Weighting the Obvious? Indexing Job Quality and the Impact of "Bad Jobs" on Wellbeing in Kyrgyzstan

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Abstract:

While there is broad agreement that job quality is a multidimensional concept, scholarship has tended to focus on the measurement, rather than effects, of bad jobs. This deficit is particularly stark in developing countries, which to date have been almost entirely ignored in academic literature. In this article, we generate four indices of job quality using a series of different weighting mechanisms and test their impact on subjective wellbeing in Kyrgyzstan. Employing OLS and ordered probits, we show that bad jobs are a significant determinant of lower subjective wellbeing across all indices. Splitting our sample into wageworkers and self-employed, however, we show this relationship holds only for former group. Subsequently, testing equality of the coefficients shows that for wageworkers with mean wellbeing, a move from equal to person-specific weights leads to a 50% increase in the impact of a one standard deviation decrease in job quality. Given the negative wellbeing impacts of bad jobs, at least for wageworkers, these results highlight the importance of further research in the developing world. Furthermore, they show both the importance of accurate job quality measurement and of the need to appropriately conceptualise labour markets in the developing world when conducting such analyses.

Keywords: Job quality; Kyrgyzstan; multidimensional indices; weighting; subjective wellbeing; development economics.

JEL Codes: I31; J01; J81; O15

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Introduction:

In recent years, a broad consensus has developed that regards job quality as a multidimensional concept, rather than one that can be measured by individual metrics. Clark (2005; 2010), for example, suggests that – in addition to income and hours worked – job security, interestingness of work and autonomy are also important. Davoine and Erhel (2006) go further, suggesting that at least ten components should be considered. It therefore follows that any attempt to measure job quality appropriately must aggregate multiple – and potentially highly correlated – indicators into a single metric. However, although more complete than univariate measures, putting together such aggregated indices is not without controversy. Even ignoring the informational challenges related to data requirements – which could inherently bias research away from regions that typically suffer from data scarcity – questions arise about how to determine the relative importance of each domain.

This question has generated a body of important and interesting research (e.g. Shokkeart et al., 2009; Boccuzzo and Gianecchini, 2014; Muñoz de Bustillo, 2011; Leschke et al., 2008; Dahl et al., 2009), yet economists have tended focus only on how to measure job quality, without reference to the welfare outcomes of those with "bad jobs". Put alternatively, focus has tended to fall on the minutiae of how to build job quality indices without pausing to ask if such approaches help to improve our understanding of what it means to have a bad job. In the developing world in particular, there are thus two interconnected knowledge gaps. First, there is a lack of evidence on the impact bad jobs have on wellbeing. Second, there is also a lack of knowledge about how important accurate measurement of job quality is in locations where data may be hard to come by. Such knowledge gaps are exacerbated by the fact that research on job quality almost exclusively focuses on developed countries (e.g. Houseman, 1995; Goos and Manning, 2007; Yogo, 2011), despite access to good jobs remaining a concern for development agencies (e.g.: Ritter and Anker, 2005; World Development Report, 2013).

In this article, we close this gap by asking two related research questions. First of all, we ascertain the direct impact of job quality on individual welfare in Kyrgyzstan using four differently weighted job quality indices. As well as typical measures – such as equal weightings – we develop a unique index drawing on both objective features of an individual's job and his or her perceptions about the importance of each in determining a good job. Secondly, we test equality of the coefficients from each index in order to ascertain whether or not different weighting mechanisms influence the coefficients. To do so, we draw on the fourth wave of the Life in Kyrgyzstan (LiK) Study and, following Clark (2005), focus on: income; hours worked; autonomy; security and the interestingness of work. To account for the Kyrgyz context, we add job formality – a common feature of labour markets of lower-income countries (see, e.g.: Yamada, 1996).

In addition to focusing on all individuals in employment, we split our sample into self-employed and wageworkers. Employing ordered probits and OLS, our results show a positive and significant relationship between job quality and wellbeing for the full sample of workers. Results are robust across weighting mechanisms, statistical techniques and model specifications. Using a Wald test to examine equality of the coefficients across the different indices, we subsequently show that the coefficients are typically statistically equal.[1] When we split the sample into wageworkers and self-employed, however, we show that bad jobs only affect the wellbeing of wageworkers, with no significant relationship found for the self-employed. For the self-employed, coefficients are equal in all cases, whilst they are significantly different across nearly all specifications for wageworkers.[2] For a wageworker with mean subjective wellbeing, the impact of a one standard deviation change in the person-specific weighted index is 1.5 times larger than from a corresponding change in an equally weighted index.

These results, embedded in a literature that has drawn relationships between single job features and wellbeing, show a statistically strong impact of wider measures of job quality on the wellbeing of the aggregated group of workers. More so, however, they also urge caution when dealing with job quality in the developing world, given the divergence of results between wageworkers and the self-employed. Welfare differences between these groups of workers may not be unexpected (e.g.: Parasuraman and Simmers, 2001) but the high proportion of self-employed in developing economies (e.g. Fields, 2013) suggests that aggregated analyses of the labour force are insufficient. Furthermore, the difference in scales of the coefficients in our wageworker sub-analysis demonstrates the importance of accurate measurement and conceptualisation of job quality. These results imply that the use of simple metrics or weighting mechanisms may significantly underestimate the scale of the effect.

The rest of this article proceeds as follows: in Section 2, we discuss the relevant background literature and findings to date. In Section 3, we discuss our data sources, including detailed information on how we construct each job quality index. In Section 4, we describe our methodology and in Sections 5 and 6 we discuss our results and conclusions.

Literature:

While there is a wide literature focusing on the determinants of subjective wellbeing (see, e.g.: Dolan et al., 2007; Kenny, 2005; Cummins et al., 2003), the general lack of research linking welfare to job quality is striking, particularly in the developing world. Hitherto, while single features of jobs have been analysed, the use of broader measures appears to be largely missing. The likes of McBride (2001), Diener and Oishi (2000), Cummins (2000), Ferrer-i-Carbonnel (2005) and Diener and Biswas-Diener (2002) all list income as a positive driver of subjective wellbeing, for example, yet do not consider other job features. Diener et al. (1993) go further, focusing on the effects of relative versus absolute income, while Kahneman and Deaton (2010) focus on the impact of income on reporting of wellbeing. The likes of Wooden et al. (2009), Meier and Stutzer

[1]Of these six comparisons, only one pair of coefficients (Index 1 and Index 3) is different statistically different.

[2]Five of six comparisons yield statistically different results, with only Index 2 and Index 3 – which are almost identical in construction – insignificant.

(2006) and Schoon et al. (2005), alternatively, focus on hours worked. Here, the picture is more complicated, yet broad agreement remains – working too few hours (or not at all), as well as overworking, negatively influences wellbeing.

As discussed in Clark (2005; 2010), however, income and hours worked, either taken in isolation or grouped together, are insufficient to fully explain job quality. In addition, Clark (2005) argues that job security, job autonomy and interesting work are all also important components. If single measures cannot fully explain job quality, however, it should follow that they are also unlikely to fully explain the impact of bad jobs on wellbeing. Despite such a logical theoretical connection, however, work focusing even on any of the single 'non-traditional' domains in Clark (2005) is rare. Dockery (2003) and Graham and Pettinato (2001) study job security but autonomy and interestingness are typically not analysed. Analyses comprising multiple domains, alternatively, are almost entirely absent from discourse, particularly that discussing developing countries.

In part, this absence – particularly in developing contexts – can be chalked down to the complexity of 'job quality' itself. As noted in the likes of Davoine and Erhel (2007), the concept is not clearly, or even well, defined. There is certainly no single definition of what makes a job good and no agreed manner of comparing different jobs. In turn, this has led to significant debate about how to measure job quality. Broadly, agreement stops at the idea that it is a multidimensional concept. Even this assertion poses a number of difficulties, however. First is the informational challenge that arises due to the need to collect data on a wide range of individuals' job features. Even in situations where such data is available, however, indexing problems are likely to arise in all but the most bizarre of situations.[3] In most cases, at least some jobs will dominate others in some domains, yet be dominated in others, implying difficulty in objectively stating which is better. To be able to rank or compare such jobs, each domain included in the index must then be given a relative importance.

As discussed in the likes of Shokkeart et al. (2009), there are two common approaches to indexing prevalent in the literature. First is the 'objective' approach. This involves applying a set of weights – equal for all individuals in the sample – to each domain. To generate these weights, one can either apply them *a priori* – such as imposing that each domain is equally important (see, e.g.: Heintz et al., 2005; Tangian, 2007), or use data reduction techniques, as in, e.g.: Davoine and Erhel (2006) and Kalleberg and Vaisey (2005). Although easy to compute, however, such approaches are not without their problems. It is highly probable, for example, that individuals have heterogeneous preferences over different domains, which is not reflected in any form of uniform weighting. Thus, for some, the index will attribute artificial importance to some domains and subjacent significance to others. Put alternatively, this approach gives preference dominance to some (hypothetical) individual over all others in society.

[3]This situation would require that each job scores better on every domain than each marginally worse job.

The alternative is to follow a 'subjective' approach, which uses a single proxy – job satisfaction. Although overcoming the weighting issue, however, this approach is also not without controversy. While it allows some opportunity for individuals to apply their preferences, a number of convoluting factors are also present. For example, individuals with different ambitions or expectations may value the same job differently, despite these phenomena being little related to the actual quality of their job or to their perceptions of what makes a job 'good'. Put alternatively, this implies that while a fully objective approach is too much of a blunt instrument, a fully subjective approach goes too far in the opposite direction, measuring much besides job quality and individual preferences. In turn, Shokkeart et al. (2009) suggest a 'third way', which mixes the subjective and objective, allowing researchers to analyse both observable features and individual preferences, without the inclusion of conflating variables.

