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The Econometrics of Happiness

A cross-sectional European analysis on the shifting importance of the determinants of happiness

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Abstract

This paper tests the hypothesis that determinants affecting an agent's happiness do so differently depending on the happiness level of the agent. What affects a happy person's well-being and to what extent is not necessarily the same as what and how it affects an unhappy person's well-being. The hypothesis is based on the idea that current methodology within the field of happiness economics is flawed. Researchers neglect to test the proportional odds assumption, latent in the ordered logit regression models which are commonly used within the field. This is an implicit assumption of constant betas for the determinants of happiness. We investigate whether the proportional odds assumption holds using a vast, cross-sectional dataset covering large portions of Europe and find that the assumption is indeed violated for several determinants of happiness. We therefore opt to apply a partial proportional odds model, and find statistically significant evidence that the betas of the determinants of happiness vary distinctly across happiness levels for 11 out of 25 variables. Some of the largest effects on an agent's (un)happiness are caused by income, health and unemployment and the effects of all these determinants vary depending on how happy the agent is. We thus find strong indications that the current negligence with regard to the assumptions of the econometric models has large implications for the field of happiness economics.

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1. Introduction

Ultimately, we all strive for happiness in one form or another. But understanding happiness is difficult, especially so given that its meaning differs depending on who one asks. Nevertheless, econometric happiness research, commonly referred to as happiness economics, concerns itself with quantifying happiness, well-being and life satisfaction. It is the science of establishing what makes us happy and why. Like most economic fields of research it has had the tendency to use income or economic growth as its independent variable. Richard Easterlin, by many considered the father of this body of research, first conducted a study in 1974 looking at the relationship between GDP and national well-being. Since then numerous studies have been made on how income and economic growth affect happiness (Easterlin, 2003; Hagerty & Veenhoven, 2003; Ovaska & Takashima, 2010 to mention a few). However, during the past few years this perspective has changed and researchers now seek to find more variables affecting happiness, and to what extent they do so (Chyi & Mao, 2012; Frey et al., 2014). In this paper we propose the idea that these so called determinants of happiness might differ in effect depending on an agent's current happiness levels. This would imply that the previously identified determinants do not necessarily exhibit diminishing returns as they increase, but rather that their importance shifts because at various levels of happiness agents are affected differently by certain factors. Simply put, people value things differently depending on how happy they are.

This idea of shifting importance for determinants of happiness stems from the fact that current practice within happiness economics is negligent with regard to the assumptions of its econometric models. Due to the obvious difficulties that come with computing happiness through the amount of neurotransmitters discharged in people's brains, happiness is instead frequently assessed on a self-reported Likert scale. Regression of a dependent variable measured in such ordinal data onto a set of independent variables usually involves an ordered logit or probit model. In econometric analysis of ordinal data, these regression models are in fact so common that they "fully dominate the literature" (Boes & Winkelmann, 2009, p. 192). Happiness economics is no exception. The use of ordered logit models within this field is widespread and would be perfectly adequate as long as its few, non-trivial assumptions were met. However, one of these assumptions, the proportional odds assumption, does not necessarily hold true and is seldom tested for.[1] Assuming proportional odds is an indirect assumption that the betas of the independent variables, in our case the determinants of happiness, are constant across all levels of the dependent variable, happiness.

[1] This is also known as the parallel lines or the parallel regression assumption. We explain it further under theoretical background along with our claim that it might be violated and the fact that it seldom is tested for.

Some research based on the inadequacy of the traditional models has previously been conducted and more satisfactory models have been developed. These models account for the possibility that the proportional odds assumption might be violated, i.e. variable betas could vary across levels of the dependent variable. However, use of these sophisticated models is rare in happiness economics and practice is still to neglect the implications of the proportional odds assumption. Furthermore, when using these models researchers have a tendency to mainly examine the effect of income on happiness. To test our idea of shifting importance for the remaining determinants of happiness we will therefore examine the current malpractice, suggest and implement a solution to it in the form of a superior statistical model and analyse the implications of this new model. Controlling for and potentially relaxing the proportional odds assumption could thus result in a completely different structure of the happiness model, where factors have varying effect on happiness across happiness levels. The potential violations of the assumption have large implications for the validity of insights from previous happiness research.

Boes and Winkelmann (2004, 2006, 2010) argue that the way we measure happiness on an ordinal scale includes a "neutral" measure in the middle and that values on either side of this neutral measure represent negative and positive well-being. The factors that allow a person to move from negative well-being to neutral, need not necessarily be the same factors that move a person from neutral to positive well-being. The same has been shown in the field of psychology (Huppert & Whittington, 2003). This can give support to the notion that while money might not buy happiness it could buy off unhappiness. What if the same is true for other determinants of happiness? We turn the classic economic notion of a linear or logarithmic relationship between income and happiness on its head by not assuming that income, nor any other happiness determinant, unequivocally increases happiness evenly across all happiness levels. By controlling for proportional odds and implementing a statistically superior model, our intention is to take the next natural step in the development of happiness economics and look at whether the importance of the determinants of happiness shifts depending on current happiness levels (as suggested by MacKerron, 2012).

2. Theoretical background

Previous research in happiness economics is vast and incorporates an array of different theories. We therefore cover previous literature and common concepts below in order to give the reader a greater understanding of the current state of the art and then move on to explain how our thesis contributes to current theory. It is important to clarify that this paper's sole focus is on the microfoundations of happiness, i.e. what makes individuals happy and not nations as a whole. Macroeconomic concepts such as HDI or GNH[2] are however typically based on individual measures. This makes personal dimensions of happiness a subspace of the macroeconomic indices and thus a highly relevant starting point for analysis.

