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Does the Risk of Poverty Reduce Happiness?

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DOES THE RISK OF POVERTY REDUCE HAPPINESS?*

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Abstract

We investigate the unexplored link between the risk of poverty and happiness in the context of a developing country. Using unique longitudinal data, we estimate workers' vulnerability to income-poverty and find a strong negative relationship between vulnerability and happiness, over and above a positive income effect. The result is robust and cannot be reduced to the effect of two-sided uncertainty. A matched behavioural experiment shows that respondents are significantly loss-averse. We conclude that downside risk is an important determinant of happiness and of economic decisions under uncertainty. Policies that mitigate downward risk may thus have direct impacts on both well-being and efficiency.

JEL codes: D60, I31, I32, D81, O12.
Keywords: poverty, vulnerability, risk, subjective well-being, happiness, loss-aversion.

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1 Introduction

Economic outcomes are often characterised by pervasive uncertainty. This is particularly true when insurance markets and safety nets are incomplete, saving opportunities limited, and many individuals rely on risky entrepreneurial activities to generate their incomes (Banerjee and Duflo, 2007). Poverty, which constitutes a possible outcome for many, has in turn profound impacts on the quality of the lives people live. Recent studies have shown that low income correlates with lower life satisfaction and with a larger loss in well-being following shocks in other domains of life (Clark, Frijters, and Shields, 2008; Kahneman and Deaton, 2010). In developing countries, where poverty is widespread, the correlation between economic outcomes and life satisfaction is even stronger (Howell and Howell, 2008).

In this study we investigate the relationship between the risk of poverty and life satisfaction (interpreted henceforth as "happiness"[1]), and the link between sensitivity to downward risks and decision-making. In particular, we tackle the following two questions. Is there a connection between happiness and the risk of poverty? And how are people's decisions affected by exposure to such risk?[2] While the connection between life satisfaction and low income has been heavily researched, the one between life satisfaction and the risk of poverty is still unexplored. This is partly due to the challenges of estimating the probability distribution of income convincingly. At the same time, it appears to be a very important area of research, especially in developing countries, where widespread exposure to uninsured shocks makes the risk of future income poverty pervasive for both poor and non poor

[1] Researchers distinguish two components of happiness (Kahneman and Deaton (2010)). The first component is life satisfaction: the evaluation we make of our own life. The second component is emotional well being, or the tendency to experience positive or negative affect. In this paper we analyse responses from a survey question on life satisfaction and hence we focus the analysis on the first component. Throughout the text, we will use the terms "happiness" and "life satisfaction" interchangeably.

[2] We choose to focus on income, rather than consumption for three reasons. First, we aim to link directly to the existing literature on subjective-well being, which has widely explored the relationship between happiness and income. Second, income is notoriously easier to measure than consumption and this is indeed reflected in the poor quality of the consumption data at our disposal. Third, in our urban context, labour earnings are typically the main source of income and earning shocks are directly transmitted to consumption. Changes in income and consumption are hence likely to be tightly correlated.

households.[3] Evidence is also missing on the connection between the determinants of happiness and those of decision making: are the same individuals whose happiness is sensitive to downside risk loss averse in economic decisions? Vulnerability may affect individual behavior in ways that are detrimental to economic efficiency. Such evidence is thus a necessary first step towards a full assessment of the welfare effects of economic vulnerability.

The context of our analysis is the urban labour market in Ghana, a fast-growing African country. Ghana is an interesting setting for our analysis as the country experienced substantial poverty reduction in recent years (Nsowah-Nuamah, Teal, and Awoonor-Williams, 2010) while, as our results will suggest, large numbers are still exposed to a significant risk of poverty. Given the novelty of the question and of the testing strategy, our results provide leads that may prove relevant in other contexts as well.

Our estimate of the risk of poverty builds upon the work by Chaudhuri (2003) and Chaudhuri, Jalan, and Suryahadi (2002), who propose two indices of vulnerability to poverty[4] that are amenable to empirical estimation based on panel and cross-sectional variation respectively.[5] Using data from the Ghana Household Urban Panel Survey (GHUPS), a long panel dataset gathered by the Centre for the Study of African Economies in urban Ghana, we obtain estimates of the two indices for a representative sample of working age Ghanaian earners. We focus more extensively on the panel measure, since it enables us to estimate individual-specific vulnerability. We further rely on the longitudinal nature of the data to investigate the relationships of interest, between the risk of income-poverty and life-satisfaction. Improving upon most of the existing literature on happiness in developing countries, we are able to control for *individual fixed effects in the happiness model*, ruling out potential biases from unobserved personality traits. Previous studies have indeed highlighted the importance of unobserved heterogeneity in happiness regressions (Ferrer-

[3] For example, in a recent study of seven west-African capitals, Bocquier, Nordman, and Vescovo (2010) construct a multi-dimensional index of employment vulnerability and find that 85% of private sector workers are vulnerable on the basis of at least one criterion in 2002-2003.

[4] Throughout the analysis the term 'vulnerability' will be used to refer to 'the risk of falling below the income poverty line'. Also, the terms happiness, life satisfaction and subjective well-being will be used interchangeably.

[5] The two indices are reviewed in a survey article by Ligon and Schechter (2004), who compare the performance of different vulnerability measures through Monte Carlo simulations.

i Carbonell and Frijters, 2004; Graham, Eggers, and Sukhtankar, 2004; Powdthavee, 2010).

Our main result is *a strong negative relationship between vulnerability to poverty and workers' happiness*, over and above the positive income effect commonly documented in the existing literature. When we bootstrap the estimation sequence to account for imprecision in the measure of vulnerability, the results do not change. Upon testing for the role of two-sided uncertainty as opposed to downward income losses, we find that the effect of downward vulnerability on happiness is more evident. These findings become more compelling when we consider the extent of the vulnerability to poverty which we uncover. About 35 percent of all workers, and 15 percent of currently non poor workers, face a probability of poverty of at least 50 percent. Vulnerability decreases the life satisfaction of a large pool of individuals.

In addition, we analyze the choices of a sub-sample of respondents in a set of behavioral games designed to elicit attitudes towards risky prospects. Our maximum likelihood estimates reveal that subjects are characterised on average by a substantial degree of loss aversion. We are careful not to collapse the distinct notions of experienced utility and decision utility (Kahneman, Wakker, and Sarin, 1997).[6] Our findings from the behavioral experiment show that, besides influencing subjective well being, downside risk also has an appreaciable impact on economic decisions.

Our work relates to two different strands of the literature. First, we contribute to the study of downside risk in developing countries. This literature has focused on measurement (Chaudhuri, 2003; Ligon and Schechter, 2004), on the persistence of downside shocks (Dercon, 2004; Dercon, Hoddinott, and Woldehanna, 2005), and on the strategies employed to minimize and cope with shocks (Rosenzweig and Binswanger, 2003; Dercon, 1996; Fafchamps, 2003; Dercon and Christiaensen, 2007; Fafchamps, 2009). We document substantial and pervasive vulnerability to income poverty in the context of urban Ghana and, by means of a behavioral experiment, further show that downside risk affects the economic

[6] Decision utility refers to the weights that people assign to outcomes when making choices. Experienced utility refers to the quality of experience. The life satisfaction question we employ in this analysis ask respondents to make an evaluation of the latter. The behavioral experiments allow us to make inferences about the former.

decisions of subjects in our sample. Our work also relates to the growing literature on the determinants of happiness. A number of empirical papers have documented a cross-sectional correlation between income and happiness (Kahneman and Deaton, 2010), which does not disappear once individual fixed effects are accounted for (Ferrer-i Carbonell and Frijters, 2004; Powdthavee, 2010). A separate concern has been that of adaptation: the happiness effects of income gains seems transitory and tends to disappear once income reference points have adjusted (Easterlin, 2001; Frey and Stutzer, 2002; Di Tella, Haisken-De New, and MacCulloch, 2007; Knight and Gunatilaka, 2008). The literature has also explored the effect of social comparisons on well being (Blanchflower and Oswald, 2002; Kingdon and Knight, 2004; Luttmer, 2005). Our contribution is to highlight the fact that risk and, in particular, the risk of poverty is a major negative determinant of life satisfaction. Morevoer, we show that the same people who manifest loss-sensitivity in life evaluation make economic decisions consistent with loss aversion.

The results of this analysis bear important policy implications that may generalise well-beyond the African context. Uncovering whether income vulnerability has a direct impact on life-satisfaction provides clear motivation for policy interventions to reduce people's exposure to (downside) risk. Moreover, our findings suggest that non-Rawlsian models of growth, whereby "someone may be left behind", may fail to enhance general welfare despite rising average incomes, if the risk of falling behind is sufficiently widespread. Lastly, loss aversion motivates individuals to forgo economic opportunities that are profitable in expectation but may involve outcomes below the reference point. A reduction in vulnerability may result in efficiency gains too.

The article is structured as follows. Section 2 introduces the data we use in the analysis. Section 3 outlines the empirical strategy. First, it explains the methodology to estimate income vulnerability; second, it outlines the happiness model. Section 4 presents and discusses the results. Section 5 concludes.

2 Data

The Ghana Urban Household Panel Survey (GUHPS) has been conducted by the Centre for the Study of African Economies in the cities of Accra, Kumasi, Takoradi and Cape-Coast since 2004. It has run annually since then and at the time of writing the first 6 waves have been made available (2004-2009).[7] Panel datasets of this length are unusual in developing countries, and are particularly uncommon for Africa.[8]

A module on subjective well-being was added to the GHUPS questionnaire in 2005 and it was administered in every subsequent wave with the exception of 2007. The questions that compose the module were designed to be in line with the existing literature on subjective well-being. For the purpose of this analysis, we will focus on the answers to the following two questions: (a) *"All things considered, how satisfied are you with your life as a whole these days?"* (b) *"All things considered, how satisfied are you with your current work?"*. In both cases, the options given to respondents were: *"1.Very Dissatisfied, 2. Dissatisfied, 3. Neither Satisfied Nor Dissatisfied, 4. Satisfied, 5. Very Satisfied"*. Figure 1 depicts the distribution of answers. Responses appear to be skewed towards positive values. For our quantitative analysis, we attribute numerical values on a scale from 1 to 5 to these answers, where 1 corresponds to "Very Dissatisfied" and 5 to "Very Satisfied". Despite early criticism of their ability to accurately capture well-being (e.g. Mullainathan and Bertrand (2001)), these measures have been consistently used throughout the literature. Moreover, psychologists have recently been able to validate the use of these questions, by

[7] There was one exception: the survey was not conducted in 2007, but information for that year was collected in 2008 as a 'recall' questionnaire. However, due to the low reliability of retrospective questions on subjective well-being, the happiness module was not part of this recall questionnaire.