While some work has focused on the use of subjective approaches (e.g. Judge and Locke, 1999; Judge and Wantanabe, 1993), the impact of objective and mixed approaches on wellbeing is lacking. Instead, recent literature has tended to focus on the determinants of job quality or on its influence on behaviour. Diaz-Serrano (2013), for example, tests the impact of immigration on job quality in Spain; Kim and Han (2015) measure the impact of body mass index on job quality in Korea; whilst Muehlau (2011) has tested the impact of age on job quality; and Winter-Ebmer et al. (2011) the impact of job quality on retirement decisions. In the context of this recent literature, it remains surprising that little work has looked, directly, at the relationship between multidimensional job quality and wellbeing. Indeed, it is also surprising that even less research has focused on job quality, in any guise, in the developing world given its importance to a number of international development agencies. One exception is Yogo (2011), who measures the impact of the method of job search on job quality, showing that jobs found via social networks are worse than those found through other means.

In this article, we overcome the limitations of the literature to date using bespoke data collected in Kyrgyzstan to test the impact of job quality on self-reported welfare. From this data, we generate a series of indices that cover the range from purely objective to mixed approaches to measuring job quality and link them to self-reported subjective wellbeing.

Data:

We source all of the data used in this article from the forth wave of the LiK Study, conducted in November and December 2013 and January 2014. All in all, this survey collected information from 13,130 individuals in 2,584 households in Kyrgyzstan. Kyrgyzstan is well placed for our study, as it is easily comparable with other developing nations, suggesting a high capacity to generalise results. Comparisons with other former Soviet republics are obvious, whilst well-documented institutional weaknesses and evolving governance and economic vulnerabilities (see, e.g.: Cooley, 2011; Ruget and Usmanalieva, 2007) also imply a high relevance for other fragile states. The survey includes information on

7,567 men and women of working age[4] and is representative at the national level, for both the north and south of the country and for both urban and rural areas. We restrict interest to a subsample who report themselves to be currently employed in some manner, giving a final sample of $n = 2{,}585$ individuals, of whom 1,103 are self-employed and the remaining 1,482 are wageworkers. We show summary statistics for the whole sample and for each subgroup in Table 1, including comparisons of the means of wageworkers and the self-employed. As shown, wageworkers tend to be significantly younger than the self-employed, more likely to be female and less likely to be of Kyrgyz ethnicity. They are also significantly more likely to live in urban, rather than rural areas and to display higher risk aversion. Finally, wageworkers report significantly lower subjective wellbeing and job satisfaction than their self-employed counterparts.

Table 1: Means of the Working Population, Wageworkers and Non-Wageworkers

VARIABLES	(1) Employed	(2) Selfemployed	(3) Wageworkers	(4) Difference
age	38.15	39.44	37.20	2.24***
male	0.62	0.72	0.54	0.18***
Kyrgyz	0.73	0.76	0.70	0.06***
urban	0.40	0.24	0.52	-0.28***
risk	2.49	2.41	2.55	-0.14***
wellbeing	7.07	7.20	6.97	0.23***
job satisfaction	6.95	6.71	7.11	0.40***

Note: *** p<0.01, ** p<0.05, * p<0.1

For these 2,585 workers, we ascertain information on six domains of job quality, following our context-augmented version of those in Clark (2005). From the survey, we thus garner information on wage income, number of hours worked, job security, job formality, interestingness of work and the amount of on-job autonomy. Direct questions on individuals' income, their autonomy and the interestingness of their work are asked in the survey. We proxy job formality for wageworkers by whether or not an individual has a written contract or uses a "workbook"[5] and for the self-employed by whether or not their business is registered with Kyrgyz authorities. Hours worked is determined from a question that asks the number of hours an individual worked in the previous week.

[4]We regard working age to be 18 – 63 for men and 18 – 58 for women. 18 is the youngest age at which individual data is collected in LiK. 63 and 58 are the respective retirement ages for men and women when the fourth wave of the survey was collected.

[5] The Kyrgyz workbook stems from the country's time as a Soviet Republic and is a record of employment, holding information on the current employment status and place of employment of an individual, which in effect acts as a written contract.

Although potentially imperfect, this proxy is commonly used in the literature (see, e.g.: Presser, 1999; Leete and Schor, 2008; Edmonds and Pavcnik, 2005; Baum-Snow and Neal, 2009). Finally, we use the duration of an individual's current employment as a proxy for job security following the literature of, e.g., Farber (1998, 1999); and Addison and Grosso (1996). In addition to information on these indicators, the LiK survey also asks respondents how important each of these domains is in contributing to a good job.

We match four indices based on these indicators to self-reported subjective wellbeing, which is also asked in the LiK survey. In addition to these intervening variables of interest, we also include controls that are typically shown to be robust determinants of subjective wellbeing (see, e.g.: Dolan et al., 2007). Thus, in addition to job quality and subjective wellbeing information, we also include information on: respondents' age, gender and ethnicity; their educational background; their participation in religious or community groups; their health status; regional controls; and information on their personality and on their attitudes to risk and other circumstances. A full list of these control variables can be found in Table A1, where we split them into five broad categories: demographic; regional; health; participation; personality; and attitudes. It should be noted that we include all of the factors shown to be statistically significantly different between wageworkers and the self-employed in Table 1.

Following the likes of Ducancq and Lugo (2013), we define our indices – in the broadest sense – through the following equation:

$$JQ_j = w_1(i_1.Y_j) + w_2(i_2.H_j) + w_3(i_3.S_j) + w_4(i_4.F_j) + w_5(i_5.I_j) + w_6(i_6.A_j) \quad (1)$$

where: w_i refers to the weight given to each domain; i_i refers to the normalisation identifier, which allows for comparison of domains with different scales and units; the subscript *j* refers to a given individual; and Y, H, S, F, I, and A respectively refer to: income, hours worked, job security, job formality, interestingness of work and job autonomy. Thus, as shown in Equation (1), the quality of an individual's job is a function of the weights and normalisations of our six domains of interest. It follows that any arbitrary changes to the weights of each domain could have significant impacts on the outcome of each index and, accordingly, on its impact on subjective wellbeing. We explore this possibility by varying the weighting mechanisms we use across four different indices. We discuss each of the four weighting regimes in depth in the following sections.[6]

[6] Another approach used in the literature is to regress each domain of interest on self-reported job satisfaction and to generate weights based on the relative explanatory power of each (e.g. Kalleberg et al., 2000). Following this literature, we generated a fifth index using this methodology, the results from which do not deviate from those presented in this article. As with the four other weighting regimes used, bad jobs are shown to result in reductions in subjective wellbeing. As none of our domains of interest is a statistically significant determinant of job satisfaction in these regressions, however, concerns arise about the usefulness and accuracy of such an approach. As such, we do not to present findings from this approach. Results from this analysis are available from the authors.

3.1 Weighting the Indices

In order to obtain both high quality and robust estimates of the effect of job quality on individuals' economic welfare and to test the role, if any, played by different weighting mechanism, we generate four different job quality indices. Each of these four approaches is described in detail in Sections 3.1.1 – 3.1.4, ranging from the most objective approach in 3.1.1 to a fully mixed approach in 3.1.4. In order to allow comparison between each index, the sum of each of our weighting mechanisms will be normalised to one, with the exception of that in Section 5.2.4, which sums to a maximum of one for internal logical consistency.

3.1.1 Equal Weighting

This approach takes the most common and easiest mechanism used in the literature and assumes that each domain is equally important. As such, the weight of each domain will be set equal to that of the other domains. As we normalise each set of weights to one and have six domains, each domain in this index is then weighted with the value of 0.167. We denote this index "Index 1".

3.1.2 Relative Proportion Reporting High Importance of a Domain

This set of weights is the first to use a series of questions in the survey that ask individuals to rate the importance of a series of features that could contribute to a good job, ranging from 1 ("not at all important") to 5 ("absolutely essential"). In Index 2, we use the proportion of individuals who indicate that a particular domain is "somewhat important" or "absolutely essential". In other words, it works on the notion that the relatively greater the number of individuals who think a domain is important, the heavier the weighting that domain is given. We thus collect the percentage of responders who answered with at least "somewhat important" for each domain and normalise these percentages to sum up to one.

3.1.3 Relative Total Value of Reported Importance of a Domain

Index 3 is a slight variation on the previous index but is more nuanced in terms of what it measures. Say 80% of respondents think that both income and hours worked are at least "somewhat important" but that the remaining 20% report that income is "neither important nor unimportant" but that hours worked is "not at all important". It follows that society places more value on income than hours worked, even though Index 2 wouldn't suggest this to be the case. We overcome this by summing all responses for each domain, ensuring we account for the full range of preferences, and then normalising as before.

3.1.4 Individual Preferences on Importance of Each Domain

Hitherto, our weighting regimes exhibit some of the major limitations of the typical objective job quality indices discussed in, e.g. Schokkaert et al. (2009). Although aligning weightings to real preferences, as we do in Index 2 and Index 3 may be more defensible than enforcing arbitrary ones, indices built in this way still attribute artificial importance to some domains, at the individual level, whilst trivialising others. We overcome this issue by aligning the reported perceptions of each individual to his or her observable job attributes. This allows two individuals with identical indicators to exhibit different job quality, given variations in their private perceptions about the components of a good job. Normalising heterogeneous weights, however, is more complicated, as it is not logically consistent for each individual's weights to sum to 1. *Ceteris* paribus, this would suggest that someone who thinks all six domains are "not at all important" would have the same job quality as one who thinks all six are "absolutely essential". We therefore generate the "potential value" of weights, which is then normalised to 1. Thus, given the inclusion of six domains, the maximum weighting for each domain would be 0.167, with each marginal reduction in reported importance corresponding to a 0.033 reduction in the weighting.

3.2 Identifying and Normalising the Six Domains

We normalise each of our six indicators onto the interval $i \in [-1, 1]$, as they are otherwise incomparable in scale and units. Income, for example, is measured in Kyrgyz Soms per month; hours spent working in discrete units of time; and autonomy and interestingness of work on a Likert scale. We choose the interval $i \in [-1, 1]$ as it exhibits a number of desirable features for this research. Most importantly, it is the only style of interval that remains logically consistent with the weighting mechanism of Index 4. Index 4 requires that an individual who believes, for example, that income is an essential component of a good job but who has an incredibly low income is worse off than an individual with the same income but who does not think income is important at all. At the other end of this scale, however, an individual with a very high income and who thinks income is an essential component of job quality should be better off than one with a high income who doesn't think income is important. Although the latter of these restrictions holds in other identification methods, such as on an interval $i \in [0, 1]$, it does not for the bottom end. In such a scenario, the individual who believes income to be very important would appear no worse off than the individual who does not value income at all. We discuss, in more detail, the specific identification of each of our domains in the following sections.

