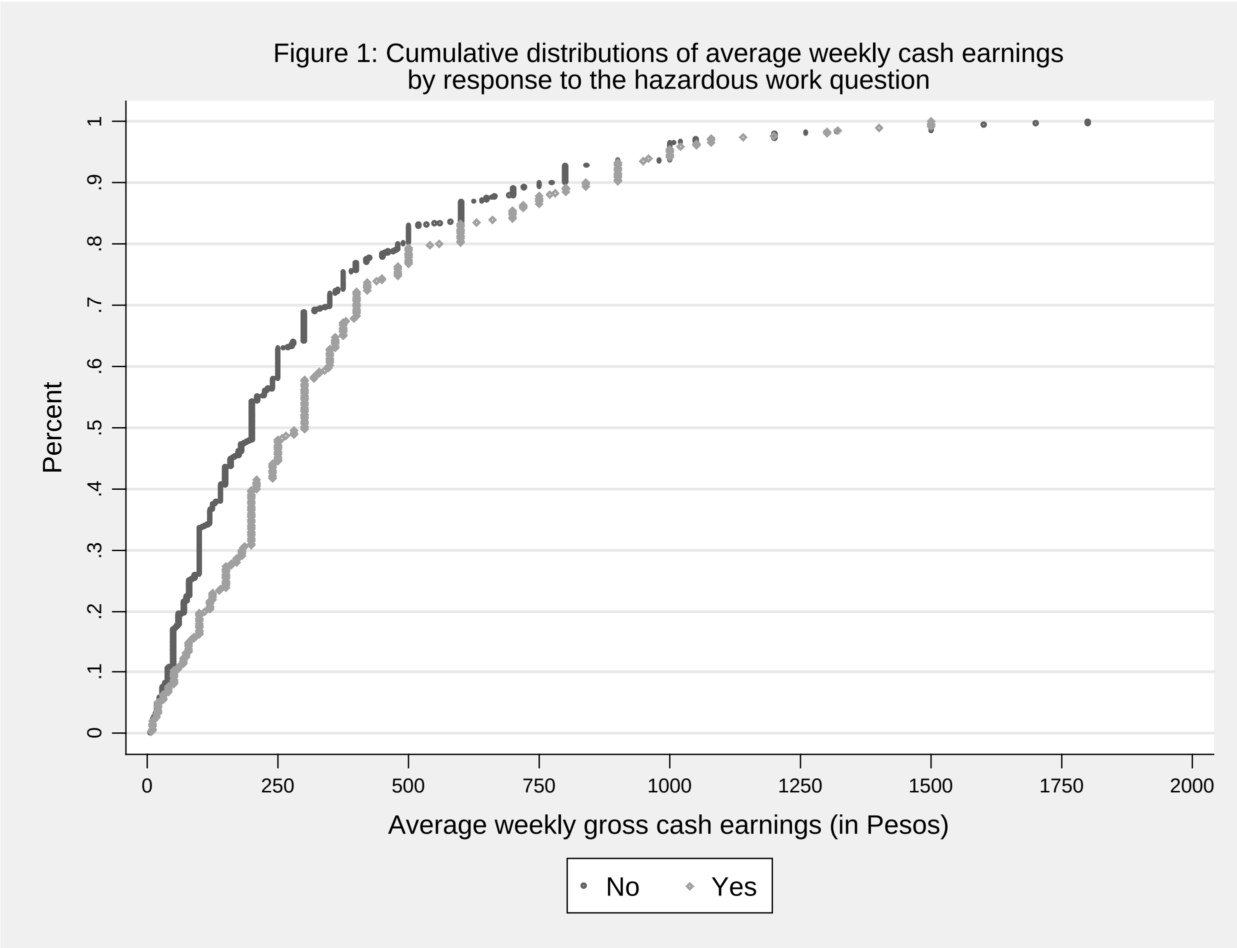
Notes: * statistically significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 4: Incidence of specific occupational hazards reported by children in hazardous workplaces

Type of occupational hazard	Percent
Vehicular accident	22.5
Burns	5.8
Fall	15.6
Hearing impairment	1.4
Visual impairment	1.1
Physical mutilation	15.3
Disease/sickness	21.9
Mental/psychological torture	1.1
Other (unknown)	15.3
Total	100.00