[8] The panel is unbalanced, but attrition is not an absorbing state, in the sense that respondents who are not interviewed in a given wave are kept in the sample and re-interviewed in subsequent years. For the purpose of our analysis, attrition may decrease the precision of our vulnerability estimates, causing a classical problem of downward bias in the happiness model (yet, the results show a large effect of vulnerability on happiness). Imprecision due to attrition may also generate anomalies in the vulnerability distribution (e.g. outliers). Our bootstrapping procedure confirms the robustness of our results to this concern. Finally, unpon confining our analysis to the balanced sub-sample of respondents who are interviewed in all survey waves, we find no evidence of attrition bias. The point-estimates of the model coefficients do not change significantly, despite a drop in precision due to the fall in sample-size. Previous studies on this data have found no evidence of attrition bias (see Falco, Kerr, Rankin, Sandefur, and Teal (2011) and Falco, Maloney, Rijkers, and Sarrias (2012) for an application to work-satisfaction across occupational categories).

showing their correlation with other measures of well-being, such as smiling more frequently (Graham, Eggers, and Sukhtankar, 2004; Layard, 2005; Oswald and Wu, 2010).

< Figure 1 here >

A selection of key summary statistics for the pooled sample over all survey waves is presented in Table 1. The average worker in our sample is 36 years old and has 8 years of formal education. Most of them are self-employed (largely in the informal sector), as it is typical in the labour markets of developing countries.[9]

< Table 1 here >

3 Empirical methodology

3.1 Constructing a vulnerability indicator

This section outlines the methodology to construct the vulnerability indicators used in the remainder of the analysis. For a detailed discussion of the relative merits of different vulnerability indices, the reader is referred to the survey paper by Ligon and Schechter (2004). The analysis in this article will mainly draw on the two measures proposed by Chaudhuri (2003) and Chaudhuri, Jalan, and Suryahadi (2002). The former relies on time-series variation in individual earnings and suits particularly well the characteristics of our dataset, where subjective well-being is recorded for the same individuals over a number of consecutive years, in addition to income and other worker characteristics from which we can model vulnerability. The latter method will produce a benchmark index that attempts to model cross-sectional variation and infer from it the degree of individual vulnerability. Ligon and Schechter (2004) compare the performance of these two (and several other) vulnerability indices via Monte Carlo simulations and their conclusion is in favour of the panel approach as the best performing indicator of actual vulnerability.[10]

9 Our analysis will focus on 'paid workers', for whom income is observed and we are therefore able to construct a measure of income vulnerability.

10 This is a sensible conclusion, considering the likely presence of unobserved individual fixed effects that cannot be controlled for in a cross sectional model of earnings and could therefore mislead the analysis of vulnerability. As part of our future research we intend to explore how the results of this analysis will change upon using new vulnerability measures, including Ligon and Shechter's own index of vulnerability (see Ligon and Schechter (2003)).

In what follows we will discuss how we obtain estimates of income vulnerability using the panel method. A section in the appendix presents alternative estimates based on the cross-sectional method.

Following Chaudhuri (2003), the income vulnerability of a worker at time t is defined as the probability that the worker's income will fall below a certain threshold (z) next period. Let ν_{it} be the inverse of vulnerability, that is, i's likelihood at t of earning an income above z at $t+1$:

$$\nu_{i,t} = Pr(y_{i,t+1} > z) \tag{1}$$

Following standard Mincerian earnings analysis, assume that income is generated by the following process:

$$ln(y_{i,t}) = \delta X_{i,t} + \eta_i + \tau_t + e_{i,t} \tag{2}$$

where X_{it} is a bundle of observable characteristics, η_i is an individual unobservable fixed effect, τ_t captures time-effects that are common across workers (e.g. aggregate income growth factors and common shocks) and e_{it} is a stochastic component.

Second, we explicitly model the heteroskedasticity in the data and assume the variance of e_{it} to be a function of worker and household characteristics.

$$ln(\sigma^2_{lny_{i,t}}) = \theta K_{i,t} + \xi_i \tag{3}$$

where $K_{i,t}$ may or may not contain additional workers' characteristics, outside the set $X_{i,t}$, depending on our priors on the role that specific workers' traits will play in determining earnings volatility over and above earnings levels, and ξ_i is an individual fixed-effect in the model of income variance.

The variance of the stochastic component can be modeled empirically using the log of first-stage residuals from the earnings model:

$$ln(\hat{e}^2_{i,t}) = \theta K_{i,t} + \xi_i + \omega_{i,t} \tag{4}$$

given that:

$$\frac{1}{T}\sum_{t=1}^{T}\hat{e}^2_{i,t} \rightarrow_p \sigma^2_{lny_{i,t}} \tag{5}$$

Assuming income to be (log)normally distributed and Φ to be the cumulative distribution function of the log normal distribution, we can now calculate the individual vulnerability index using the following expression. [11]

$$\nu_{it} = Pr(ln(y_{it}) > ln(z)|X_{it,}K_{it}, \hat{\delta}, \hat{\theta}) = 1 - \Phi\left[\frac{ln(z) - \hat{\delta}X_{it}}{\hat{\theta}K_{it}}\right] \tag{6}$$

This measure is designed to capture income-fluctuations without explicitly trying to differentiate transitory from permanent shocks. In the presence of an effective saving technology, the two are likely to have different impact on welfare, since transitory fluctuations can be smoothed out through precautionary savings. This is unlikely to be the case in an economy where saving and formal insurance devices are generally lacking and accumulated wealth is limited. In such an economy transitory shocks can be expected to have a significant impact on consumption and the use of the vulnerability index above appears to be justified. Moreover, attempting to explicitly separate the permanent from the transitory component of income variation (e.g. following the approach by Meghir and Pistaferri (2004)) would pose major challenges given the length of the GHUPS panel, though it remains an open alley for future research.[12]

3.2 Empirical model of happiness

Having constructed a measure of vulnerability, we can now explore its relation with subjective-well being. The following equation describes our workhorse model of happiness:

$$h_{i,t} = \beta y_{i,t} + \gamma\nu_{i,t} + \delta Z_{i,t} + \kappa_i + \epsilon_{i,t} \tag{7}$$

[11] The reader should note that, differently from the definition in 1, our estimates of vulnerability will be obtained as the probability of falling below the poverty line given worker characteristics at t, rather than $t + 1$. This choice was made based on the idea that workers are most likely to assess their future prospects on the basis of their current characteristics, some of which might themselves be stochastic and subject to unpredictability.

[12] Similarly, it will be interesting to extend the current analysis to incorporate data on savings and wealth that will become available in the next-coming waves of GHUPS, which may enable us to control for precautionary savings.

where h_{it} is worker i's level of life satisfaction in period t, y_{it} is income at time t and ν_{it} is the index of (the inverse of) vulnerability in the same period; Z_{it} is a vector of worker characteristics that are expected to be correlated with life-satisfaction. κ_i is an unobserved happiness fixed-effect that accounts for unobserved traits that make an individual naturally more (or less) prone to be satisfied with his/her life (e.g. optimism). Our main hypothesis is that β and γ are positive (once again, note that $\nu_{i,t}$ is the inverse of vulnerability and, hence a 'good' in this specification): *increasing income and decreasing vulnerability enhances life satisfaction*. In order to test it, we will attempt to overcome several identification challenges.

First, a number of time-varying and time-invariant determinants of happiness may be correlated with income and vulnerability. If omitted from the analysis, those variables may bias the results. Among the time-invariant factors, one can think of *personality traits* or endowments of *social and human capital*, which may have a direct impact on life-satisfaction. More extroverted and optimistic individuals, for instance, may be both 'naturally' satisfied with their life and more likely to find good, secure employment, or, equally plausibly, more willing to face the risks and uncertainty of entrepreneurship. The same may hold for educated or well-connected people. Among the time varying unobservables, *working conditions* are a first, obvious source of bias. Powdthavee (2010) argues that income gains are often correlated with deterioration in the conditions of work and the latter may have an important influence on life satisfaction. Vulnerability might also be correlated with working conditions, though we have no strong a-priori evidence of the sign of such correlation. *Relative income* is a third potentially confounding factor. Extensive empirical evidence has been generated showing that relative income is correlated with the life satisfaction of individuals in both developed and developing countries (Blanchflower and Oswald, 2002; Luttmer, 2005; Kingdon and Knight, 2004) and it is natural to assume that relative income will be correlated with absolute income and vulnerability. We will attempt to account for these potential sources of bias by including in the model controls for working-conditions (proxied by a measure of satisfaction with work) and for a worker's position in the income distribution. Most importantly, thanks to our panel dataset we will be able to *control for all time-invariant individual characteristics correlated with happiness (e.g. personality* *traits).*[13]

The second challenge is methodological: life-satisfaction is generally recorded in datasets like GHUPS as a categorical variable. Modeling it as a discrete (ordered) outcome would, therefore, appear to be the most appropriate approach. However, such approach would not easily lend itself to controlling for those time invariant unobservables that we have argued are of great relevance in the determination of life satisfaction. To address this issue Ferrer-i Carbonell and Frijters (2004) develop a conditional estimator for the fixed effects logit model. Their findings show that *"it makes virtually no difference whether one assumes ordinality or cardinality of happiness answers, whilst allowing for fixed effects does change results substantially"* (Ferrer-i Carbonell and Frijters, 2004). It therefore seems justifiable to assume cardinality of the life satisfaction indicator and use the corresponding estimators.