3.2.1 Identifying Income

In the survey, individuals report their net monthly income in Kyrgyz Soms. In our sample, the distribution runs from 0 to 80,000 Soms/month, with a mean of 8,669 Soms/month. While we can safely assume, *ceteris* paribus, that higher income should be better, it is unclear whether or not an individual with an income twice the mean is doubly better off than one with a mean income. Similarly, it is unclear if the difference in welfare between an individual with an income four times the mean and one with an income double the mean is the same as the gap between an individual with a mean income and one with an income double the mean. We thus split the sample into deciles and map each decile onto the $[-1, 1]$ interval. This means that individuals in the top decile have an income value of 1, whilst those in the bottom decile have a value of -1. Those whose income lies in the other deciles are then mapped at even spaces in-between. This ensures that job quality increases in income without the need to impose assumptions on its marginal benefit. Given the work of, e.g. Diener et al. (1993) and a long line of economic thought, a further benefit accrues from this approach – relative income may be more important than absolute income.

3.2.2 Identifying Hours Worked

In the survey, individuals are asked to report the number of hours they spent working on their main job in the last seven days. In this scenario, too few hours worked may be just as indicative of a bad job as working too many. As such, we look at the deviation of an individual's hours worked from some "optimal" baseline, such as the number of hours a fulltime worker may expect to work. Given the seasonal nature of many jobs in Kyrgyzstan, however, an objective baseline is undesirable, as the month in which an individual was interviewed may influence his or her response. As such, we take the mean of hours worked in each month as the baseline. All individuals whose hours worked do not fall within two standard deviations of this mean are given a value of -1, whilst those who worked exactly the mean take a value of 1. The remainder are distributed across the interval based on how many hours more, or fewer, than the monthly mean they worked. In this way, the indicator converges to -1 as deviations from the monthly mean – in either direction – increase.

3.2.3: Identifying Job Security

We identify job security through the duration an individual has spent working in his or her current job. It follows that an individual who has been in a position for 10 years is likely to have higher job security than someone who has only been in a position for 1 year. That said, as with income, it does not immediately follow that someone who has worked a job for 30 years is twice as secure as someone who has worked a job for 15 years. Again, therefore, we split the duration of employment into deciles, with each decile evenly spaced across the interval.

3.2.4: Identifying Job Formality

This indicator relies on three questions in the survey: for self-employed individuals, we focus on whether or not his or her business is officially registered with the Kyrgyz government. For wageworkers, we focus on two subsequent questions – whether or not an individual has a written contract and whether or not he or she has a workbook. Affirmative answers to any of these three questions corresponds to a job formality value of 1, whilst if the answer to all is negative, job formality takes a value of -1. This makes the assumption that formal jobs are better than informal ones, which requires some justification in the case of Kyrgyzstan. Given weak institutions and low trust in the government, individuals may actually prefer to work informally, in order to avoid paying taxes for public and welfare services they do not believe they will receive, thus maximising income. Rather than suggesting that informal jobs are better, however, we view such selection as a trade-off between income and formality. *Ceteris paribus*, we therefore assert that for a set level of income, formal jobs are still better than informal ones.

3.2.5: Identifying Interestingness of a Job

In the survey, individuals are asked to report the interestingness of their job on a Likert scale running from 1 (“uninteresting”) to 3 (“very interesting”). We transpose these responses onto the interval at equal spaces, such that “very interesting” takes the value of 1, “somewhat interesting” a value of 0 and “uninteresting” a value of -1. Superficially, this may appear to pose a logical problem. All individual’s reporting a “somewhat interesting” job will score the same for this domain in the index, regardless of how important they perceive job interestingness to be. That said, whilst it is clear, *ceteris paribus*, that an individual should be better off with a “very interesting” job than a “somewhat interesting” one, it is less clear if a “somewhat interesting” job is objectively “good” or “bad”. Thus, it is also unclear whether or not an individual who thinks interestingness of work is very important and who has a “somewhat interesting” job is better or worse off than one who has a “somewhat interesting” job but who thinks interestingness is unimportant. This approach avoids the need to make value judgements on this matter, whilst still satisfying the more meaningful constraint of our approach – that individuals with more interesting jobs are always better off than those with less interesting ones.

3.2.6: Identifying Job Autonomy

This question is also asked on a Likert scale, this time running from 1 (“no autonomy”) to 4 (“high autonomy”). These responses are, again, mapped onto the interval $[-1, 1]$ at even spaces, with a gap of approximately 0.67 between each response. Thus, a report of “high autonomy” takes a value of 1, a report of “some autonomy” a value of 0.33, a report of “little autonomy” -0.33 and a report of “no autonomy” a value of -1.

Table 2: Summary Statistics of Job Quality Indices

VARIABLES	(1) Employed	(2) Selfemployed	(3) Wageworkers	(4) Difference
Index 1	55.54	52.41	57.88	-5.47***
Index 2	56.54	53.67	58.67	-5.01***
Index 3	56.24	53.09	58.58	-5.49***
Index 4	48.28	45.82	50.12	-4.30***
Observations	2,585	1,103	1,482	

Note: *** p<0.01, ** p<0.05, * p<0.1

It follows from our weighting and normalisation methodologies the job quality of each individual in each index will lie on the interval $JQ_i \in [-1, 1]$. In a final step, we conduct a further normalisation, which linearly transposes each index onto a new interval $JQ_j \in [0, 100]$. Such a linear transformation does not affect our statistical outputs but ensures more manageable summary statistics and regression coefficients. These summary statistics are presented in Table 2, where Column 4 shows the differences between the job quality of self-employed and wageworkers. As can be seen, across all four indices, wageworkers are shown to have significantly better jobs than the self-employed. In the context of Table 1, which shows the self-employed to have higher subjective wellbeing than wageworkers, this may seem counter intuitive but shows the necessity of our analysis. Within each subsample, however, there is little difference between Indices 1 – 3. Unsurprisingly, given the nature of the weighting, Index 4 exhibits a lower mean than the others. The distribution of Index 1 and Index 4 are shown in Figure 1, with Index 1 represented on the left hand side for all workers, the self-employed and wageworkers respectively. Generally, Figure 1 shows a smaller range in Index 4 than Index 1, with a smaller variance around the mean.

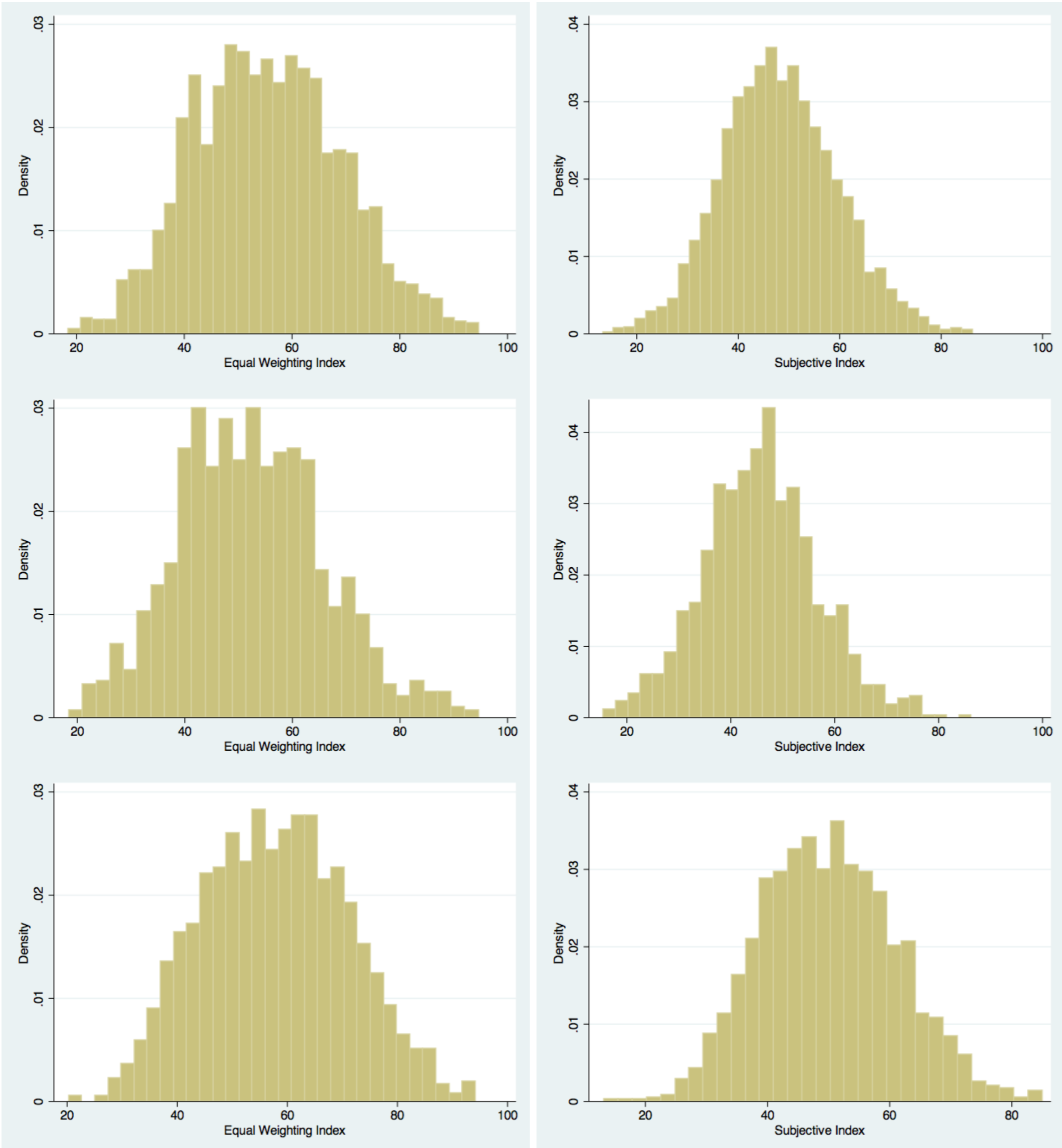

Figure 1: Histograms showing the distribution of Index 1 (left hand side) and Index 4 (right hand side) for all workers (top row), the self-employed (middle row) and wageworkers (bottom row).