Sample size: 360

Earnings: hazardous and non-hazardous work



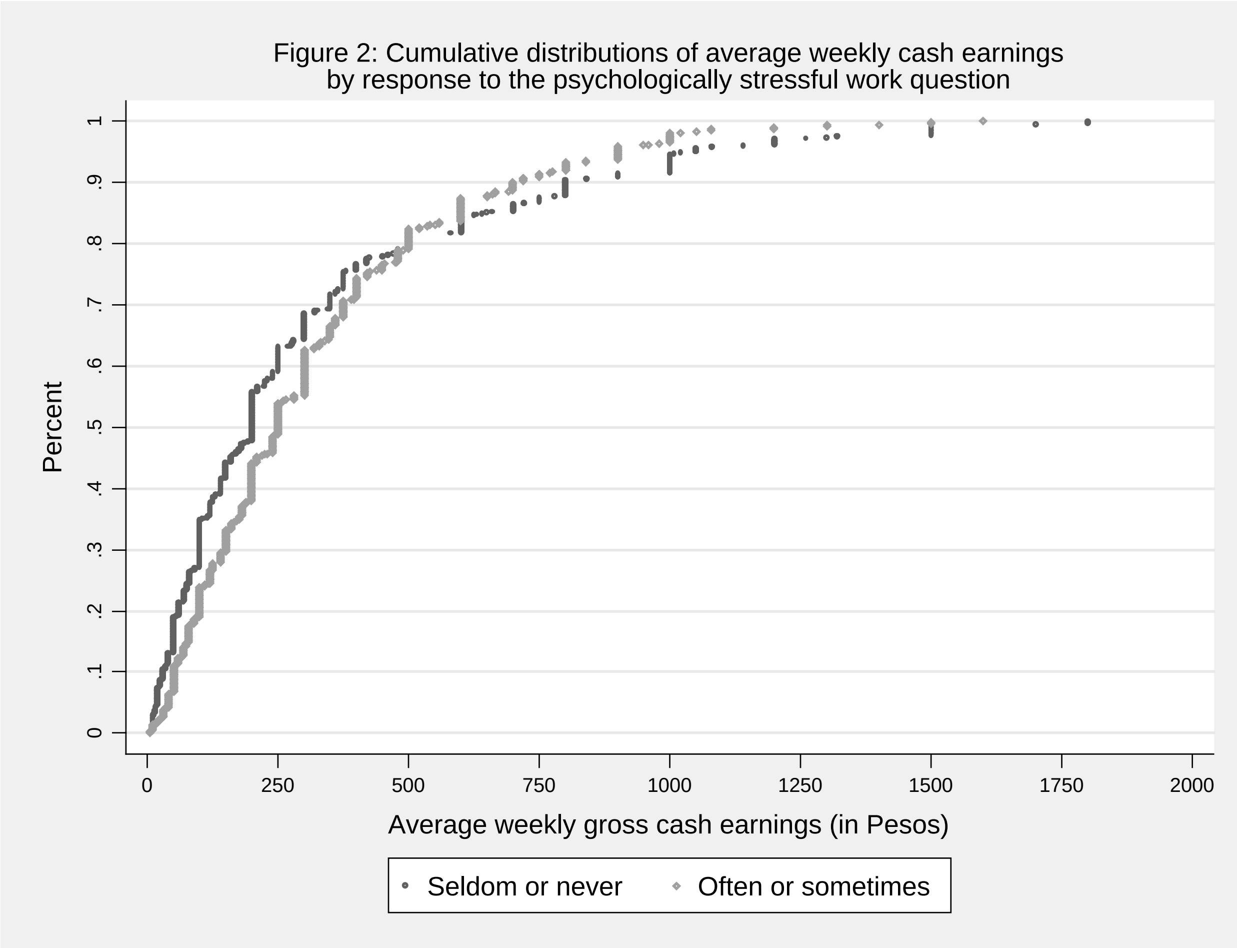
N(*HAZARDOUS* = 0) = 937, *N*(*HAZARDOUS* = 1) = 360, *N*(Total) = 1,297.

Equality of distributions tests:
Kolmogorov-Smirnov test: *D*-statistic = 0.1788, *P*-value = 0.000.
Wilcoxon Mann-Whitney test: *z*-statistic = -5.187, *P*-value = 0.0000.

Equality of means
Mean(weekly cash earnings (in Pesos) | *HAZARDOUS* = 0) = 301.
Mean(weekly cash earnings (in Pesos) | *HAZARDOUS* = 1) = 362.
F-statistic = 8.19, *P*-value = 0.0043.

Equality of medians
Median(weekly cash earnings (in Pesos) | *HAZARDOUS* = 0) = 200.
Median(weekly cash earnings (in Pesos) | *HAZARDOUS* = 1) = 300.
Chi-squared statistic = 17.75, *P*-value = 0.0000.