Third, issues of reverse causality may arise in the analysis. High levels of life satisfaction may help individuals earn higher incomes or reduce their income vulnerability (Graham, Eggers, and Sukhtankar (2004), De Neve and Oswald (2012)). Such effects may again bias the estimated coefficients β and γ. In order to fully address this problem, we would be required to specify an FE-IV regression approach. However, doubts are often raised about the validity of the instruments proposed by the authors who have attempted the IV or FE-IV approach for income such as Knight and Gunatilaka (2008); Powdthavee (2010).[14] Hence, we do not attempt to instrument vulnerability, while fully acknowledging the possibility that these concerns might be important.

Finally, the vulnerability index is a non-linear function of the first two moments of the earnings distribution, which are both modeled as functions of household and individual characteristics in the first stage of the estimation. It follows that the happiness model (where we include both income and vulnerability on the right-hand side) contains *two* functions of

[13] By means of *within group* and *differenced* estimators, we are able to exclude the possibility that personality traits that are time-invariant, such as innate optimism, are the drivers of the relationship between happiness and income, and between happiness and vulnerability. And, perhaps more interestingly for the advancement of the literature, we can study directly how such personality traits may bias the results if they are not controlled for.

[14] Furthermore, the vulnerability variable has been constructed as a deterministic function of the predicted values of an earnings model, which would complicate an IV strategy.

those characteristics among the regressors. Separate identification of these two functions implicitly relies on assumptions regarding the relationship between income and well-being. Existing studies have often imposed *linearity* on the relationship and, for comparability, we choose the same approach.[15]

4 Results

We present here three sets of results. First, we discuss our estimates of vulnerability. Second, we present a number of regressions of happiness on vulnerability, which constitute the central results of our analysis. This section also offers a test to distinguish between the effect of vulnerability and that of two-sided uncertainty. Third, we show an additional set of results obtained using experimental measures of attitudes to gains and losses.

4.1 Vulnerability Estimates

Table 2 shows the results from estimating the earnings and variance models used to predict vulnerability later in the analysis.[16] The first feature of the results is that while the income model (col 1) shows a relatively high predictive power, trying to predict the variance of earnings proves to be a much more challenging exercise. This is to be expected, given that part of what appears to be true variation in earnings may in fact be due to random measurement error. Upon experimenting with different specifications, we conclude that the best model is one that controls for individual fixed effects (col 5) and for a set of key time-varying covariates, the choice of which is grounded in a long-established literature on mincerian earnings regressions (see Rankin, Sandefur, and Teal (2010) for an application on Ghana using the GHUPS dataset). The results in col 1 confirm a number of standard patterns observed in related studies of earnings in Sub-Saharan Africa. First, we find a statistically significant effect of firm-size on earnings (captured by positive coefficients on the log of firm-size for wage-employees and on the log of the number of hired employees for

[15] Fafchamps and Shilpi (2008, 2009) report non-parametric results that show a linear relationship between consumption expenditures and subjective satisfaction with consumption levels, lending empirical support to this modeling choice.

[16] We document the results from the income model in col. 1 and from several specifications of the variance model in col. 2 -5.

the self-employed). Second, we detect a sizable civil service premium and a positive premium for longer tenure in the job. Third, while the linear effect of age cannot be estimated when time-trends are also controlled for, we are able instead to capture the typical concavity of the age-earnings profile (albeit the coefficient appears to be insignificant). Since estimation in col 1 is carried out with controls for individual fixed effects, it is not possible to separately identify the coefficients on time-invariant characteristics such as education and gender.

Turning to the variance model, upon scanning the information available in the GHUPS, we identified two sets of worker characteristics (available for a sufficiently large portion of the sample) that should, in principle, drive the variance of earnings. The first one is *ethnicity*, following the idea that social networks provide an important buffer against negative shocks and can help insulate one's earnings through several channels (e.g. informal lending to cover variable business costs). The strength of one's network largely depends on family ties, which in the Ghanaian context are highly intertwined with tribal and ethnic background, and different ethnic groups may be able to count on support networks of different strength. Second, respondents' *marital status* should drive the degree of income variability they can expect, for at least two reasons. First, marriage enlarges one's network and increases the scope for risk-pooling. Second, forming a family is likely to change the risk-management strategies of income earners as they become responsible for a larger group of people. While including these variables in the variance model should in principle allow us to separately identify the second moment of the distribution, we are aware that some caution may be necessary when interpreting the results. Unforuntately, the data at our disposal does not currently provide us with more satisfactory sources of identification.[17]

< Table 2 here >

Given our estimates of the earnings model, before we can calculate vulnerability we need to define a low-earning threshold (alternatively referred to as 'poverty line'), z. Figure 2 shows the percentage of people who, in every year, are below different income thresholds, while figure 3 shows the resulting cumulative distribution of the vulnerability index. As one

[17] We find that ethnic ties are a significant predictor of the variance of earnings, while the role of marriage is statistically weaker (col 2, table 2).

would expect in the presence of positive (real) earnings growth, the percentage of people in poverty falls over time (albeit not substantially). Our choice for the remainder of the paper will be to set z = 10 real (1997) GHC, which approximately translates into 40 (1997) USD (approx. 1.5 USD per day). This choice is grounded in the proximity to the widely used measure of 1 Dollar per day. When we experimented with alternative lines in the vicinity of this value, the main patterns in our results did not change.[18] In the next section, we will show that our chosen threshold lies below a self-reported measure of *minimum desirable income* for the vast majority of the sample (see figure 9). This lends strong support to the assertion that our low-income range lies within the domain of poverty as perceived by urban Ghanaians. For $z = 40$ USD the risk of poverty we estimate is substantial for large portions of our sample. The central line in Figure 3 shows that 35 percent of workers face a probability of poverty of at least 50 percent. We we disaggregate between currently poor and non poor workers, we find that among the latter 15 percent have at least a 50 percent chance of falling into poverty.

< Figure 2 here >

< Figure 3 here >

< Figure 4 here >

4.2 Happiness

This section will present the results from estimating our happiness model. Figure 5 plots the histogram of happiness responses that was presented in section 2, after now splitting the sample by low/high income relative to the poverty line. The histogram shows prima-facie evidence for the link between income and happiness that we are attempting to formally test, with people who are above the low-income threshold more likely to report to be "satisfied" with their life.

< Figure 5 here >

[18] These figures are unadjusted for PPP; and the reader should be alerted to the fact that in 2007 the Ghana Cedi was converted into the New Ghana Cedi at a rate of 10,000 Ghana Cedi to 1 New Ghana Cedi. All the analysis in this paper is conducted in New Ghana Cedi (loosely referred to as Ghana Cedi in the remainder of the paper), into which also the 1997 (pre-reform) figures have been converted for uniformity.

Table 3 reports the results from estimating the workhorse model of happiness (equation 7) using first OLS (col 1-2) and then controlling for fixed effects (col 3-4).

Our first result is a positive and significant effect of absolute income on life-satisfaction, in line with the existing literature (e.g. De Neve and Cooper (1998)). This relationship is evident in OLS and, rather strikingly, it does not change significantly once we control for fixed effects. It appears, therefore, that time-invariant unobservables correlated with earnings are not biasing upwards the effect of income on happiness as one may expect. This constitutes evidence against the hypothesis that individuals who are 'naturally' more positive and optimistic (and hence tend to be 'naturally happier') tend to achieve higher earnings. Interestingly, the size of the estimated coefficient on the log of income under WG (1), 0.017, is remarkably close to that estimated by Powdthavee (2010) using data from the British Households Panel Survey and a fixed-effect estimator, 0.019.

On the other hand Table 3 shows that individual fixed effects play an important role in the relationship between vulnerability and life-satisfaction. Once we control for them, we find *a strong negative relationship between vulnerability and happiness, over and above the income effect* just described (recall that in the regression tables this is reported as a *positive* relationship between the *inverse of vulnerability* and happiness). This is the key finding in the paper. The fact that the main result becomes significant upon controlling for fixed effects is an indication that unobserved time-invariant determinants of life-satisfaction are also playing a role in determining vulnerability. The negative bias in the OLS coefficient of the (inverse of) vulnerability can be read as evidence that the time-invariant traits that induce people to be 'naturally' happier (high κ_i) correlate positively with the amount of uncertainty they face. [19] This could be the result, for instance, of innately optimistic people seeking employment opportunities that are riskier, a hypothesis that we do not deem unreasonable.

Our estimation also includes controls for work satisfaction (proxying changes in working conditions), income quartile, age and its square and marital status. Work satisfaction

[19] They correlate negatively with the 'inverse' of vulnerability. Hence, they correlate positively with vulnerability

is closely correlated with life satisfaction and shows by far the biggest positive coefficient in the life satisfaction regression.[20] On the other hand, the income quartile the respondent belongs to does not show a significant effect.[21] Absolute income remains a significant driver of happiness and the strong role of vulnerability changes negligibly. The result suggests that it is not a respondent's rank in the income distribution, but rather his/her level of earnings what really matters for life-satisfaction. This contradicts some of the established evidence on the role of relative income for life satisfaction. However, it should be remarked that the relevant reference group may be a subset of the whole sample, cutting across income quantiles. Urban Ghanaians may, for instance, compare their income to that of people in the same neighborhood, social class or ethnicity. If so, the position in the overall distribution may not matter significantly.

Finally, the vulnerability index has been constructed using estimates from a first-stage model of earnings. Hence, it carries a degree of statistical imprecision that could pose a challenge to the significance of our estimates in the second stage model of happiness. In order to check the robustness of our results to such concern, we have bootstrapped the entire estimation sequence (including the first stage to construct the vulnerability index), sampling with replacement to obtain 200 replications of the original sample. The results are summarised in Figure 6 and 7, where we have plotted the distribution of the bootstrapped coefficients on Income and on (the inverse of) vulnerability, and they are consistent with the discussion so far. The effect of income on happiness remains statistically different from zero in every specification. The effect of vulnerability is significant once the fixed effects in the happiness model are controlled for.

< Table 3 here >

< Figure 6 here >

< Figure 7 here >

[20] As a robustness check, we tried to exclude work-satisfaction from the estimation and the results did not change significantly (we only detected a slight increase in the effect of vulnerability).

[21] In addition to what is reported in the table, we experimented with finer quantile disaggregation (quintiles and deciles) and the main results outlined above did not change.