We match each of these indices to a measure of subjective wellbeing in the LiK study, which asks, “How satisfied are you with your life, all things considered?”

Responses to this question are given on an 11-point Likert scale, running from 0 ("completely dissatisfied") to 10 ("completely satisfied"). A common criticism of the use of such simple measures is that they tend to be upwardly skewed and typically lack variation (e.g. Conceição and Bandura, 2008). As shown in Table 1, our sample mean for subjective wellbeing is 7.07, whilst Figure 2 shows our measures to be clustered at the upper end, across all of our samples. At the same time, however, it also shows there is significant variation in responses, particularly within those answering between 5 and 10, suggesting that this data is still suitable for our purposes.

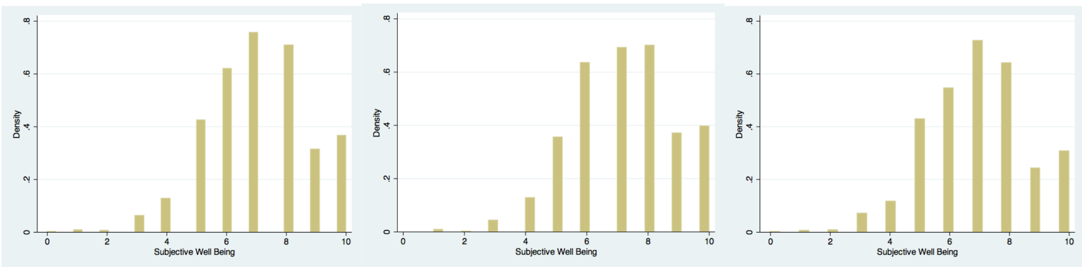

Figure 2: Distribution of Subjective Wellbeing showing, from left to right; all workers, self-employed workers and wageworkers.

Methodology:

At the core of this article are two interrelated research questions. The first asks whether or not higher (lower) job quality has a causal impact on better (worse) subjective wellbeing. The second then asks if such impacts vary statistically depending on precisely how one builds each measure of job quality. We augment these analyses by splitting the main sample into self-employed and wageworkers and testing for variations in outcomes across the two groups. We do so in order to ensure we appropriately analyse the labour market of Kyrgyzstan and developing countries more broadly, which tend to have a much higher proportion of self-employed than in developed countries. In the first stage of our analyses, therefore, we will regress self-reported wellbeing on each of the four indices of job quality and on a set of individual-specific and regional control variables for the whole sample and for each subsample.[7] Having obtained estimates of the impact of each index, we then use a Wald test to compare linear hypotheses about the coefficients derived from each model. This approach allows us to jointly measure the impact of high or low job quality on individual welfare, whilst also statistically testing for equality of the coefficients generated from each of the four indices.

The use of self-reported variables of wellbeing is not with controversy (see: e.g. Andrews and McKennell, 1980; Pavot and Diener, 1993), as a number of features of an individual's psychology may be represented in his or her response. Put alternatively, this opens up the possibility that two individuals with the same objective welfare indicators may report different levels of self-perceived welfare

[7] In another approach, we also cluster errors at the household level. As this does not affect any of the findings of our analyses, we take clustering to be superfluous and do not include these results here. Results from the clustered analysis are available from the author's upon request.

due to their own values or personality traits. Should the traits that partially determine reported subjective wellbeing also correlate with those that affect labour market performance (see: e.g., Groves, 2005; Borghans, et al., 2008; Heckman et al., 2006; Brunello and Schlotter, 2011), biases may arise through the use of OLS models. In such a setting, individuals who have high (low) quality jobs could be falsely linked to high (low) subjective wellbeing. We overcome this potential bias by included two sets of personality controls in our analysis. The first set can broadly be regarded as "attitudinal" – this includes individual's response to particular circumstances and their attitude to risk. The second set uses data reduction techniques to reduce a 21-question personality test into the factors that explain a majority of the variation in the personality data.

A similar bias could arise as selection into self-employment or wage work is unlikely to be random. If any of the omitted variables that determine such selection were also correlated either with job quality or with our SWB measure, then coefficients from our regressions would be unreliable. In the developing world, many individuals are self-employed through necessity rather than choice (e.g. Huijgen et al., 2000), however. In turn, this implies that major unobservable phenomena such as 'entrepreneurial spirit' are unlikely to be important determinants of selection into self-employment, at least in the aggregate. Other observable features of such selection typically cited in the literature, such as risk aversion, education background and personality features (see, e.g. Dawson et al., 2009) are already included as control variables. Otherwise, we see no obvious sources of bias in the relationship between subjective wellbeing and job quality. There are no strong reasons, for example, to suspect that subjective wellbeing should influence job quality indicators directly. Similarly, it is not obvious, for example, how an individual's (subjective) wellbeing should influence the features that he or she thinks contribute to a good job. In turn, we determine that the use of one-stage OLS is appropriate in answering our research questions. We thus estimate the following equation:

$$SWB_j = \alpha + \beta_i JQ_{ij} + \gamma X_j + \rho PERS_j + \delta OBLAST_k + u_j \tag{2}$$

where; SWB_j is the subjective wellbeing of individual j; JQ_{ij} is the job quality of individual j as measured by job quality index i; X_j is an $(h \times 1)$ vector of h individual level control variables for individual j; $PERS_j$ is an $(l \times 1)$ vector of individual j's l personality controls; $OBLAST_k$ is a regional fixed effect for location k; u_j is an idiosyncratic error term; and β_i, γ, ρ and δ_k are vectors of regression coefficients. Having obtained the coefficients of the impact of each job quality index on subjective wellbeing ($\beta_1, \beta_2, \beta_3$ and β_4) we test the equality of each, such that: $\beta_1 = \beta_2, \beta_1 = \beta_3, \beta_1 = \beta_4, \beta_2 = \beta_3, \beta_2 = \beta_4$ and $\beta_3 = \beta_4$.

As SWB_j is implicitly ordinal, running on a Likert scale from 0 ("completely dissatisfied") to 10 ("completely satisfied"), we repeat the analysis using ordered probits. We thus implement:

$$SWB_j^* = \beta_i JobQuality_{ij} + \gamma_h X_{hj} + \rho_h personality_{hj} + \delta_k oblast_k + u_j \tag{3}$$

where; SWB_j^* is now a latent variable measuring individual j's self-reported welfare; and the other components of Equation (3) are as previously described. For any given individual, it is likely that a high level of job quality will translate into a high level of welfare and that low job quality will translate into low welfare. Therefore, the observed and coded discrete subjective wellbeing, SWB_j^* is determined from the model as follows:

$$SWB_j = \begin{cases} 0 \; if - \infty \leq SWB_j^* \leq \mu_1 \; ("completely\; dissatisfied") \\ \vdots \\ m \; if \; \mu_{m+1} \leq SWB_j^* \leq \mu_m \\ \vdots \\ 10 \; if \; \mu_{10} \leq SWB_j^* \leq \infty \; ("completely\; satisfied") \end{cases} \tag{4}$$

where; the threshold values μ_n are unknown parameters to be estimated using maximum likelihood. This then allows us to estimate the predicted probability that an individual reports a subjective wellbeing of level m given his or her job quality JQ_{ij}:

$$\Pr\left(\widehat{SWB_J} = m \mid JQ_{ij}\right) = F\left(\hat{\mu}_m - JQ_{ij}\hat{\beta}\right) - F(\hat{\mu}_{m-1} - JQ_{ij}\hat{\beta}) \tag{5}$$

We present our OLS approach as our baseline analysis. Here, we link each index of an individual's job quality to his or her self-reported wellbeing. We then repeat this analysis using ordered probits to predict the probability that a given job quality is associated with a particular level of subjective wellbeing. Having derived these estimates, we perform parameter tests on the equality of the coefficients across job quality indices. Given the noted complexity and uncertainty associated with comparing outcomes across ordered probit models (see, e.g. Allison, 1999; Williams, 2009), we compare the coefficients only from our OLS models. Following our main analyses, we perform robustness checks of our results. First of all, we use a fifth index of job quality derived from the relative explanatory power of each domain of interest when regressed on job satisfaction. Next, we include different combinations of control variables. We present five OLS and five ordered probit models for each measure of job quality. Model 1 includes individual demography controls and oblast (regional) fixed effects; Model 2 augments Model 1 by adding whether an individual lives in an urban or rural area; Model 3 further adds information on an individual's health; Model 4 adds personality controls; and, finally, Model 5 adds attitudinal controls.

Results:

In the first instance, our results link each index of job quality to an individual's self-reported wellbeing. Our first analysis focuses on the whole sample and is, thus, comprised of both wageworkers and the self-employed. Two further analyses split the sample into its two constituent employment types to understand if our baseline results hold for both groups of workers. Results from the OLS analyses are presented in Table 3, with the results from the ordered probits in Table 4. In Tables 3 and 4, we present our main results as those derived from Model 5, which uses the full set of controls listed in Table A1. The full results from these analyses, including the effects of our control variables, can be found in Tables A2-A4 for the OLS specifications and Tables A5-A7 for the ordered probit specifications.[8] In each of these tables, we show: the impact of the equal weighting index (Index 1) in Column 1; the proportional relative importance index (Index 2) in Column 3; the total relative importance index (Index 3) in Column 3; and the individual preferences index (Index 4) in Column 4. In Table 5, we present comparisons of the OLS coefficients shown in Table 3.[9] The first group of results in Tables 3 and 4 are for the full sample, with wageworkers and the self-employed following respectively.