Earnings: psychologically stressful *vs.* non-stressful work



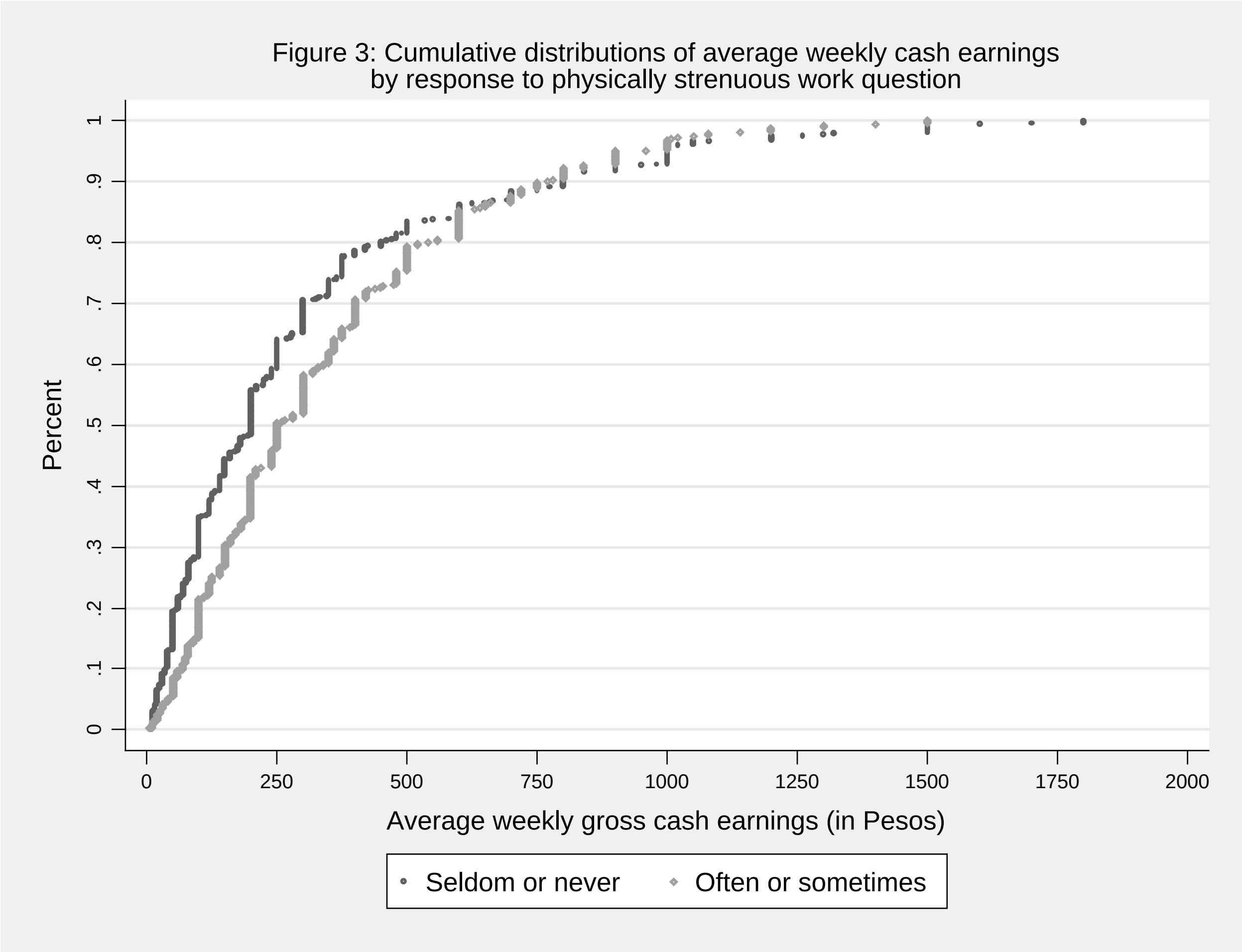
N(*STRESSFUL* = 0) = 691, *N*(*STRESSFUL* = 1) = 606, *N*(Total) = 1,297.

Equality of distributions tests
Kolmogorov-Smirnov test: *D*-statistic = 0.1303, *P*-value = 0.0000.
Wilcoxon Mann-Whitney test: *z*-statistic = -4.189, *P*-value = 0.0000.

Equality of means
Mean(weekly cash earnings (in Pesos) | *STRESSFUL* = 0) = 315.
Mean(weekly cash earnings (in Pesos) | *STRESSFUL* = 1) = 321.
F-statistic: 0.11, *P*-value = 0.7415.

Equality of medians
Median(weekly cash earnings (in Pesos) | *STRESSFUL* = 0) = 200.
Median(weekly cash earnings (in Pesos) | *STRESSFUL* = 1) = 250.
Chi-squared statistic = 9.69, *P*-value = 0.0019.