4.2.1 Alternative explanations

In the analysis above we argued that the risk of income poverty has a significant impact on respondents' well-being. The measures of vulnerability we have employed in this paper are restricted to the notion of *exposure to downside risk*, since they are based on the probability of falling below a certain income threshold. An alternative interpretation of our finding is that individuals dislike income volatility per se. In this section we will make a further step towards disentangling the two by replacing the vulnerability measure with *two-sided measures* of variation. The results are shown in table 4 and 5. First, we use the raw squared residual $\hat{e}_{it}^2$ from a first stage earnings regression with fixed effects, as a proxy of income volatility and find no significant relationship with happiness (table 4), despite the sign of the estimated effect is always negative, as we would expect if workers are risk-averse (and our experimental measure of risk-aversion shows that is indeed the case). The lack of statistical significance might be due to the fact that ex-post realizations of the shock are a noisy realization of the expected degree of vulnerability workers perceive (and are affected by). A way to circumvent the problem is to model the variance of these residuals, as we already did in section 3.1, and use the predicted value as a measure of expected variance. The results are reported in table 5, where we use the predicted standard deviation of e_{it} (obtained, using the results in table 2). As in the previous table, we document a negative effect that is not statistically significant. Overall, this evidence points to the conclusion that vulnerability to downside income risk, as analysed in the previous section, plays a more prominent role in the determination of well-being than two-sided volatility.

< Table 4 here >

< Table 5 here >

Our choice to focus the analysis on the risk of income poverty is further supported by the responses to a question we added to the GHUPS questionnaire in 2009, which asked respondents to report the income level they deemed sufficient to cater for (i) basic needs and (ii) a comfortable life. We interpret the answers as a direct, albeit crude, measure of workers' reference points. Variation below the reference point can be considered as downside risk. We plot the answers in figure 9, after deflating the figures in line with our previous analysis. They show very clearly that for the vast majority of the sample (more than 90%), our chosen poverty threshold lies below both measures of minimum desirable income.[22]

< Figure 9 here >

4.3 Choice among risky prospects

Our final piece of evidence comes from a behavioural experiment which studies individual choices between risky prospects when downside risk is present and when it is absent. Our objective is to find out whether downside risk impacts the economic decisions of subjects in our sample. This complements our analysis of life satisfaction and highlights the role of downside risk in a different domain (Kahneman, Wakker, and Sarin, 1997).

The experiment, extensively described in Falco (2010), was run in 2007, with a random sub-sample of 307 GUHPS respondents. It consisted of 21 choices between pairs of monetary lotteries. Each 'game' was framed as a choice between two opaque urns containing marbles of different colours and, correspondingly, different monetary values.[23] After being shown the composition of each urn, respondents were asked to choose the one from which they would prefer to draw a marble. Prior to making their choices, they were informed that at the end of the game one of their 21 preferred lotteries would be randomly selected and played out. The winnings of that game would then be paid to the respondent. Monetary incentives of this kind are used to induce truthful revelation of preferences.

Choices were framed in terms of losses and gain with respect to the reference point of no gain over the initial endowment. This standard manipulation is ubiquitous in the experimental literature on loss aversion.

We perform maximum likelihood estimation of the parameters of the following utility function, which incorporates a loss aversion parameter, λ, and allows for hetereogenity in

[22] This data motivates our choice to focus on income vulnerability, as opposed to expected income. In future work we plan to elaborate further on a credible econometric strategy to disentangle the two.

[23] A detailed description of the experimental setup is contained in (Barr, 2007). "Attitudes to Risk in Ghana: Field Manual." Unpublished.

the curvature of the utility function in the gain and loss domain: [24]

$$u(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x^{\beta}) & \text{if } x < 0 \end{cases} \tag{8}$$

This is a standard parametrization of utility functions in the prospect theory literature (Wakker, 2010). An estimate of λ greater than one is evidence of loss aversion: losses are felt more than gains. In line with prospect theory, we further assume that prospects are evaluated as a weighted sum of the utilities of the various outcomes, where the weights are transformations of the actual probabilities given by the following probability weighting function:

$$\begin{aligned} \omega(p) &= \tfrac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{\frac{1}{\gamma}}} \quad \text{if } x \geq 0 \\ \omega(p) &= \tfrac{p^{\phi}}{(p^{\phi}+(1-p)^{\phi})^{\frac{1}{\phi}}} \quad \text{if } x < 0 \end{aligned} \tag{9}$$

Imposing a common error specification (Hey and Orme, 1994; Andersen, Harrison, Lau, and Rutstrom, 2010), we calculate the differences in the utility given by the two lotteries. For each two lotteries R and L we obtain:

$$\nabla PU = \frac{\sum_R \omega(p_R)u(x_R) - \sum_L \omega(p_L)u(x_L)}{\mu} \tag{10}$$

The choice of a lottery is modelled as a stochastic function of ∇PU. The log likelihood is hence given by:

$$lnL(\alpha, \beta, \lambda, \gamma, \phi, \mu; y, X) = \sum_i [(ln\Phi(\nabla PU)|y_i = R) + (ln\Phi(1 - \nabla PU)|y_i = L) \tag{11}$$

Details on the estimation procedure are further outlined in Harrison (2008) and Falco (2010).

[24] Notice in the specification below we assume the reference point is 0. This ensures consistency with our experimental tasks

We first estimate utility function 8 over the whole sample of choices, clustering standard errors at the individual level. Andersen, Harrison, Lau, and Rutstrom (2010) recommend such empirical approach. Our estimate of the loss aversion coefficient is 1.77, which is in line with previous experimental findings (Booij, Praag, and Kuilen, 2010; Wakker, 2010). Using a standard test, we can reject the null of $\lambda = 1$ at 1 percent significance level.

< Table 6 here >

Furthermore, we attempt estimation of individual coefficients. Our maximum likelihood routine converges for 266 respondents. However, for 45 of them we obtain estimates of λ above 10, which are inconsistent with the upper bounds reported in other studies. We exclude these from the analysis. Out of the remaining observations, we estimate a λ coefficient above 1, indicating loss aversion, for 55 percent individuals. The precision of this individual estimates is however low, so we are able to reject the null hypothesis of $\lambda = 1$ for only 22 percent of the respondents. Figure 8 shows the distribution of estimated loss aversion coefficients.

< Figure 8 here >

Overall, our results suggest that individuals in our sample are on average charaterised by significant loss aversion.

5 Conclusions

This article investigates the relationship between income and well-being in a fast-growing developing country, with a focus on the previously unexplored link between *the risk of income poverty and happiness*. Using unique longitudinal data from a representative household survey from urban Ghana, we are able to measure the probability of income poverty at the individual level and explore its relationship with life-satisfaction. Our results are compelling.

First, our analysis reveals a substantial risk of poverty for both currently poor and non poor respondents. Second, we find *a significant negative relationship between vulnerability and life-satisfaction*, over and above the positive income effect commonly documented in the literature. Interestingly, we find that failing to control for individual fixed effects leads to significant bias and misleading conclusions. Further, we attempt to disentangle the effect of *downside risk* on happiness from the effect of *two-sided uncertainty*. We find that the former has the clearest impact on subjective well-being. Finally, in a matched behavioural experiment which elicits respondents' attitudes towards risky prospects we find evidence of significant levels of loss aversion among our respondents. This suggests that the effect of downside risk is not limited to life evaluation, but extends to decision in economic environments.

The results in this paper bear important policy-implications. In particular, they lend clear support to policy interventions that reduce earnings uncertainty and vulnerability to poverty, as we expect such policies to have an immediate positive impact on agents' life-satisfaction. Moreover, our findings suggest that non-Rawlsian models of growth, whereby "someone may be left behind", may fail to enhance general welfare despite rising average incomes, if the risk of falling behind is sufficiently widespread. Loss-averse agents will also be more willing to undertake productive investments when safety nets and insurance minimize the risk of falling into poverty after an unsuccessful business experiment.

Several leads for future research emerge from this work. Eliciting income-expectations directly will allow us to test how strong is the perceived risk of poverty among workers. Second, with additional data on peers' income, we aim to shed further light on the formation of reference points and on their implications for workers welfare.

References

ANDERSEN, S., G. W. HARRISON, M. I. LAU, AND E. E. RUTSTROM (2010): "Behavioral econometrics for psychologists," *Journal of Economic Psychology*, 31(4), 553–576.

BANERJEE, A. V., AND E. DUFLO (2007): "The economic lives of the poor," *The journal of economic perspectives*, 21(1), 141.

BARR, A. (2007): "Attitudes to Risk in Ghana: Field Manual," unpublished manuscript.

BLANCHFLOWER, D., AND A. OSWALD (2002): "Well-being over time in Britain and the USA," *Journal of Public Economics*, 88 (7-8), 1359–1386.

BOCQUIER, P., C. J. NORDMAN, AND A. VESCOVO (2010): "Employment Vulnerability and Earnings in Urban West Africa," *World Development*, 38(9), 1297–1314.

BOOIJ, A., B. PRAAG, AND G. KUILEN (2010): "A parametric analysis of prospect theory's functionals for the general population," *Theory and Decision*, 68(1), 115–148.

CHAUDHURI, S. (2003): "Assessing vulnerability to poverty: concepts, empirical methods and illustrative examples," Columbia University, unpublished manuscript.

CHAUDHURI, S., J. JALAN, AND A. SURYAHADI (2002): "Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia," Columbia University, Department of Economics Discussion Paper 0102-52.

CLARK, A. E., P. FRIJTERS, AND M. A. SHIELDS (2008): "Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles," *Journal of Economic Literature*, pp. 95–144.

DE NEVE, J.-E., AND A. J. OSWALD (2012): "Estimating the Influence of Life Satisfaction and Positive Affect on Later Income Using Sibling Fixed-Effects," CEP Discussion Papers dp1176, Centre for Economic Performance, LSE.

DE NEVE, K., AND H. COOPER (1998): "The happy personality: a meta analysis of 127 personality traits of subjective well being," *Psychological Bulletin*, 125, 197–229.

DERCON, S. (1996): "Risk, crop choice and savings: evidence from Tanzania," *Economic Development and Cultural Change*, 44(3), 485–514.

——— (2004): "Growth and shocks: evidence from rural Ethiopia," *Journal of Development Economics*, 74(2), 309–329.