The results of the main analyses shown in Tables 3 and 4 confirm the hypothesis that job quality is positively and significantly linked with subjective wellbeing across the whole sample. Put alternatively, this shows that high job quality is linked with higher perceptions of personal wellbeing. The coefficients listed in these tables show that each of the four job quality indices is a significant determinant of self-reported welfare at the 1% level in both the OLS and ordered probit specifications. In Table 3, this implies that an exogenous marginal increase in job quality is associated with an increase in wellbeing of just under 0.1 points. Although this effect may seem small, it implies that, for an individual at the mean, a one standard deviation increase in job quality is associated with an increased in wellbeing of between 1.5% and 2%. Given the depth of the subjective wellbeing literature and the number of factors that contribute to wellbeing, this effect – while economically small – remains very strong. This is particularly the case as we look only at a subsection of society that is currently employed, which is known to bestow welfare benefits (see, e.g., McKee-Ryan et al., 2005). Furthermore, in our specific context, over 95% of our sample report a level of wellbeing that lies within just over 50% of the full range, with very few reporting subjective wellbeing below 5 on the Likert scale. In turn, this implies that the effective relative impact on job quality on welfare almost doubles, when considered in such a context.

When we split the sample, however, our results change drastically. The coefficients remain positive and significant for the wageworkers sample, with the marginal effect increasing the scale of the impact by between approximately 0.01 to 0.05 points. For the self-employed, however, whilst the sign of the coefficient remains positive, the impact becomes statistically insignificant, suggesting that job quality is not an important feature of wellbeing for those who are self-employed. In turn, it follows that the significant effect found across the whole sample, particularly given the smaller coefficients in this analysis, simply average two different outcomes across the population.

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[8]A more detailed breakdown of these results, focusing on all combinations of control variables (Model 1 – Model 5) and including our additional job quality measures, are available on request from the authors.

[9]We do not include the results from the job satisfaction analyses in our results presented in this article as biases are likely to be present due to subjective perceptions being present on both sides of the equation. As such, it is impossible to draw meaningful inference from such results.

Table 3: Results from OLS Estimations

VARIABLES	(1) Index 1	(2) Index 2	(3) Index 3	(4) Index 4
index1	0.00786***			
	(0.00246)			
index2		0.00767***		
		(0.00252)		
index3			0.00707***	
			(0.00257)	
index4				0.00796***
				(0.00295)
Sample	Full			
Observations	2,460			
R-squared	0.355	0.355	0.354	0.354
index1	0.00887***			
	(0.00268)			
index2		0.00850***		
		(0.00268)		
index3			0.00825***	
			(0.00273)	
index4				0.0126***
				(0.00378)
Sample	Wageworkers			
Observations	1,425			
R-squared	0.356	0.355	0.355	0.356
index1	0.00243			
	(0.00388)			
index2		0.00228		
		(0.00393)		
index3			0.00175	
			(0.00402)	
index4				0.000930
				(0.00478)
Sample	Self-Employed			
Observations	1,044			
R-squared	0.382	0.382	0.382	0.381

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Results from Ordered Probit Estimations

VARIABLES	(1) Index 1	(2) Index 2	(3) Index 3	(4) Index 4
index1	0.00595***			
	(0.00182)			
index2		0.00580***		
		(0.00187)		
index3			0.00536***	
			(0.00199)	
index4				0.00599***
				(0.00218)
Sample	Full			
Observations	2,460			
R-squared	0.115	0.115	0.114	0.114
index1	0.01009***			
	(0.00248)			
index2		0.01003***		
		(0.00255)		
index3			0.00958***	
			(0.00259)	
index4				0.01091***
				(0.00290)
Sample	Wageworkers			
Observations	1,425			
R-squared	0.116	0.116	0.116	0.116
index1	0.00192			
	(0.00294)			
index2		0.00182		
		(0.00300)		
index3			0.00140	
			(0.00305)	
index4				0.00055
				(0.00363)
Sample	Self-Employed			
Observations	1,044			
R-squared	0.126	0.126	0.126	0.126

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Subsequently, in Table 5 we show the p-values of a comparison of the coefficients from each formation of our job quality indices from the OLS analyses shown in Table 3. Table 5 suggests that there is little difference between the reported coefficients across the full sample, with only Index 1 and Index 3 reporting significantly different effect sizes. Again, however, these results change dramatically when we split our sample into wageworkers and the self-employed. Whilst there are no significant differences between the coefficients for the self-employed, only Index 2 and Index 3 are insignificantly different for the wageworkers sample. Given the close relationship between Index 2 and Index 3, this outcome should not be surprising.

Table 5: Testing for Equality of OLS Coefficients Across Job Quality Indices

Full Sample				
	Index 1	Index 2	Index 3	Index 4
Index 1	XXX			
Index 2	0.328	XXX		
Index 3	0.026**	0.101	XXX	
Index 4	0.913	0.752	0.302	XXX
Wageworkers				
	Index 1	Index 2	Index 3	Index 4
Index 1	XXX			
Index 2	0.002***	XXX		
Index 3	0.009***	0.274	XXX	
Index 4	0.066*	0.048**	0.035**	XXX
Self-employed				
	Index 1	Index 2	Index 3	Index 4
Index 1	XXX			
Index 2	0.643	XXX		
Index 3	0.321	0.455	XXX	
Index 4	0.435	0.481	0.633	XXX

Note: Figures reported in this table are P-Values. Coefficient comparison tests conducted using Stata's "suest" module and using results from OLS analyses with a full set of controls presented in Table 3. *** p<0.01, ** p<0.05, * p<0.1

At the same time the impact of the difference between the coefficients of Index 1 and Index 4 is more startling. For a wageworker who reports the mean value of subjective wellbeing, the impact of a one standard deviation change in Index 4 is about 1.5 times larger than for Index 1. Whilst this difference may seem small in absolute terms, the proportional scale of this effect is very large. Perhaps more importantly, the nature of these differences is revealing. Index 1 is based on a weighting methodology that entirely lacks a theoretical grounding and imposes the same weights on each member of society. Index 4, on the other hand, generates a set of person-specific weights grounded in his or her own perceptions and preferences. The results in Table 5 imply that, when researchers ignore preferences at the individual level, they are likely to significantly underestimate the impact of low job quality, at least for wageworkers.

More generally, however, our findings suggest a much more complicated picture when it comes to analysing job quality in the developing world. The starkly different statistical outcomes for the wageworkers and self-employed samples, at best, imply significant divergence in the preferences and welfare determinants of the two samples. Such a finding is particularly stark, given that in Table 2, we show the self-employed to typically have much worse jobs than wageworkers. Given the findings of literature to date, linking welfare with aspects of job quality, however, deeper concerns could also be present. As these results defy prior theoretical predictions, however, it is also plausible that (rather than the self-employed having a different set of welfare determinants) there are problems with how we measure job quality of the self-employed. At best, this would imply that conventional conceptualisations of job quality are insufficient to fully understand the structures and intricacies of labour markets in developing countries. Here, more careful consideration must be given to the job quality of a group who make up a significantly greater proportion of the labour force than in developed countries. At worst, it could imply a more general failure, also relevant to the developed world, where current approaches allow the self-employed to be dominated by wageworkers in terms of measuring job quality.

Conclusions:

In this article, we ask two interlinked research questions. On the one hand, we link a range of measures of job quality to subjective wellbeing in a lower-middle income country. On the other hand, we then seek to contextualise the statistical and economic impacts of a range of measurement approaches on the outcomes of three samples of workers: all employed, wageworkers and the self-employed. In our baseline analyses, we confirm that low job quality is associated with lower subjective wellbeing amongst wageworkers in Kyrgyzstan, with strong effects shown across all measures of job quality, model specifications and econometric techniques. Subsequently, however, we show insignificant differences in the scales of the coefficients across most job quality indices. When we split the sample, however, we see stark divergence in the results of wageworkers and the self-employed. For the self-employed, our measures of job quality are shown to be an insignificant determinant of subjective wellbeing, with the coefficients exhibiting no differences across indices. For wageworkers, however, the effect remains significant and grows in size with significant differences in the scales of the coefficients of different indexing methods. Although perhaps economically small, the relative impacts of these differences are large. Effect sizes vary by up to 150% across different specifications for a one standard deviation in job quality.

In combination, these results support a number of different conclusions that point to the importance of accurate conceptualisation and measurement of job quality. First and foremost, they suggest that – particularly in the developing world – traditional measures of job quality may be insufficient to fully and properly analyse labour markets with a high proportion of self-employed workers. It is thus important to more deeply conceptualise the determinants of job quality for the self-employed in the developing world and, indeed, more generally. Although it is not unexpected to find welfare differences between different kinds of employment, it does not necessarily follow that one should not expect to find links between job quality and wellbeing for certain employment types. By a similar token, the significant differences in the scales of the coefficients for the wageworkers subsample also point to the importance of better measuring job quality in a more general context. Although academically important, our findings show that accurate measurement is also critical to fully measuring and understanding the real economic effects of bad jobs. This plugs a major gap in research, which to date has not stopped to ask if more complicated measurement strategies really help to improve our understanding of the effects of bad jobs.

At the same time, however, that our more simple measures of job quality perform equivalently in the terms of statistical significance and the sign of the coefficients is also revealing. On the one hand, it suggests that analyses using only simple measures run the risk of underestimating the scale of the impact of bad jobs on wellbeing, at least for wageworkers. On the other hand, however, it also implies that restrictive data requirements should not deter researchers from analysing the effects and determinants of low job quality in the developing world. It follows that in situations where data limitations are so severe that it remains impossible to generate more complete measures of job quality, that simpler indices remain eminently useful.