Earnings: physically strenuous vs. non-strenuous work



N(*STRENUOUS* = 0) = 802, *N*(*STRENUOUS* = 1) = 495, *N*(Total) = 1,297.

Equality of distributions tests
Kolmogorov-Smirnov test: *D*-statistic = 0.1649, *P*-value = 0.000.
Wilcoxon Mann-Whitney test: *z*-statistic = -6.209, *P*-value = 0.0000.

Equality of means
Mean(weekly cash earnings (in Pesos) | *STRENUOUS* = 0) = 289.87.
Mean(weekly cash earnings (in Pesos) | *STRENUOUS* = 1) = 345.70.
F-statistic: 5.99, *P*-value = 0.0145.

Equality of medians
Median(weekly cash earnings (in Pesos) | *STRENUOUS* = 0) = 200.
Median(weekly cash earnings (in Pesos) | *STRENUOUS* = 1) = 250.
Chi-squared statistic = 4.62, *P*-value = 0.0317.

Table 5: Summary statistics

Variable	Median	Mean	Standard deviation	Maximum	Minimum
Average weekly gross cash earnings	200.00	317.83	315.07	1800.00	6.00
Natural log avg. weekly gross cash earnings	5.30	5.25	1.12	7.50	1.79
Urban	1.00	0.56	0.50	1.00	0.00
Male	1.00	0.63	0.48	1.00	0.00
Age	15.00	14.75	2.01	17.00	8.00
Age-squared	225.00	221.65	55.35	289.00	64.00
Highest level of education					
No or elementary education	1.00	0.57	0.50	1.00	0.00
Secondary school student	0.00	0.43	0.50	1.00	0.00
Currently attending school	0.00	0.45	0.50	1.00	0.00
Potential work experience	1.00	1.97	1.91	10.00	0.00
Potential work experience-squared	1.00	7.52	13.13	100.00	0.00
Work hours per day					
1-4 hours	0.00	0.22	0.41	1.00	0.00
5-8 hours	1.00	0.55	0.50	1.00	0.00
9+ hours	0.00	0.23	0.42	1.00	0.00
Work days/week	5.00	4.29	2.21	7.00	1.00
Work days/week squared	25.00	23.28	18.32	49.00	1.00
HAZARDOUS	0.00	0.28	0.45	1.00	0.00
STRENUOUS	0.00	0.38	0.49	1.00	0.00
STRESSFUL	0.00	0.47	0.50	1.00	0.00
STRESSFUL × *HAZARDOUS*	0.00	0.19	0.39	1.00	0.00
STRESSFUL × *STRENUOUS*	0.00	0.29	0.45	1.00	0.00
HAZARDOUS × *STRENUOUS*	0.00	0.18	0.38	1.00	0.00
HAZARDOUS × *STRENUOUS* × *STRESSFUL*	0.00	0.14	0.35	1.00	0.00
OFTEN STRENUOUS	0.00	0.11	0.31	1.00	0.00
OFTEN STRESSFUL	0.00	0.08	0.28	1.00	0.00
Night work	0.00	0.29	0.45	1.00	0.00
Meals at work	0.00	0.21	0.41	1.00	0.00
Work location					
Farm	0.00	0.33	0.47	1.00	0.00
Non-house & non-farm	0.00	0.28	0.45	1.00	0.00
House (own or other)	0.00	0.39	0.49	1.00	0.00
Worker in private household	0.00	0.31	0.46	1.00	0.00
Worker in private establishment	1.00	0.69	0.46	1.00	0.00
Piece rate pay	0.00	0.24	0.43	1.00	0.00
Time rate pay	1.00	0.76	0.43	1.00	0.00

N = 1,297

Notes: Summary statistics for region dummies are excluded.