DERCON, S., AND L. CHRISTIAENSEN (2007): "Consumption risk, technology adoption and poverty traps: evidence from Ethiopia," CSAE Working Paper.

DERCON, S., J. HODDINOTT, AND T. WOLDEHANNA (2005): "Shocks and consumption in 15 Ethiopian villages, 1999-2004," *Special Issue on Risk, Poverty and Vulnerability in Africa, Journal of African Economies*, 14(4), 559–585.

DI TELLA, R., J. HAISKEN-DE NEW, AND R. MACCULLOCH (2007): "Happiness adaptation to income and to status in an individual panel," NBER working paper 13159.

EASTERLIN, R. (2001): "Income and happiness: towards a unified theory," *Economic Journal*, 111(473), 465–484.

FAFCHAMPS, M. (2003): *Rural Poverty, Risk, and Development*. Elgar Publishing.

——— (2009): "Vulnerability, Risk Management, and Agricultural Development," paper presented at the AERC Conference on Agriculture and Development held in Mombasa, Kenya, on May 28-30, 2009.

FAFCHAMPS, M., AND F. SHILPI (2008): "Subjective welfare, isolation, and relative consumption," *Journal of Development Economics*, 86(1), 43 – 60.

——— (2009): "Isolation and Subjective Welfare: Evidence from South Asia," *Economic Development and Cultural Change*, 57(4), 641–683.

FALCO, P. (2010): "Risk Aversion and Occupational Choices: evidence from matched field experiments and survey data in urban Ghana," paper presented at the WB-IZA Conference on 'Employment and Development' (Cape Town, May 2010).

FALCO, P., A. KERR, N. RANKIN, J. SANDEFUR, AND F. TEAL (2011): "The returns to formality and informality in urban Africa," *Labour Economics*, 18(S1), S23–S31.

FALCO, P., W. F. MALONEY, B. RIJKERS, AND M. SARRIAS (2012): "Heterogeneity in subjective wellbeing : an application to occupational allocation in Africa," (6244).

FERRER-I CARBONELL, A., AND P. FRIJTERS (2004): "How important is methodology for the estimates of the determinants of happiness?," *Economic Journal*, 114(497), 641–659.

FREY, B., AND A. STUTZER (2002): "What can economists learn from happiness research?," *Journal of Economic Literature*, 40(2), (402:435).

GRAHAM, C., A. EGGERS, AND S. SUKHTANKAR (2004): "Does happiness pay?: An exploration based on panel data from Russia," *Journal of Economic Behavior and Organization*, 55(3), 319 – 342.

HARRISON, G. W. (2008): "Maximum Likelihood Estimation of Utility Functions using Stata," *University of Central Florida, Working Paper 06-12*.

HEY, J. D., AND C. ORME (1994): "Investigating Generalizations of Expected Utility Theory Using Experimental Data," *Econometrica*, 62(6), 1291–1326.

HOWELL, R. T., AND C. J. HOWELL (2008): "The relation of economic status to subjective well-being in developing countries: A meta-analysis," *Psychological bulletin*, 134(4), 536.

KAHNEMAN, D., AND A. DEATON (2010): "High income improves evaluation of life but not emotional well-being," *Proceedings of the National Academy of Sciences*, 107(38), 16489–16493.

KAHNEMAN, D., P. P. WAKKER, AND R. SARIN (1997): “Back to Bentham? Explorations of Experienced Utility,” *The Quarterly Journal of Economics*, 112(2), 375–405.

KINGDON, G., AND J. KNIGHT (2004): “Community, Comparisons and Subjective Well-being in a Divided Society,” CSAE Working Paper.

KNIGHT, J., AND R. GUNATILAKA (2008): “Aspirations, Adaptation and Subjective Well-Being of Rural-Urban Migrants in China,” University of Oxford, Economics Working Paper Series, No. 381.

LAYARD, R. (2005): *Happiness: lessons from a new science*. Penguin.

LIGON, E., AND L. SCHECHTER (2003): “Measuring Vulnerability,” *Economic Journal*, 113(486), C95–C102.

——— (2004): “Evaluating different approaches to estimating vulnerability,” The World Bank, Social Protection Discussion Paper No. 0410.

LUTTMER, E. (2005): “Neighbours as negatives: relative earnings and well-being,” *Quarterly Journal of Economics*, 120, 963–1002.

MEGHIR, C., AND L. PISTAFERRI (2004): “Income Variance Dynamics and Heterogeneity,” *Econometrica*, 72(1), 1–32.

MULLAINATHAN, S., AND M. BERTRAND (2001): “Do People Mean What They Say? Implications for Subjective Survey Data,” *American Economic Review*, 91(2), 67–72.

NICKELL, S. (1981): “Biases in Dynamic Models with Fixed Effects,” *Econometrica*, 49(6), 1417–1426.

NSOWAH-NUAMAH, N., F. TEAL, AND M. AWOONOR-WILLIAMS (2010): “Jobs, Skills and Incomes in Ghana: How was poverty halved?,” *CSAE Working Paper Series*, 2010-01.

OSWALD, A. J., AND S. WU (2010): “Objective Confirmation of Subjective Measures of Human Well-being: Evidence from the USA,” IZA Discussion Papers 4695, Institute for the Study of Labor (IZA).

POWDTHAVEE, N. (2010): “How much does money really matter? Estimating the causal effects of income on happiness,” *Empirical Economics*, 39(1), 77–92.

RANKIN, N., J. SANDEFUR, AND J. TEAL (2010): “Learning and Earning in Africa: Where are the Returns to Education High?,” *CSAE Working Paper Series*, 2010-02.

ROSENZWEIG, M., AND H. BINSWANGER (2003): "Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments," *Economic Journal*, 103(416), 56–78.

WAKKER, P. P. (2010): *Prospect Theory*, no. 9780521765015 in Cambridge Books. Cambridge University Press.

6 Figures

Figure 1: Distribution of Life-Satisfaction

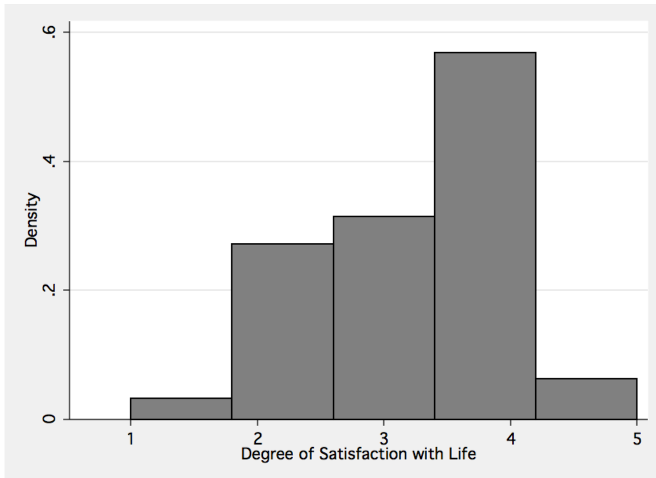


Figure 2: Percentage of employed with $y < z$

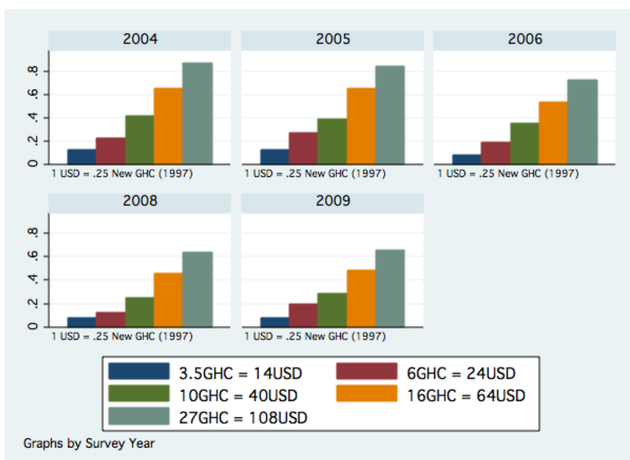


Figure 3: Cumul. Dist. of Vulnerability for different poverty lines (z_t)