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Appendix:

Table A1: Description of Control Variables

Control	Variable Name	Description
age	age*	Respondent's age at the time of the survey.
	age2*	Respondent's age squared.
gender	gender*	Respondent's gender.
ethnicity	ethnicity*	Respondent's ethnicity, split into Kyrgyz and other.
urban	urban*	Variable accounting for whether an individual lives in an urban or rural area.
education	education*	Ordinal variable listing individual's highest level of educational attainment.
illness	illness1* illness2*	Variables indicating whether or not an individual as suffered a serious illness in the year before the survey was taken. "illness1" counts the number of illnesses an individual experienced and "illness2" a binary variable taking the value of one if one or more serious illnesses were suffered.
health condition	condition1* condition2*	Variables indicating whether or not an individual is suffering from a chronic health condition. As above, condition1 is a count variable of the number of conditions and condition2 a binary variable.
community	community1* community2	Variables indicating individual's involvement in community groups. community1 is a binary variable of involvement and community2 a count variable of the number of groups in which an individual participates.

religion	religion*	Binary variable indicating whether or not an individual belongs to a religious group.
personality	personality1* personality2* personality3* personality4*	Set of variables based on a factor analysis of a 21-question personality test. All factors that explained at least 10% of the variation in personality are included and the individual response that is most highly (positively) correlated with the factor included. Only the first four factors satisfied this criterion. The individual variables correlated with this factors are, respectively: ingenuity; sociability; depressedness; and nervousness.
attitudes	risk* circumstances* trust	Set of indicators based directly on questions asked in the survey, with individuals reporting their attitudes on Likert scales. As trust is highly collinear with subjective wellbeing, we exclude it from our final analyses.
oblast	oblast1* oblast2* oblast3* oblast4* oblast5* oblast6* oblast7* oblast8* oblast9	Oblasts are sub-national administrative divisions in Kyrgyzstan, akin to states or provinces. We generate a dummy variable for each oblast to use as a regional fixed effect. Oblasts 1 – 9 are, respectively: Issyk-kul; Jalal-Abad, Naryn, Batken, Osh, Talas, Chui, Bishkek and Ost City. We include obast1-oblast8 in our analysis, choosing Osh City (oblast9) as the reference category.

* indicates that a variable is used in the main analyses

Table A2: Results from OLS Estimations with Control Variables for Full Sample of Workers

VARIABLES	(1) Index 1	(2) Index 2	(3) Index 3	(4) Index 4
index1	0.00786***			
	(0.00246)			
index2		0.00767***		
		(0.00252)		
index3			0.00707***	
			(0.00257)	
index4				0.00796***
				(0.00295)
age	-0.0447**	-0.0450**	-0.0435**	-0.0442**
	(0.0190)	(0.0190)	(0.0190)	(0.0190)
age2	0.0457*	0.0461*	0.0446*	0.0453*
	(0.0240)	(0.0240)	(0.0240)	(0.0240)
gender	0.00549	0.00199	0.00422	0.00444
	(0.0630)	(0.0631)	(0.0631)	(0.0631)
ethnicity	0.0179	0.0179	0.0173	0.0190
	(0.0693)	(0.0693)	(0.0693)	(0.0694)
urban	-0.0422	-0.0419	-0.0430	-0.0384
	(0.0889)	(0.0889)	(0.0890)	(0.0889)
education	0.0317	0.0332	0.0349	0.0356
	(0.0245)	(0.0245)	(0.0245)	(0.0245)
employer	0.0156	0.0188	0.0205	0.0301
	(0.296)	(0.296)	(0.296)	(0.296)
wageworker	-0.148**	-0.146**	-0.147**	-0.145**
	(0.0701)	(0.0701)	(0.0702)	(0.0702)
family	0.0804	0.0799	0.0761	0.0699
	(0.118)	(0.118)	(0.119)	(0.118)
illness2	-0.0739	-0.0732	-0.0746	-0.0731
	(0.0642)	(0.0642)	(0.0642)	(0.0642)
condition2	-0.108	-0.108	-0.109	-0.110
	(0.0802)	(0.0803)	(0.0803)	(0.0803)
community1	0.0399	0.0418	0.0430	0.0442
	(0.0579)	(0.0579)	(0.0579)	(0.0579)
religion	-0.187	-0.187	-0.187	-0.191
	(0.257)	(0.257)	(0.257)	(0.257)
personality1	0.0958***	0.0957***	0.0965***	0.0977***
	(0.0312)	(0.0312)	(0.0312)	(0.0312)
personality2	-0.0413*	-0.0412*	-0.0413*	-0.0412*
	(0.0220)	(0.0220)	(0.0220)	(0.0220)
personality3	-0.0470*	-0.0467	-0.0470	-0.0466
	(0.0286)	(0.0286)	(0.0286)	(0.0286)
personality4	0.0353	0.0352	0.0361	0.0358
	(0.0286)	(0.0286)	(0.0286)	(0.0286)
risk	-0.211***	-0.211***	-0.211***	-0.212***
	(0.0488)	(0.0488)	(0.0488)	(0.0488)

circumstances	0.493***	0.493***	0.493***	0.493***
	(0.0177)	(0.0177)	(0.0177)	(0.0177)
oblast1	0.808***	0.811***	0.811***	0.821***
	(0.171)	(0.171)	(0.172)	(0.172)
oblast2	0.254	0.257	0.261	0.267
	(0.180)	(0.180)	(0.180)	(0.180)
oblast3	-0.403**	-0.402**	-0.404**	-0.400**
	(0.200)	(0.200)	(0.200)	(0.200)
oblast4	1.089***	1.092***	1.094***	1.102***
	(0.177)	(0.177)	(0.177)	(0.177)
oblast5	0.260	0.264	0.262	0.276
	(0.180)	(0.180)	(0.180)	(0.180)
oblast6	0.954***	0.958***	0.967***	0.980***
	(0.192)	(0.192)	(0.192)	(0.191)
oblast7	0.660***	0.662***	0.662***	0.674***
	(0.169)	(0.169)	(0.169)	(0.169)
oblast8	0.408***	0.411***	0.415***	0.423***
	(0.153)	(0.153)	(0.153)	(0.153)
Constant	4.288***	4.287***	4.273***	4.280***
	(0.469)	(0.469)	(0.470)	(0.470)
Observations	2,460	2,460	2,460	2,460
R-squared	0.355	0.355	0.354	0.354

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A3: Results from OLS Estimations with Control Variables for Wageworkers Sample

VARIABLES	(1) Index 1	(2) Index 2	(3) Index 3	(4) Index 4
index1	0.00887***			
	(0.00268)			
index2		0.00850***		
		(0.00268)		
index3			0.00825***	
			(0.00273)	
index4				0.0126***
				(0.00378)
jobsat				
age	-0.0873***	-0.0876***	-0.0862***	-0.0875***
	(0.0249)	(0.0250)	(0.0250)	(0.0250)
age2	0.104***	0.105***	0.103***	0.105***
	(0.0319)	(0.0319)	(0.0319)	(0.0319)
gender	-0.107	-0.110	-0.109	-0.121
	(0.0787)	(0.0787)	(0.0788)	(0.0789)
ethnicity	0.0920	0.0923	0.0917	0.102
	(0.0875)	(0.0876)	(0.0876)	(0.0876)
urban	-0.124	-0.125	-0.127	-0.116
	(0.115)	(0.115)	(0.115)	(0.115)
education	0.00797	0.0102	0.0122	0.0200
	(0.0320)	(0.0320)	(0.0320)	(0.0305)
illness2	-0.164*	-0.165**	-0.166**	-0.163*
	(0.0837)	(0.0838)	(0.0838)	(0.0837)
condition2	-0.116	-0.115	-0.116	-0.114
	(0.109)	(0.109)	(0.109)	(0.109)
community1	-0.0172	-0.0151	-0.0142	-0.0141
	(0.0741)	(0.0741)	(0.0741)	(0.0740)
religion	-0.294	-0.298	-0.302	-0.298
	(0.400)	(0.400)	(0.400)	(0.400)
personality1	0.0877**	0.0877**	0.0882**	0.0875**
	(0.0405)	(0.0406)	(0.0406)	(0.0405)
personality2	-0.0106	-0.0105	-0.0109	-0.00909
	(0.0285)	(0.0285)	(0.0285)	(0.0285)
personality3	-0.0425	-0.0422	-0.0428	-0.0427
	(0.0374)	(0.0374)	(0.0374)	(0.0374)
personality4	0.0454	0.0453	0.0456	0.0411
	(0.0374)	(0.0374)	(0.0374)	(0.0374)
risk	-0.164**	-0.163**	-0.164**	-0.169***
	(0.0653)	(0.0653)	(0.0653)	(0.0653)
circumstances	0.501***	0.502***	0.501***	0.503***
	(0.0231)	(0.0231)	(0.0231)	(0.0230)
oblast1	0.687***	0.689***	0.687***	0.691***
	(0.223)	(0.223)	(0.223)	(0.223)

oblast2	0.336	0.339	0.342	0.357
	(0.228)	(0.228)	(0.228)	(0.228)
oblast3	-0.0371	-0.0352	-0.0346	-0.0245
	(0.279)	(0.279)	(0.279)	(0.279)
oblast4	0.844***	0.845***	0.843***	0.875***
	(0.236)	(0.236)	(0.237)	(0.236)
oblast5	0.287	0.288	0.285	0.305
	(0.237)	(0.237)	(0.237)	(0.237)
oblast6	1.039***	1.042***	1.043***	1.049***
	(0.282)	(0.282)	(0.282)	(0.282)
oblast7	0.760***	0.758***	0.756***	0.777***
	(0.215)	(0.215)	(0.215)	(0.215)
oblast8	0.617***	0.618***	0.618***	0.613***
	(0.192)	(0.192)	(0.192)	(0.192)
Constant	4.713***	4.721***	4.696***	4.482***
	(0.601)	(0.601)	(0.602)	(0.604)
Observations	1,425	1,425	1,425	1,425
R-squared	0.356	0.355	0.355	0.356

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Results from OLS Estimations with Control Variables for Self-employed Sample