Table 6: Estimation results

Dependent variable: Natural log of average weekly gross cash earnings						
Independent variables	Specification 1		Specification 2		Specification 3	
	OLS†	LAD‡	OLS†	LAD‡	OLS†	LAD‡
Urban	-0.009 (0.065)	0.010 (0.061)	-0.010 (0.065)	0.016 (0.061)	-0.014 (0.065)	0.033 (0.062)
Male	0.096 (0.067)	0.199 *** (0.065)	0.096 (0.067)	0.201 *** (0.065)	0.094 (0.067)	0.159 ** (0.068)
Age	0.316 ** (0.151)	0.449 ** (0.177)	0.316 ** (0.151)	0.423 ** (0.177)	0.324 ** (0.152)	0.429 ** (0.175)
Age-squared	-0.007 (0.005)	-0.013 ** (0.006)	-0.007 (0.005)	-0.012 * (0.006)	-0.008 (0.005)	-0.012 * (0.006)
Secondary school student [No schooling or elementary school only]	0.035 (0.059)	0.077 (0.049)	0.035 (0.059)	0.075 (0.050)	0.035 (0.059)	0.071 (0.053)
Currently attending school	-0.278 *** (0.080)	-0.155 ** (0.076)	-0.278 *** (0.080)	-0.159 ** (0.075)	-0.282 *** (0.080)	-0.163 ** (0.076)
HAZARDOUS	0.063 (0.063)	0.021 (0.065)	0.062 (0.064)	0.025 (0.063)	0.032 (0.134)	0.172 (0.125)
STRENUOUS	0.128 ** (0.059)	0.108 * (0.061)	0.124 ** (0.062)	0.108 * (0.062)	0.278 ** (0.108)	0.211 ** (0.105)
STRESSFUL	-0.038 (0.056)	-0.029 (0.058)	-0.039 (0.058)	-0.020 (0.060)	0.016 (0.078)	0.014 (0.087)
OFTEN STRENUOUS	--	--	0.020 (0.079)	-0.056 (0.769)	--	--
OFTEN STRESSFUL	--	--	-0.003 (0.090)	0.102 (0.103)	--	--
STRESSFUL × *HAZARDOUS*	--	--	--	--	0.031 (0.177)	-0.091 (0.179)
STRESSFUL × *STRENUOUS*	--	--	--	--	-0.252 * (0.142)	-0.091 (0.127)
HAZARDOUS × *STRENUOUS*	--	--	--	--	-0.124 (0.205)	-0.231 (0.182)
HAZARDOUS × *STRENUOUS* × *STRESSFUL*	--	--	--	--	0.197 (0.251)	0.143 (0.237)

Potential work experience	-0.017 (0.036)	0.004 (0.033)	-0.017 (0.036)	0.007 (0.034)	-0.024 (0.036)	0.006 (0.036)
Potential work experience-squared	-0.001 (0.005)	-0.005 (0.004)	-0.001 (0.005)	-0.006 (0.004)	-0.000 (0.005)	-0.005 (0.005)
Work hours/day: 1-4 [Work hours/day: 5-8]	-0.452 *** (0.083)	-0.555 *** (0.090)	-0.452 *** (0.083)	-0.563 *** (0.084)	-0.453 *** (0.082)	-0.567 *** (0.085)
Work hours/day: 9+ [Work hours/day: 5-8]	0.106 (0.076)	-0.037 (0.083)	0.107 (0.076)	-0.025 (0.072)	0.102 (0.076)	-0.044 (0.077)
Work days per week	0.360 *** (0.087)	0.511 *** (0.075)	0.361 *** (0.087)	0.519 *** (0.076)	0.354 *** (0.087)	0.500 *** (0.082)
Work days per week-squared	-0.023 ** (0.010)	-0.039 *** (0.009)	-0.023 ** (0.010)	-0.040 *** (0.009)	-0.023 ** (0.010)	-0.038 *** (0.010)
Night work	0.041 (0.066)	0.010 (0.079)	0.041 (0.066)	-0.009 (0.080)	0.045 (0.066)	-0.006 (0.079)
Meals at work	-0.149 ** (0.066)	-0.155 *** (0.056)	-0.149 ** (0.066)	-0.148 *** (0.055)	-0.149 ** (0.066)	-0.162 *** (0.059)
Place of work: non-farm and non-house [Farm]	-0.081 (0.085)	-0.015 (0.076)	-0.083 (0.086)	-0.011 (0.095)	-0.084 (0.086)	-0.049 (0.095)
Place of work: house (own or other) [Farm]	-0.116 (0.095)	0.023 (0.077)	-0.117 (0.096)	0.040 (0.092)	-0.118 (0.095)	0.025 (0.094)
Worker in private household [Worker in private establishment]	0.166 ** (0.080)	-0.210 *** (0.065)	0.165 ** (0.080)	0.214 *** (0.079)	0.161 ** (0.081)	-0.227 *** (0.082)
Form of payment: Piece rate [Time rate]	-0.167 ** (0.072)	-0.161 ** (0.071)	-0.167 ** (0.072)	-0.165 ** (0.077)	-0.161 ** (0.072)	-0.176 ** (0.082)
Intercept	1.171 (1.126)	0.380 (1.301)	1.171 (1.126)	0.181 (1.297)	1.125 (1.135)	0.188 (1.285)
N = 1,297						
R-squared§	0.47	0.33	0.47	0.33	0.47	0.33
F-test of model significance, *p*-value	0.000	--	0.000	--	0.000	--