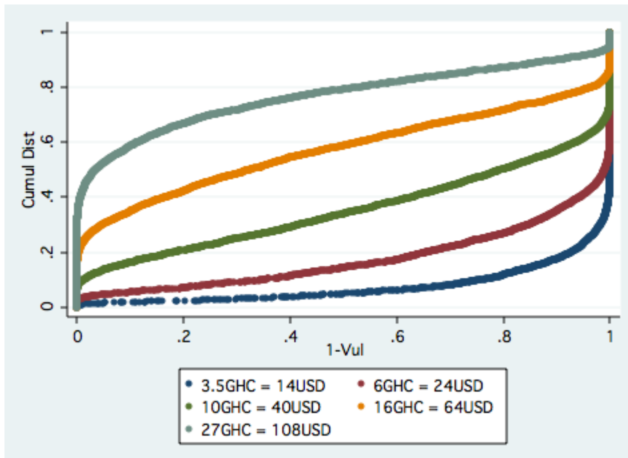


Figure 4: Cumul. Dist. of Vulnerability by current poverty status

z_t = 10 (1997) GhCedis

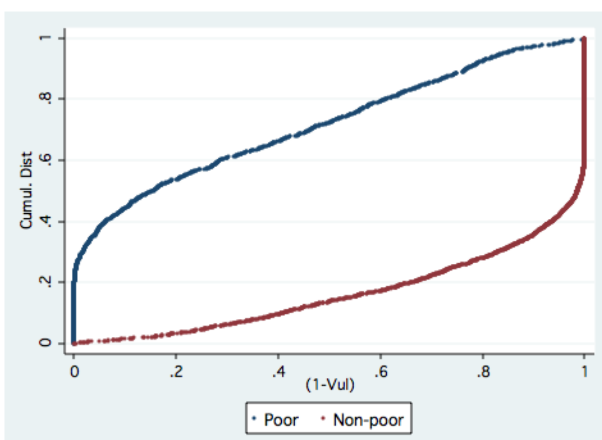


Figure 5: Happiness and Income

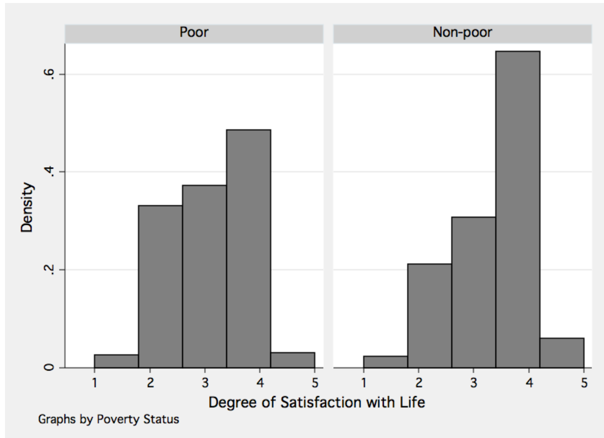


Figure 6: Bootstrapped distribution of the coeff on *LnRealEarn*

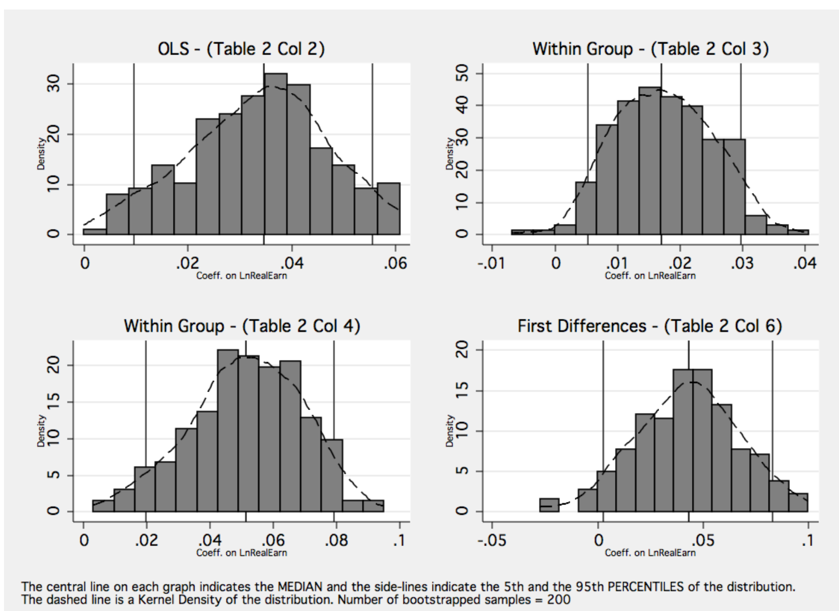


Figure 7: Bootstrapped distribution of the coeff. on *(1-Vul)*

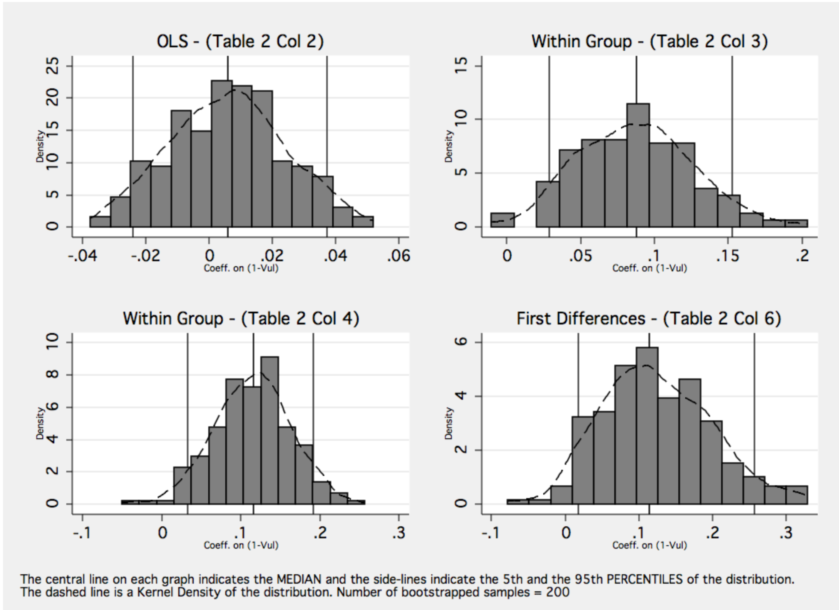


Figure 8: Distribution of λ

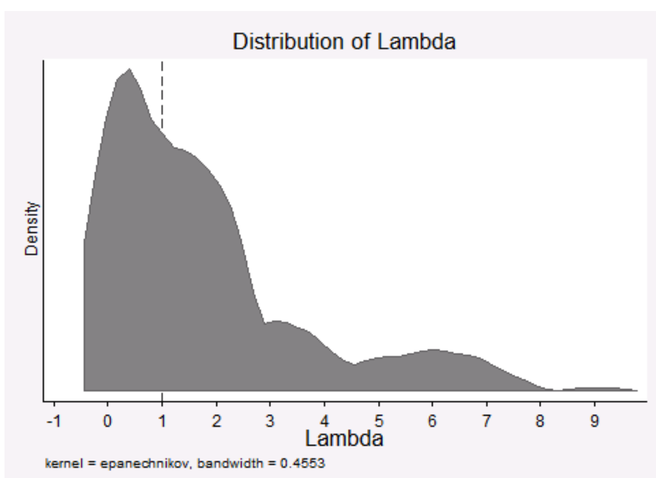
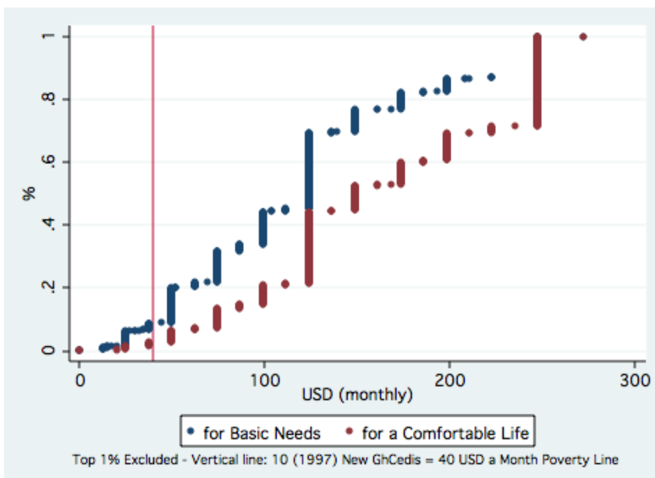


Figure 9: Subjective Perceptions of Minimum Desirable Income

(Cumulative Distribution)



7 Tables

Table 1: Summary Statistics†

Variable	Mean	Std. Dev.
Age	36.239	10.67
Educ	8.072	3.973
Male	0.439	0.496
Priv Wage (Dummy)	0.315	0.464
Public (Dummy)	0.072	0.259
Ln(employees)	0.145	0.41
Ln(firmsize)	0.866	1.493
Ys. since started curr. job	9.147	9.043
Married	0.525	0.499
Ga-Dangme	0.167	0.373
Ewe	0.071	0.256
Mole-Dagbani and Hausa	0.102	0.303
Other ethnicity	0.083	0.276
Obs.		2507

†Restricted to observations in the happiness model, pooling survey waves.
††Only 2,438 observations include ethnic origin.

Table 2: Estimation of Vulnerability - *Panel Approach*

Dep. Var.	y	$\sigma^2(K)$	$\sigma^2(X)$	$\sigma^2(X^2)$	$\sigma^2(X, FE)$
	(1)	(2)	(3)	(4)	(5)
Age		.035	.019		-.0005
		(.028)	(.026)		(.001)
Age2	-.0003	-.0004	-.0002	-5.49e-08	-.0005
	(.0004)	(.0003)	(.0003)	(4.76e-08)	(.001)
Educ		-.028	-.055		
		(.034)	(.032)*		
Educ2		.003	.004	7.17e-06	
		(.002)	(.002)*	(8.15e-06)	
Male		.134	.133	.127	
		(.095)	(.092)	(.092)	
Priv Wage	-.147	-.991	-.944	-.967	-.234
	(.074)**	(.149)***	(.145)***	(.121)***	(.177)
Civil or Pubent	.196	-1.342	-1.319	-1.313	-.120
	(.112)*	(.184)***	(.180)***	(.177)***	(.269)
Ln(employees)	.187	.008	.040	.044	-.030
	(.051)***	(.115)	(.113)	(.057)	(.121)
Ln(firmsize)	.055	.005	-.013	-.0003	.062
	(.021)**	(.042)	(.042)	(.008)	(.051)
Yrs since curr. job start	.005	.003	.004	.0002	.005
	(.003)*	(.006)	(.006)	(.0002)	(.007)
Married		-.052			
		(.095)			
Eth.: Ga-Dangme		-.037			
		(.119)			
Eth.: Ewe		.392			
		(.171)**			
Eth.: Mole Dag. - Hausa		.578			
		(.155)***			
Other ethnicity		-.181			
		(.162)			
Const.	2.588	-3.041	-2.642	-2.514	-3.293
	(1.346)*	(.519)***	(.491)***	(.190)***	(1.294)**
Indiv. Fixed Effects	Yes				Yes
Time Dum.	Yes	Yes	Yes	Yes	Yes
Obs.†	3659	3014	3110	3110	3110
R^2	.685	.073	.065	.064	.627

Notes: y: (log) real monthly earnings; $\sigma^2(K)$: (log) variance of y modelled as a function of K; $\sigma^2(X)$: (log) variance of y modelled as a function of X; $\sigma^2(X^2)$: (log) variance of y modelled as a function of X^2; $\sigma^2(X, FE)$: (log) variance of y modelled as a function of X incl. indiv. fixed effects (this specification is used to compute vulnerability subsequently in the paper); X is the set of key regressors in the income model, K is an augmented set of regressors to include potential determinants of the variance; omitted occupational category = self-employed; omitted ethnicity = Akan; †NxT; *Confidence:* *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%; Robust standard errors in parentheses;

Table 3: Happiness and vulnerability - *Panel Approach*

	Pooled OLS		*Fixed Effects*	
	(1)	(2)	(3)	(4)
(1-Vul)	-.006	.005	.087	.117
	(.017)	(.018)	(.036)**	(.044)***
LnRealEarn	.013	.033	.017	.051
	(.006)**	(.012)***	(.008)**	(.017)***
LnWorkSatis	.618	.615	.588	.587
	(.014)***	(.014)***	(.025)***	(.025)***
Married		.027		.023
		(.010)**		(.020)
Age		-.006		-.019
		(.003)*		(.014)
Age2		.00007		.0002
		(.00004)*		(.0002)
EarnQuart=2		-.0009		-.026
		(.018)		(.025)
EarnQuart=3		-.048		-.069
		(.023)**		(.034)**
EarnQuart=4		-.060		-.099
		(.032)*		(.048)**
Const.	.426	.489	.388	.784
	(.019)***	(.059)***	(.036)***	(.273)***
Obs.†	2507	2507	2507	2507
R^2	.45	.454	.422	.425

Confidence: *** ↔ 99%, ** ↔ 95%, * ↔ 90%; Robust standard errors in parentheses; †NxT.