VARIABLES	(1) Index 1	(2) Index 2	(3) Index 3	(4) Index 4
index1	0.00243			
	(0.00388)			
index2		0.00228		
		(0.00393)		
index3			0.00175	
			(0.00402)	
index4				0.000930
				(0.00478)
age	-0.000767	-0.000712	-0.000107	0.000248
	(0.0296)	(0.0296)	(0.0296)	(0.0296)
age2	-0.0122	-0.0122	-0.0128	-0.0131
	(0.0367)	(0.0367)	(0.0367)	(0.0367)
gender	0.226**	0.226**	0.228**	0.230**
	(0.105)	(0.105)	(0.105)	(0.105)
ethnicity	-0.107	-0.107	-0.107	-0.108
	(0.115)	(0.115)	(0.115)	(0.115)
urban	0.234	0.235	0.236	0.242
	(0.147)	(0.147)	(0.147)	(0.147)
education	0.0522	0.0524	0.0530	0.0544
	(0.0423)	(0.0423)	(0.0423)	(0.0422)
employer	0.0800	0.0816	0.0849	0.0927
	(0.296)	(0.296)	(0.297)	(0.296)
family	0.0812	0.0809	0.0776	0.0712
	(0.126)	(0.126)	(0.126)	(0.126)
illness2	-0.0107	-0.0101	-0.0108	-0.0112
	(0.100)	(0.100)	(0.100)	(0.100)
condition2	-0.0876	-0.0876	-0.0877	-0.0876
	(0.119)	(0.119)	(0.119)	(0.119)
community1	0.120	0.121	0.122	0.124
	(0.0948)	(0.0948)	(0.0948)	(0.0947)
religion	-0.357	-0.356	-0.353	-0.351
	(0.333)	(0.333)	(0.333)	(0.333)
personality1	0.115**	0.115**	0.116**	0.117**
	(0.0489)	(0.0489)	(0.0489)	(0.0488)
personality2	-0.0632*	-0.0632*	-0.0629*	-0.0626*
	(0.0348)	(0.0348)	(0.0348)	(0.0348)
personality3	-0.0560	-0.0558	-0.0555	-0.0547
	(0.0440)	(0.0440)	(0.0440)	(0.0440)
personality4	0.0116	0.0117	0.0122	0.0129
	(0.0444)	(0.0444)	(0.0444)	(0.0444)
risk	-0.248***	-0.248***	-0.248***	-0.249***
	(0.0732)	(0.0732)	(0.0733)	(0.0732)
circumstances	0.472***	0.472***	0.472***	0.472***
	(0.0278)	(0.0278)	(0.0278)	(0.0277)

oblast1	0.964***	0.966***	0.966***	0.967***
	(0.272)	(0.272)	(0.272)	(0.273)
oblast2	0.152	0.152	0.154	0.157
	(0.290)	(0.290)	(0.290)	(0.290)
oblast3	-0.549*	-0.548*	-0.548*	-0.544*
	(0.299)	(0.299)	(0.299)	(0.299)
oblast4	1.410***	1.412***	1.415***	1.422***
	(0.273)	(0.273)	(0.273)	(0.272)
oblast5	0.357	0.360	0.360	0.367
	(0.279)	(0.279)	(0.279)	(0.279)
oblast6	1.109***	1.112***	1.119***	1.131***
	(0.286)	(0.286)	(0.285)	(0.284)
oblast7	0.609**	0.613**	0.617**	0.629**
	(0.272)	(0.272)	(0.272)	(0.270)
oblast8	-0.129	-0.125	-0.119	-0.105
	(0.266)	(0.265)	(0.265)	(0.263)
Constant	3.796***	3.797***	3.799***	3.817***
	(0.739)	(0.740)	(0.741)	(0.742)
Observations	1,044	1,044	1,044	1,044
R-squared	0.382	0.382	0.382	0.381

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Results from Ordered Probit Estimations with Control Variables for Full Sample

VARIABLES	(1) Index 1	(2) Index 2	(3) Index 3	(4) Index 4
index1	0.00595**			
	(0.00182)			
index2		0.00580**		
		(0.00187)		
index3			0.00536**	
			(0.00190)	
index4				0.00599**
				(0.00218)
age	-0.03288*	-0.03313*	-0.03196*	-0.03254*
	(0.01399)	(0.01400)	(0.01398)	(0.01399)
age2	0.03366	0.03399	0.03283	0.03340
	(0.01766)	(0.01767)	(0.01766)	(0.01766)
gender	0.00384	0.00117	0.00285	0.00316
	(0.04644)	(0.04648)	(0.04646)	(0.04646)
ethnicity	0.01476	0.01478	0.01430	0.01560
	(0.05097)	(0.05097)	(0.05096)	(0.05097)
urban	-0.03770	-0.03746	-0.03829	-0.03460
	(0.06563)	(0.06563)	(0.06567)	(0.06560)
education	0.02357	0.02472	0.02598	0.02659
	(0.01810)	(0.01807)	(0.01809)	(0.01807)
employer	0.03665	0.03893	0.04026	0.04768
	(0.22246)	(0.22244)	(0.22253)	(0.22236)
wageworker	-0.10669*	-0.10470*	-0.10566*	-0.10432*
	(0.05169)	(0.05167)	(0.05168)	(0.05167)
family	0.05230	0.05187	0.04917	0.04449
	(0.08724)	(0.08733)	(0.08741)	(0.08720)
illness2	-0.06416	-0.06370	-0.06467	-0.06352
	(0.04737)	(0.04737)	(0.04737)	(0.04738)
condition2	-0.07535	-0.07540	-0.07593	-0.07672
	(0.05903)	(0.05903)	(0.05902)	(0.05902)
community1	0.03035	0.03183	0.03269	0.03372
	(0.04286)	(0.04284)	(0.04285)	(0.04283)
religion	-0.12420	-0.12451	-0.12431	-0.12767
	(0.18978)	(0.18977)	(0.18979)	(0.18975)
personality1	0.07290**	0.07276**	0.07338**	0.07431**
	(0.02299)	(0.02299)	(0.02299)	(0.02297)
personality2	-0.03246*	-0.03239*	-0.03246*	-0.03242*
	(0.01625)	(0.01625)	(0.01625)	(0.01625)
personality3	-0.03329	-0.03300	-0.03321	-0.03294
	(0.02102)	(0.02102)	(0.02102)	(0.02102)
personality4	0.02842	0.02832	0.02901	0.02876
	(0.02104)	(0.02105)	(0.02104)	(0.02105)

risk	-0.15569***	-0.15581***	-0.15564***	-0.15618***
	(0.03597)	(0.03597)	(0.03597)	(0.03597)
circumstances	0.36377***	0.36371***	0.36367***	0.36415***
	(0.01410)	(0.01411)	(0.01411)	(0.01410)
oblast1	0.59735***	0.59951***	0.59915***	0.60626***
	(0.12635)	(0.12637)	(0.12637)	(0.12647)
oblast2	0.18623	0.18876	0.19145	0.19631
	(0.13167)	(0.13164)	(0.13163)	(0.13156)
oblast3	-0.29243*	-0.29191*	-0.29293*	-0.29066*
	(0.14649)	(0.14649)	(0.14651)	(0.14648)
oblast4	0.84926***	0.85144***	0.85229***	0.85864***
	(0.13111)	(0.13110)	(0.13110)	(0.13105)
oblast5	0.17971	0.18248	0.18042	0.19119
	(0.13188)	(0.13186)	(0.13189)	(0.13182)
oblast6	0.69424***	0.69672***	0.70285***	0.71289***
	(0.14094)	(0.14093)	(0.14086)	(0.14058)
oblast7	0.48419***	0.48523***	0.48493***	0.49392***
	(0.12366)	(0.12366)	(0.12368)	(0.12360)
oblast8	0.31271**	0.31454**	0.31738**	0.32351**
	(0.11212)	(0.11211)	(0.11210)	(0.11196)
cut1	-2.19149***	-2.19081***	-2.17891***	-2.18812***
	(0.47047)	(0.47055)	(0.47109)	(0.47105)
cut2	-1.48298***	-1.48237***	-1.47059***	-1.47905***
	(0.37220)	(0.37233)	(0.37295)	(0.37286)
cut3	-1.24956***	-1.24894***	-1.23733***	-1.24506***
	(0.36168)	(0.36181)	(0.36246)	(0.36234)
cut4	-0.46203	-0.46139	-0.45026	-0.45640
	(0.34819)	(0.34833)	(0.34902)	(0.34890)
cut5	0.11890	0.11959	0.13021	0.12440
	(0.34632)	(0.34647)	(0.34715)	(0.34704)
cut6	0.96474**	0.96528**	0.97517**	0.96918**
	(0.34593)	(0.34608)	(0.34675)	(0.34663)
cut7	1.65441***	1.65468***	1.66431***	1.65798***
	(0.34607)	(0.34622)	(0.34690)	(0.34676)
cut8	2.37597***	2.37601***	2.38550***	2.37917***
	(0.34684)	(0.34698)	(0.34767)	(0.34753)
cut9	3.13486***	3.13475***	3.14401***	3.13773***
	(0.34828)	(0.34842)	(0.34910)	(0.34897)
cut10	3.62476***	3.62464***	3.63379***	3.62741***
	(0.34964)	(0.34979)	(0.35048)	(0.35035)
Observations	2,460	2,460	2,460	2,460
R-squared	0.115	0.115	0.114	0.114

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Results from Ordered Probit Estimations with Control Variables for Wageworkers Sample