Notes:
All specifications include region dummies.
Reference categories for dummy variables are provided in square parentheses.
† The formula for estimating standard errors (in parentheses) incorporates the survey sample design.
‡ The standard errors (in parentheses) are computed using a bootstrap estimator which mimics the survey sample design. The total number of bootstraps replications implemented was 200.
§ Pseudo *R*-squared statistic reported for LAD estimations.
* statistically significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 7: Estimates of weekly earnings premia for occupational harm

Occupational harm variable	Statistic	OLS[†]	Quantile[‡]		
			0.25	0.50	0.75
	b	0.063	0.074	0.021	-0.016
HAZARDOUS	100*(exp(*b*)-1)	6.5	7.7	2.1	-1.6
	s.e.	(0.063)	(0.082)	(0.065)	(0.069)
	b	0.128 **	0.250 ***	0.108 *	0.070
STRENUOUS	100*(exp(*b*)-1)	13.7	28.4	11.4	7.3
	s.e.	(0.059)	(0.069)	(0.061)	(0.080)
	b	-0.038	-0.074	-0.029	-0.012
STRESSFUL	100*(exp(*b*)-1)	-3.7	-7.1	-2.9	-1.2
	s.e.	(0.056)	(0.076)	(0.058)	(0.071)
N = 1,297					

Notes:
Ordinary least squares provide the mean weekly earnings premia.
[†] The formula for estimating standard errors (in parentheses) incorporates the survey sample design.
[‡] Standard errors (in parentheses) are computed using a bootstrap estimator which mimics the survey sample design. The total number of bootstrap replications implemented was 200.
* statistically significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