Table 4: Vulnerable to Downside Risk or Averse to Uncertainty? *(Residual)*

	Pooled OLS		*Fixed Effects*	
	(1)	(2)	(3)	(4)
$\hat{e}^2_{lny}$	-.003	-.003	-.009	-.011
	(.007)	(.007)	(.010)	(.010)
LnRealEarn	.016	.036	.021	.051
	(.004)***	(.010)***	(.008)***	(.017)***
LnWorkSatis	.611	.609	.588	.588
	(.013)***	(.013)***	(.025)***	(.025)***
Married		.027		.018
		(.010)***		(.020)
Age		-.006		-.007
		(.003)**		(.013)
Age2		.00008		.0001
		(.00003)**		(.0002)
EarnQuart=2		-.003		-.027
		(.016)		(.026)
EarnQuart=3		-.040		-.068
		(.021)*		(.035)*
EarnQuart=4		-.053		-.096
		(.029)*		(.049)**
Const.	.424	.499	.437	.523
	(.017)***	(.050)***	(.031)***	(.245)**
Obs.†	2978	2978	2978	2978
R^2	.452	.456	.42	.423

Confidence: *** ↔ 99%, ** ↔ 95%, * ↔ 90%; Robust standard errors in parentheses; †NxT.

Table 5: Vulnerable to Downside Risk or Averse to Uncertainty? *(Predicted Variance)*

	Pooled OLS		*Fixed Effects*	
	(1)	(2)	(3)	(4)
$\hat{\sigma}_{lny}$	-.012	-.014	-.009	-.127
	(.015)	(.016)	(.058)	(.084)
LnRealEarn	.013	.032	.021	.049
	(.005)**	(.012)***	(.008)**	(.018)***
LnWorkSatis	.600	.596	.580	.580
	(.015)***	(.015)***	(.028)***	(.028)***
Married		.033		.021
		(.011)***		(.023)
Age		-.008		-.003
		(.003)**		(.014)
Age2		.0001		.0001
		(.00004)**		(.0002)
EarnQuart=2		.006		-.024
		(.019)		(.026)
EarnQuart=3		-.041		-.065
		(.025)		(.036)*
EarnQuart=4		-.051		-.096
		(.035)		(.051)*
Const.	.452	.555	.454	.411
	(.023)***	(.063)***	(.044)***	(.280)
Obs.†	2144	2144	2144	2144
R^2	.437	.442	.417	.421

Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%; Robust standard errors in parentheses; †NxT.

Table 6: Maximum likelihood estimates of utility function (8)

Parameter	Estimate	Robust standard error	z	$P > \|z\|$
α	0.42	0.017	24.24	0.00
β	1.90	0.074	25.77	0.00
λ	1.77	0.169	10.45	0.00

APPENDIX

A Cross-Sectional (CS) Approach to the Estimation of Vulnerability

A.1 The CS Method

This section outlines an alternative cross-sectional approach to estimating vulnerability, based on Chaudhuri, Jalan, and Suryahadi (2002), which will serve as a useful benchmark for the results discussed in the paper. The method is very similar to the panel approach outlined earlier, except for the fact that it relies on cross-sectional variation in earnings to obtain measures of income vulnerability. It may therefore suffer from inconsistency due to confounding individual fixed effects in the earnings model. Comparing the results with the ones we obtained from the panel-approach, our aim is precisely to assess the strength of such concerns. The main advantage of this methodology is that it allows us to gain precision, using a three-step feasible generalised least squares estimator (FGLS).

The definition of income vulnerability and the structure of the income and variance models remain the same as in the previous section. Differently from above, though, we now take each of the available cross sections in isolation. For each one of them, consistent estimates of δ and θ can be obtained with a three-step feasible generalised least squares estimator (FGLS) (Chaudhuri, Jalan, and Suryahadi (2002)). First, we estimate equation (2) using Ordinary Least Squares (on each cross-section separately). Next, we obtain the squared residuals from the first stage (which now contain both the idiosyncratic component and the fixed effect, i.e. $u_{it}^2 = (\hat{\eta}_i + \hat{e}_{it})^2$, and use them as the dependent variable in a second stage model of the variance:

$$\hat{u}_{it}^2 = \theta K_{it} + \omega_{it} \tag{12}$$

At this point we can obtain predicted values for the variance of income - $\hat{\theta} K_{it}$ and use them to adjust equation (12) as follows:

$$\frac{\hat{u}_{it}^2}{\hat{\theta} K_{it}} = \frac{\theta K_{it}}{\hat{\theta} K_{it}} + \frac{\omega_{it}}{\hat{\theta} K_{it}} \tag{13}$$

From this adjusted equation, Chaudhuri, Jalan, and Suryahadi (2002) show that one can estimate the asymptotically efficient FGLS estimator - $\hat{\theta}_{FGLS}$. The next step is to obtain a consistent prediction for the variance of income, $\hat{\sigma}^2 = (\hat{\theta}_{FGLS} K_{it})$ and use it to adjust equation (2):

$$\frac{ln(y_{it})}{\hat{\sigma}^2} = \frac{\delta X_{it}}{\hat{\sigma}^2} + \frac{e_{it}}{\hat{\sigma}^2} \tag{14}$$

which delivers $\hat{\delta}_{FGLS}$.
As in the panel analysis, having obtained asymptotically efficient estimates of δ and θ, we can now obtain consistent predictions for the first two moments of the income distribution:

$$E(ln(y_{it})|X_i t) = \hat{\delta}_{FGLS} X_{it} \tag{15}$$

$$V(ln(y_{it})|K_i t) = \hat{\theta}_{FGLS} K_{it} \tag{16}$$

and given the same assumption of (log)normally distributed earnings, we can obtain estimates of vulnerability as in (6).

A.2 Results: Vulnerability Estimates

The results of the first stage estimations are reported in Table 7 to 10, but in the interest of conciseness we will not discuss them in detail. It will suffice to note that our choice of regressors for the earnings and the variance model follows the same principles as in the panel approach and, as in the previous section, we find that while the earnings regressions (Step 1 and 3) show a relatively high predictive power, trying to predict the variance of earnings (Step 2 and 4) is considerably more difficult.
More interestingly, when we plot the cumulative distribution of the estimated levels of vulnerability for z = 10 (1997) Cedis per month (Figure 10) and we compare it to the same distribution in our results section (Figure 4), we find that vulnerability to being poor next period is now much more widespread, both among the current poor and the current non-poor[25]) than it was according to the estimates in the paper (where a sizable proportion of respondents was clustered at $\nu_{it} = 0$ and $\nu_{i,t} = 1$, as shown by the lower and upper tails of the lines in Figure 3). This is in itself an interesting result, drawing a clear distinction between the two methodologies, though one that might be expected, considering that vulnerability estimated through a cross-section compounds true idiosyncratic variation and unobserved heterogeneity across individuals that cannot be controlled by means of fixed-effects estimators. As mentioned above, one of the goals of this appendix is to assess whether failing to control for such potentially confounding effects will make a significant difference in the results of our happiness model.

< Figure 10 here >

< Table 7 to 10 here >

[25] Vulnerability is obviously lower among the currently high-earners, but still considerable, indicating that the risk of falling into poverty between periods is widespread across the labour market (50% of the currently poor face a likelihood of 50% or higher to be poor next period; the same level of risk is faced by approximately 20% of the currently non-poor).

A.3 Results: Happiness

We can now employ the measure of vulnerability obtained with the CS method to re-estimate the happiness model (equation 7). Our main interest is to explore the role of (time-invariant) unobserved heterogeneity *in the vulnerability specification* (which we cannot control for in the cross section) in potentially confounding the results of the happiness regressions. The reader should pay attention not to confuse such fixed effects in the vulnerability model (which are the ones the CS approach cannot control for, η_i and ξ_i) with the fixed effects in the happiness model mentioned hereafter (κ_i).
Table 11 reports the estimates from our happiness model with vulnerability obtained through the CS methodology. The results are very similar to the ones in the previous section. We estimate a positive and significant effect of absolute income on life-satisfaction and a strong negative impact of vulnerability, *over and above* the income effect.[26] Interestingly, therefore, we conclude that estimating vulnerability via a cross-sectional approach does not bias the results of our happiness model. This may partly be expected, since, by definition, the individual fixed effects in the earnings model (η_i) are constant over time and hence do not form part of the idiosyncratic variation that constitutes ex-ante vulnerability. Hence, we may not expect them to have an impact on our analysis of how ex-ante vulnerability impacts happiness. This finding contributes to the methodological debate led by Ligon and Schechter (2002, 2004) on the relative merits of different approaches to computing vulnerability.

< Table 11 here >

[26] It should further be remarked how the estimated effect of vulnerability grows larger as we move from the WG to the FD estimator. This is at least partly due to the well known downward bias that affects WG estimators (the well-known 'Nickell Bias', see Nickell (1981)). However, the fact that both these estimation strategies deliver a considerably large and significant vulnerability effect is *per se* an important indication that vulnerability plays a significant role in driving happiness.