VARIABLES	(1) Index 1	(2) Index 2	(3) Index 3	(4) Index 4
index1	0.01009***			
	(0.00248)			
index2		0.01003***		
		(0.00255)		
index3			0.00958***	
			(0.00259)	
index4				0.01091***
				(0.00290)
age	-0.06606***	-0.06686***	-0.06495***	-0.06556***
	(0.01835)	(0.01837)	(0.01834)	(0.01835)
age2	0.07844***	0.07943***	0.07751***	0.07792***
	(0.02346)	(0.02347)	(0.02346)	(0.02346)
gender	-0.06908	-0.07488	-0.07225	-0.07229
	(0.05774)	(0.05779)	(0.05777)	(0.05776)
ethnicity	0.07948	0.07984	0.07860	0.08343
	(0.06445)	(0.06445)	(0.06444)	(0.06446)
urban	-0.08247	-0.08383	-0.08637	-0.08435
	(0.08436)	(0.08435)	(0.08434)	(0.08435)
education	0.00657	0.00843	0.01023	0.01006
	(0.02266)	(0.02258)	(0.02260)	(0.02256)
employer	0.00000	0.00000	0.00000	0.00000
	(.)	(.)	(.)	(.)
wageworker	0.00000	0.00000	0.00000	0.00000
	(.)	(.)	(.)	(.)
family	0.00000	0.00000	0.00000	0.00000
	(.)	(.)	(.)	(.)
illness2	-0.12587*	-0.12684*	-0.12815*	-0.12665*
	(0.06154)	(0.06154)	(0.06153)	(0.06153)
condition2	-0.08126	-0.08071	-0.08083	-0.08171
	(0.07985)	(0.07984)	(0.07984)	(0.07984)
community1	-0.00730	-0.00554	-0.00465	-0.00462
	(0.05451)	(0.05449)	(0.05451)	(0.05449)
religion	-0.19814	-0.20020	-0.20715	-0.22119
	(0.29046)	(0.29044)	(0.29038)	(0.29021)
personality1	0.06460*	0.06443*	0.06529*	0.06688*
	(0.02974)	(0.02975)	(0.02974)	(0.02972)
personality2	-0.01037	-0.01009	-0.01067	-0.01024
	(0.02092)	(0.02092)	(0.02092)	(0.02092)
personality3	-0.03298	-0.03247	-0.03330	-0.03256
	(0.02734)	(0.02734)	(0.02735)	(0.02734)
personality4	0.03445	0.03391	0.03463	0.03378
	(0.02743)	(0.02743)	(0.02743)	(0.02744)

risk	-0.11859*	-0.11808*	-0.11840*	-0.11827*
	(0.04795)	(0.04795)	(0.04794)	(0.04794)
circumstances	0.37208***	0.37213***	0.37161***	0.37173***
	(0.01837)	(0.01837)	(0.01838)	(0.01838)
oblast1	0.51108**	0.51316**	0.51231**	0.51490**
	(0.16398)	(0.16398)	(0.16397)	(0.16398)
oblast2	0.25334	0.25689	0.25923	0.25924
	(0.16681)	(0.16678)	(0.16677)	(0.16677)
oblast3	-0.01713	-0.01435	-0.01362	-0.01204
	(0.20285)	(0.20283)	(0.20284)	(0.20282)
oblast4	0.65689***	0.65817***	0.65452***	0.65295***
	(0.17478)	(0.17478)	(0.17475)	(0.17476)
oblast5	0.21057	0.21277	0.20880	0.21483
	(0.17351)	(0.17351)	(0.17351)	(0.17351)
oblast6	0.73070***	0.73367***	0.73543***	0.75354***
	(0.20800)	(0.20798)	(0.20799)	(0.20777)
oblast7	0.59364***	0.59001***	0.58655***	0.58894***
	(0.15773)	(0.15770)	(0.15768)	(0.15770)
oblast8	0.46672***	0.46602***	0.46814***	0.46915***
	(0.14022)	(0.14024)	(0.14023)	(0.14022)
cut1	-2.17797***	-2.17859***	-2.15589***	-2.17744***
	(0.55525)	(0.55526)	(0.55600)	(0.55545)
cut2	-1.66716***	-1.66821***	-1.64581***	-1.66723***
	(0.48262)	(0.48273)	(0.48368)	(0.48308)
cut3	-1.36383**	-1.36495**	-1.34267**	-1.36332**
	(0.46462)	(0.46475)	(0.46577)	(0.46510)
cut4	-0.49022	-0.49124	-0.46953	-0.48792
	(0.44730)	(0.44744)	(0.44855)	(0.44781)
cut5	0.01057	0.00949	0.03103	0.01359
	(0.44569)	(0.44583)	(0.44694)	(0.44622)
cut6	0.87701*	0.87571*	0.89667*	0.87984*
	(0.44512)	(0.44526)	(0.44638)	(0.44567)
cut7	1.52422***	1.52249***	1.54286***	1.52572***
	(0.44541)	(0.44554)	(0.44666)	(0.44593)
cut8	2.28191***	2.27980***	2.29961***	2.28232***
	(0.44657)	(0.44670)	(0.44782)	(0.44706)
cut9	3.06019***	3.05793***	3.07732***	3.06043***
	(0.44859)	(0.44871)	(0.44985)	(0.44910)
cut10	-2.17797***	-2.17859***	-2.15589***	-2.17744***
	(0.55525)	(0.55526)	(0.55600)	(0.55545)
Observations	1,425	1,425	1,425	1,425
R-squared	0.116	0.116	0.116	0.116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A7: Results from Ordered Probit Estimations with Control Variables for Self-employed Sample

VARIABLES	(1) Index 1	(2) Index 2	(3) Index 3	(4) Index 4
index1	0.00192			
	(0.00294)			
index2		0.00182		
		(0.00298)		
index3			0.00140	
			(0.00305)	
index4				0.00055
				(0.00363)
age	-0.00045	-0.00042	0.00004	0.00042
	(0.02241)	(0.02242)	(0.02239)	(0.02244)
age2	-0.00919	-0.00921	-0.00965	-0.00997
	(0.02779)	(0.02779)	(0.02777)	(0.02781)
gender	0.16396*	0.16372*	0.16504*	0.16753*
	(0.08008)	(0.08017)	(0.08015)	(0.08016)
ethnicity	-0.08040	-0.08042	-0.08058	-0.08118
	(0.08683)	(0.08683)	(0.08683)	(0.08682)
urban	0.16867	0.16942	0.17089	0.17597
	(0.11233)	(0.11230)	(0.11247)	(0.11216)
education	0.04194	0.04210	0.04256	0.04382
	(0.03212)	(0.03212)	(0.03214)	(0.03207)
employer	0.09090	0.09201	0.09456	0.10191
	(0.22912)	(0.22909)	(0.22924)	(0.22910)
wageworker	0.00000	0.00000	0.00000	0.00000
	(.)	(.)	(.)	(.)
family	0.05242	0.05228	0.04972	0.04375
	(0.09552)	(0.09570)	(0.09577)	(0.09552)
illness2	-0.01018	-0.00974	-0.01031	-0.01094
	(0.07596)	(0.07599)	(0.07598)	(0.07602)
condition2	-0.06470	-0.06471	-0.06474	-0.06459
	(0.08944)	(0.08944)	(0.08944)	(0.08944)
community1	0.08133	0.08179	0.08246	0.08456
	(0.07185)	(0.07183)	(0.07187)	(0.07179)
religion	-0.23338	-0.23269	-0.23050	-0.22811
	(0.25568)	(0.25567)	(0.25563)	(0.25569)
personality1	0.08993*	0.08994*	0.09048*	0.09147*
	(0.03701)	(0.03703)	(0.03702)	(0.03699)
personality2	-0.04725	-0.04725	-0.04703	-0.04670
	(0.02644)	(0.02644)	(0.02644)	(0.02645)
personality3	-0.03914	-0.03903	-0.03880	-0.03799
	(0.03328)	(0.03328)	(0.03330)	(0.03330)
personality4	0.00956	0.00963	0.01008	0.01075
	(0.03362)	(0.03363)	(0.03361)	(0.03362)

risk	-0.18919***	-0.18941***	-0.18936***	-0.19004***
	(0.05569)	(0.05569)	(0.05570)	(0.05568)
circumstances	0.35950***	0.35942***	0.35955***	0.35999***
	(0.02254)	(0.02255)	(0.02255)	(0.02253)
oblast1	0.74319***	0.74443***	0.74438***	0.74458***
	(0.20713)	(0.20715)	(0.20717)	(0.20760)
oblast2	0.12782	0.12828	0.12955	0.13111
	(0.21891)	(0.21890)	(0.21888)	(0.21890)
oblast3	-0.42526	-0.42500	-0.42447	-0.42085
	(0.22576)	(0.22577)	(0.22583)	(0.22570)
oblast4	1.14240***	1.14400***	1.14656***	1.15228***
	(0.20858)	(0.20847)	(0.20842)	(0.20802)
oblast5	0.26939	0.27101	0.27154	0.27668
	(0.21069)	(0.21060)	(0.21069)	(0.21041)
oblast6	0.84737***	0.84927***	0.85465***	0.86497***
	(0.21671)	(0.21659)	(0.21636)	(0.21537)
oblast7	0.46386*	0.46652*	0.47004*	0.48015*
	(0.20516)	(0.20484)	(0.20498)	(0.20385)
oblast8	-0.07894	-0.07608	-0.07141	-0.05953
	(0.19992)	(0.19954)	(0.19967)	(0.19838)
cut1	-1.05087	-1.05122	-1.05226	-1.06994
	(0.60078)	(0.60097)	(0.60207)	(0.60250)
cut2	-0.91951	-0.91986	-0.92092	-0.93844
	(0.59101)	(0.59120)	(0.59231)	(0.59276)
cut3	-0.26163	-0.26195	-0.26335	-0.28099
	(0.56843)	(0.56864)	(0.56980)	(0.57036)
cut4	0.51484	0.51463	0.51273	0.49492
	(0.56213)	(0.56237)	(0.56348)	(0.56402)
cut5	1.36632*	1.36611*	1.36380*	1.34575*
	(0.56135)	(0.56160)	(0.56268)	(0.56316)
cut6	2.15583***	2.15555***	2.15319***	2.13493***
	(0.56173)	(0.56198)	(0.56307)	(0.56352)
cut7	2.85095***	2.85064***	2.84833***	2.83013***
	(0.56298)	(0.56322)	(0.56432)	(0.56479)
cut8	3.60495***	3.60459***	3.60225***	3.58405***
	(0.56530)	(0.56553)	(0.56662)	(0.56708)
cut9	4.13222***	4.13187***	4.12952***	4.11123***
	(0.56780)	(0.56804)	(0.56913)	(0.56957)
cut10	-1.05087	-1.05122	-1.05226	-1.06994
	(0.60078)	(0.60097)	(0.60207)	(0.60250)
Observations	1,044	1,044	1,044	1,044
R-squared	0.126	0.126	0.126	0.126

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1