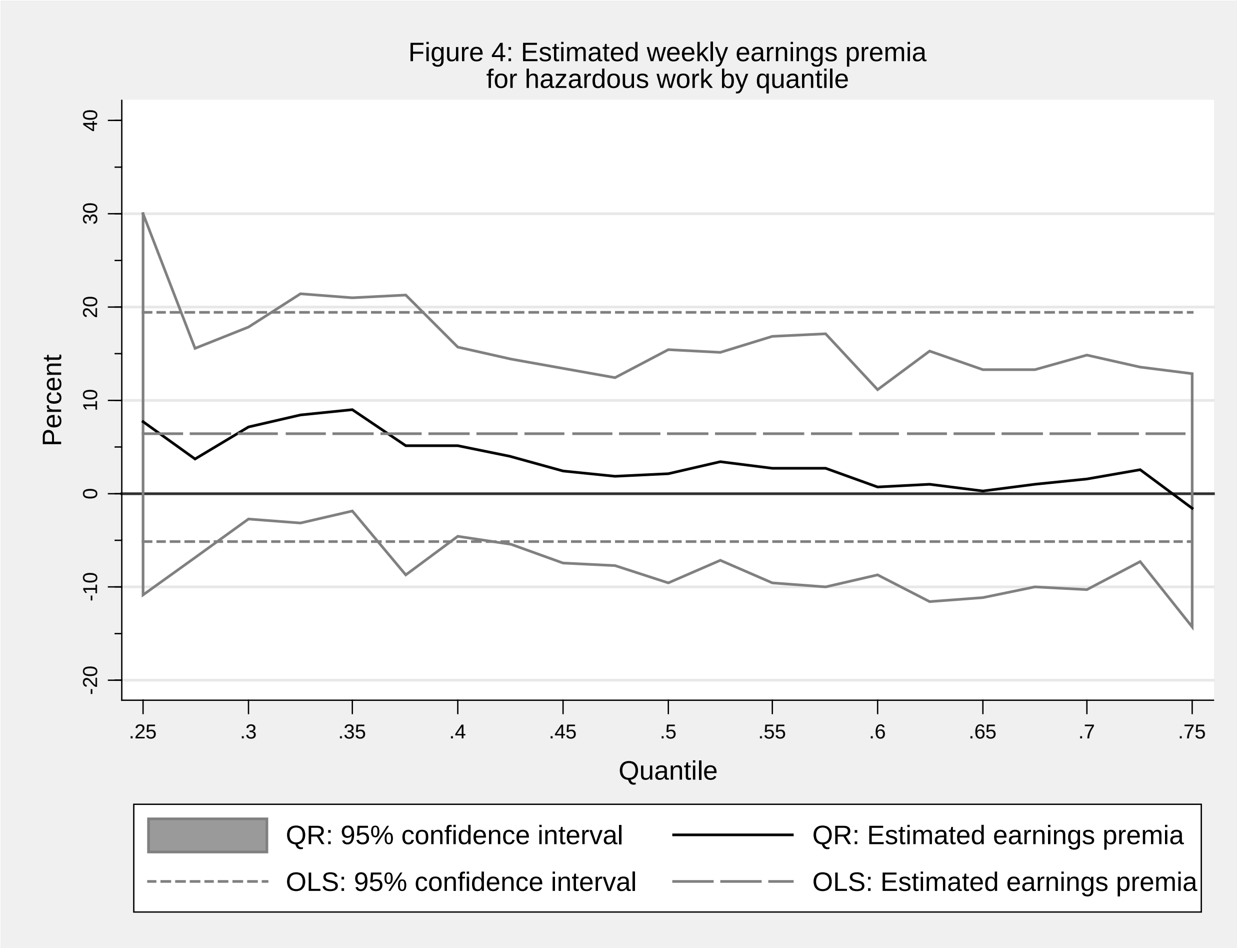


Figure 4: Estimated weekly earnings premia
for hazardous work by quantile
Percent
40
30
20
10
0
-10
-20
.25
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
Quantile
QR: 95% confidence interval
QR: Estimated earnings premia
OLS: 95% confidence interval
OLS: Estimated earnings premia

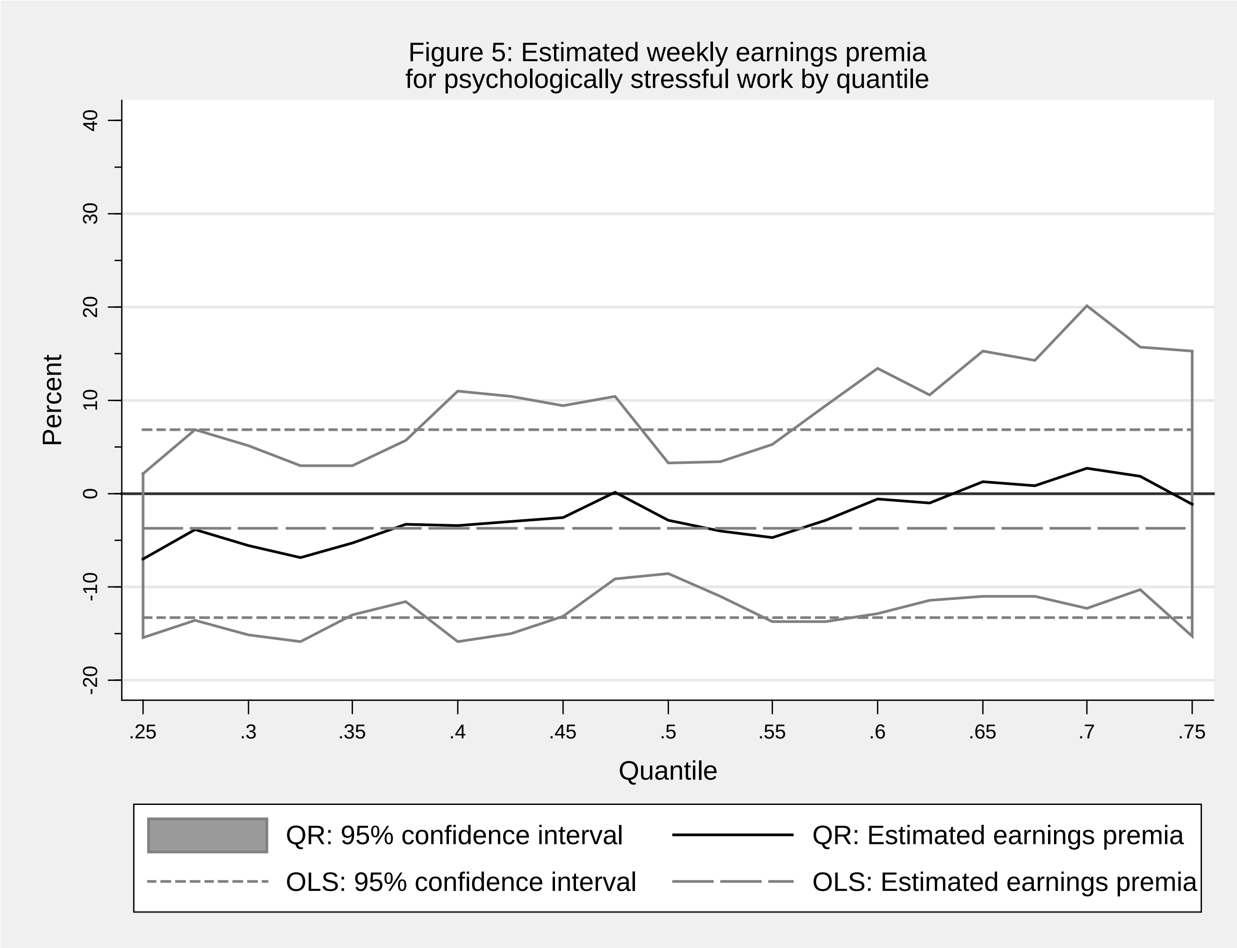


Figure 5: Estimated weekly earnings premia
for psychologically stressful work by quantile
Percent
40
30
20
10
0
-10
-20
.25
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
Quantile
QR: 95% confidence interval
QR: Estimated earnings premia
OLS: 95% confidence interval
OLS: Estimated earnings premia