Figure 10: Vulnerability by current poverty status - CS Approach

(z_t = 10 (1997) GhCedis)

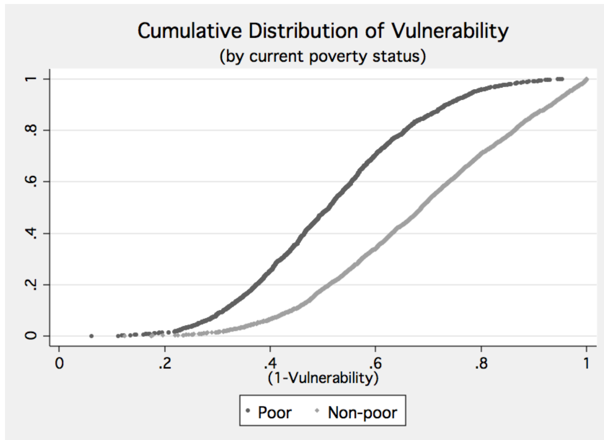


Table 7: Earnings Regression by year (STEP1 - CS Approach)

	Y2004	Y2005	Y2006	Y2008	Y2009
	(1)	(2)	(3)	(4)	(5)
Age	.064	.079	.100	.107	.097
	(.022)***	(.016)***	(.015)***	(.024)***	(.023)***
Age2	-.0008	-.0008	-.001	-.001	-.001
	(.0003)***	(.0002)***	(.0002)***	(.0003)***	(.0003)***
Educ	-.058	-.026	-.052	-.021	-.031
	(.025)**	(.020)	(.020)**	(.031)	(.030)
Educ2	.005	.005	.006	.005	.005
	(.002)***	(.001)***	(.002)***	(.002)**	(.002)**
Male	.223	.281	.264	.373	.442
	(.069)***	(.061)***	(.059)***	(.091)***	(.089)***
Priv Wage	-.157	-.258	-.186	-.164	-.161
	(.109)	(.098)***	(.092)**	(.144)	(.154)
Civil or Pubent	.304	.242	.446	.310	.338
	(.138)**	(.134)*	(.117)***	(.174)*	(.156)**
Ln(employees)	.441	.180	.271	.262	.280
	(.113)***	(.072)**	(.096)***	(.104)**	(.088)***
Ln(firmsize)	.154	.134	.122	.146	.111
	(.030)***	(.028)***	(.030)***	(.041)***	(.045)**
Years since started current job	.011	.008	.023	.015	.018
	(.005)**	(.004)**	(.004)***	(.006)**	(.006)***
Const.	.898	.331	.291	.147	.389
	(.388)**	(.299)	(.280)	(.462)	(.444)
Obs.	619	826	1007	593	614
R^2	.212	.261	.243	.208	.188

Confidence: *** ↔ 99%, ** ↔ 95%, * ↔ 90%

Table 8: Residual Regression by year (STEP2 - CS Approach)

	Y2004	Y2005	Y2006	Y2008	Y2009
	(1)	(2)	(3)	(4)	(5)
Age	-.049	-.030	-.056	.008	.020
	(.028)*	(.019)	(.023)**	(.037)	(.038)
Age2	.0007	.0003	.0007	.0001	-.0003
	(.0004)*	(.0002)	(.0003)**	(.0005)	(.0005)
Educ	.071	-.012	-.030	-.126	-.060
	(.030)**	(.023)	(.030)	(.046)***	(.050)
Educ2	-.004	.001	.002	.010	.004
	(.002)*	(.002)	(.002)	(.003)***	(.004)
Male	.087	.024	-.049	-.030	.151
	(.083)	(.068)	(.083)	(.134)	(.146)
Priv Wage	-.324	-.110	-.474	-.820	-.788
	(.131)**	(.108)	(.129)***	(.213)***	(.249)***
Civil or Pubent	-.347	-.387	-.317	-.611	-.546
	(.165)**	(.146)***	(.167)*	(.255)**	(.255)**
Ln(employees)	-.070	-.138	-.098	-.043	.218
	(.135)	(.080)*	(.133)	(.152)	(.141)
Ln(firmsize)	-.028	.002	.002	-.019	.029
	(.036)	(.030)	(.043)	(.061)	(.073)
Years since started current job	.003	.004	-.006	-.017	-.005
	(.006)	(.004)	(.006)	(.009)*	(.009)
Married	-.180	.033	.126	-.127	-.126
	(.088)**	(.069)	(.084)	(.136)	(.145)
Ga-Dangme	.232	-.084	.060	-.243	-.143
	(.110)**	(.089)	(.106)	(.168)	(.165)
Ewe	.408	.245	.170	.097	.098
	(.151)***	(.133)*	(.155)	(.209)	(.245)
Mole-Dagbani and Hausa	-.006	-.048	.358	-.168	-.550
	(.150)	(.111)	(.130)***	(.201)	(.268)**
Other ethnicity	.255	-.048	.160	-.088	-.029
	(.138)*	(.104)	(.132)	(.286)	(.286)
Const.	1.279	1.300	1.993	1.282	1.079
	(.478)***	(.346)***	(.420)***	(.716)*	(.738)
Obs.	617	813	852	591	595
R^2	.069	.028	.07	.106	.059

Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%

Table 9: Weighted Residual Regressions by year (STEP3 - CS Approach)

	Y2004	Y2005	Y2006	Y2008	Y2009
	(1)	(2)	(3)	(4)	(5)
Age	-.056	-.024	-.047	.005	-.010
	(.026)**	(.019)	(.021)**	(.026)	(.032)
Age2	.0007	.0002	.0006	.0001	.0001
	(.0003)**	(.0002)	(.0003)**	(.0003)	(.0004)
Educ	.067	-.016	-.035	-.137	-.024
	(.022)***	(.022)	(.029)	(.040)***	(.047)
Educ2	-.003	.001	.002	.010	.003
	(.002)*	(.002)	(.002)	(.003)***	(.003)
Male	.080	.026	-.022	.022	.098
	(.067)	(.064)	(.070)	(.099)	(.127)
Priv Wage	-.199	-.132	-.448	-.819	-.687
	(.098)**	(.098)	(.088)***	(.146)***	(.183)***
Civil or Pubent	-.273	-.342	-.239	-.643	-.549
	(.127)**	(.111)***	(.102)**	(.206)***	(.209)***
Ln(employees)	-.023	-.124	-.117	.027	.123
	(.117)	(.068)*	(.128)	(.153)	(.168)
Ln(firmsize)	-.047	.004	-.0002	.021	.046
	(.024)*	(.025)	(.029)	(.034)	(.052)
Years since started current job	-.0001	.001	-.004	-.012	.004
	(.005)	(.004)	(.005)	(.007)*	(.008)
Married	-.127	.018	.061	-.054	.003
	(.076)*	(.064)	(.071)	(.103)	(.129)
Ga-Dangme	.195	-.089	.067	-.209	-.064
	(.105)*	(.078)	(.088)	(.100)**	(.139)
Ewe	.287	.201	.127	.103	.160
	(.162)*	(.148)	(.148)	(.172)	(.253)
Mole-Dagbani and Hausa	.073	-.013	.324	-.056	-.213
	(.108)	(.107)	(.137)**	(.109)	(.179)
Other ethnicity	.186	-.060	.188	-.172	-.068
	(.133)	(.099)	(.125)	(.204)	(.265)
-con	1.406	1.216	1.861	1.386	1.308
	(.441)***	(.345)***	(.381)***	(.487)***	(.624)**
Obs.	614	813	851	588	591
R^2	.114	.03	.101	.173	.051

Confidence: *** ↔ 99%, ** ↔ 95%, * ↔ 90%

Table 10: Weighted Earnings Regression by year (STEP4 - CS Approach)

	Y2004	Y2005	Y2006	Y2008	Y2009
	(1)	(2)	(3)	(4)	(5)
Age	.068	.079	.099	.099	.095
	(.022)***	(.017)***	(.017)***	(.022)***	(.022)***
Age2	-.0009	-.0008	-.001	-.001	-.001
	(.0003)***	(.0002)***	(.0002)***	(.0003)***	(.0003)***
Educ	-.050	-.024	-.055	-.037	-.034
	(.024)**	(.020)	(.024)**	(.032)	(.030)
Educ2	.005	.005	.007	.006	.005
	(.002)***	(.001)***	(.002)***	(.002)***	(.002)**
Male	.233	.290	.233	.351	.427
	(.067)***	(.061)***	(.063)***	(.084)***	(.089)***
Priv Wage	-.138	-.214	-.155	-.178	-.139
	(.104)	(.095)**	(.092)*	(.124)	(.142)
Civil or Pubent	.311	.265	.435	.310	.317
	(.130)**	(.121)**	(.121)***	(.160)*	(.149)**
Ln(employees)	.437	.147	.277	.254	.297
	(.110)***	(.068)**	(.105)***	(.108)**	(.096)***
Ln(firmsize)	.149	.116	.112	.143	.105
	(.027)***	(.026)***	(.030)***	(.035)***	(.042)**
Years since started current job	.011	.007	.022	.014	.018
	(.005)**	(.004)**	(.004)***	(.006)**	(.006)***
Const.	.805	.324	.271	.341	.413
	(.392)**	(.304)	(.318)	(.427)	(.440)
Obs.	614	813	851	588	591
R^2	.254	.271	.242	.229	.193

Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%

Table 11: Happiness and vulnerability - CS Approach

	Pooled OLS		*Fixed Effects*	
	(1)	(2)	(3)	(4)
(1-Vul)	-.024	-.006	.141	.237
	(.027)	(.032)	(.055)**	(.080)***
LnRealEarn	.019	.037	.016	.048
	(.005)***	(.011)***	(.008)*	(.017)***
LnWorkSatis	.601	.599	.590	.589
	(.013)***	(.013)***	(.026)***	(.026)***
Married		.031		.025
		(.010)***		(.020)
Age		-.007		-.035
		(.003)**		(.016)**
Age2		.00008		.0003
		(.00004)**		(.0002)*
EarnQuart=2		.002		-.021
		(.017)		(.026)
EarnQuart=3		-.040		-.066
		(.021)*		(.035)*
EarnQuart=4		-.052		-.094
		(.030)*		(.049)*
Const.	.440	.516	.354	1.019
	(.021)***	(.054)***	(.041)***	(.313)***
Obs.†	2814	2814	2814	2814
R^2	.441	.445	.424	.429

Confidence: *** ↔ 99%, ** ↔ 95%, * ↔ 90%; Robust standard errors in parentheses; †NxT