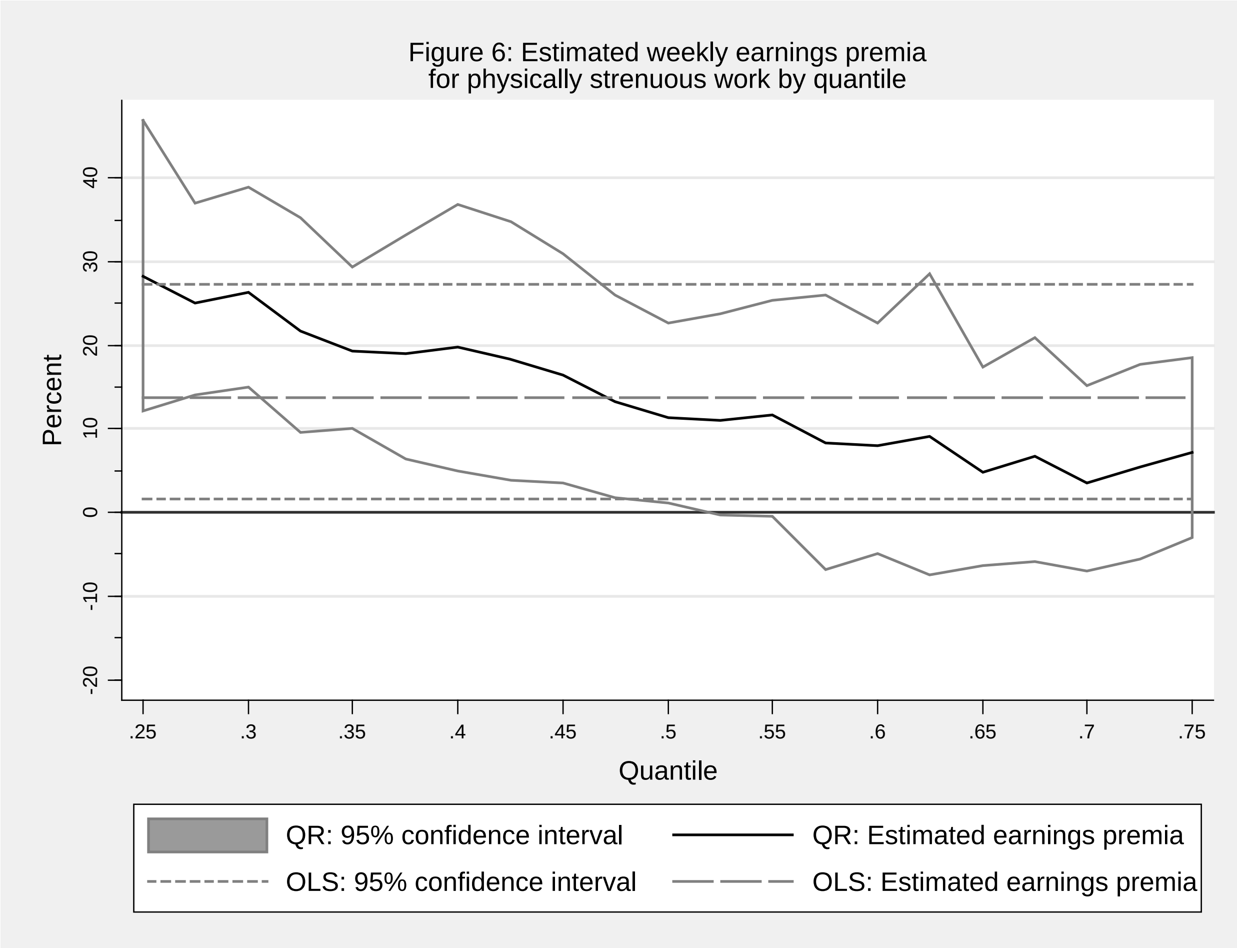


Figure 6: Estimated weekly earnings premia
for physically strenuous work by quantile
Percent
40
30
20
10
0
-10
-20
.25
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
Quantile
QR: 95% confidence interval
QR: Estimated earnings premia
OLS: 95% confidence interval
OLS: Estimated earnings premia