2.1. Happiness

More so than many other fields of research, happiness economics struggles with terminology. "Happiness" in itself is a rather ambiguous expression and will differ in meaning depending on who defines it. The most common expressions used in previous research are "subjective well-being", "life satisfaction" and "happiness". While their respective de facto definitions are not completely clear, the three concepts have been found to be so similar, overlapping and dependent on the same variables that they are often used interchangeably (Clark et al., 2002; Sacks et al., 2010; MacKerron, 2012) which will also be the case in this paper. Moreover, the concept of utility is so heavily linked to happiness and well-being that happiness scores provide a close estimation of experienced utility (Clark et al., 2008). Clark and Senik (2011) distinguish between hedonic well-being and eudaimonic well-being. In their paper, the former consists of happiness and life satisfaction while the latter incorporates such things as vitality and resilience. They found heavy correlation between life satisfaction and happiness as well as between hedonic and eudaimonic well-being. The same results were found in a study by Jeffrey et al. (2015).

A common definition in the field is that life satisfaction, happiness, pleasant affect and unpleasant affect are all components of subjective well-being, which is a more general term (Kahneman et al., 1999). As such, the term subjective well-being includes an estimation of a person's satisfaction with life as a whole, as well as temporary measures of pleasant or unpleasant affect. However, the understanding of the meaning of the word happiness varies across cultures and languages. MacKerron (2012) points out that the English word "happy" is weaker than its equivalents in other European languages, such as the French *heureux*, Italian *felice* and Russian *sčastlívyj*. Subsequently, the very meaning of "happiness" has many cultural aspects to it and differs substantially between countries. Such potential translation issues are discussed further under section 5.1.

[2] Human Development Index and Gross National Happiness, respectively.

Furthermore, there is an important distinction to be made between subjective and objective happiness. Happiness economics mostly concerns itself with self-reported data, hence the expression *subjective* well-being. While this is the case for the vast majority of research within happiness economics, it is important to acknowledge that the data on which analysis is conducted does not necessarily reflect objective, hormonal happiness in the form of endorphins or dopamine. Whether or not subjective well-being can still be considered "real" happiness is a debate we leave to scholars of philosophy.

There is an array of psychological motivational theories closely related to subjective well-being. Self-determination theory concludes that when motivational factors are curbed it results not only in decreasing motivation but a reduction in happiness and productivity as well (Deci & Ryan, 2000). We argue that the motivational theories are closely linked to theories of happiness because the factors that motivate people can reasonably be expected to be a good approximation of what makes us happy. Motivational theories range from rational motivations, on which fundamental economic theory is based, to more emotionally based content theories such as Maslow's hierarchy of needs and Hertzberg's two-factor theory. Although both Maslow's and Hertzberg's theories have been discredited a number of times,[3] there is credit to the idea that certain factors have varying importance for affecting our motivation. Similarly, psychologists have found a degree of independence between factors affecting positive well-being (happiness) and negative well-being (depression, unhappiness or anxiety). Factors which influence the former have a smaller effect on the latter and vice versa (Huppert & Whittington, 2003).

Maslow's hierarchy of needs suggests that individuals derive motivation from survival values before self-expression values. It has been found that when one maps countries based on similar cultural values on a spectrum from high survival values to high self-expression values, many formerly communist European countries, as well as low-income African and Middle-Eastern countries, lie on the high survival part of the scale (Inglehart & Baker, 2000). These countries also tend to have lower levels of life satisfaction than countries with high self-expression values (Inglehart, 2000). Whether this is based on that countries with high self-expression values simply have access to a higher standard of living or the fact that self-expression values themselves make people happy is unclear. Studies have found, however, that there is an indication that self-expression is a component of subjective well-being (Waterman, 1993; Jeffrey et al. 2015). This clearly illustrates that motivational factors, determinants of happiness and life satisfaction are connected.

[3] See for instance Wahba and Bridwell (1976) for the former and Hackman and Oldham (1976) for the latter.

2.2. Determinants of happiness

Tradition in happiness economics has been to examine the effects of income or growth on subjective well-being. As the field has developed, researchers have found various other variables that also affect well-being, called determinants of happiness. Research into these variables is vast and one can create a life satisfaction model incorporating many different factors (Yushkina, 2010; Chyi & Mao 2012). These determinants are typically sense of personal fulfilment and belonging, altruistic behaviour, demographic factors and the state of the country that one lives in. There is much research on the effects of income on happiness and it is considered such an important variable that we discuss it in a separate passage below.

Extensive research has found that when plotting happiness against age the function has a U-shaped curve, meaning that life satisfaction levels are higher during youth and senescence than they are mid-life. There are many plausible explanations for this. One of them is thought to be that "individuals learn to adapt to their strengths and weaknesses, and in mid-life quell the infeasible aspirations of their youth" as suggested by Blanchflower and Oswald (2008). They also argue it could be that happy people tend to live longer or simply that people appreciate their last years of life.

Easterlin (2006) found that health is an important driver of happiness, and even more so found a negative relationship between bad health and happiness. Gerdtham and Johannesson (2001) established the same results. They further found that gender is an important determinant of happiness. Even though previous research is not unanimous, most studies find that being male has a negative effect on self-reported well-being, although women's happiness has been found to be decreasing over time (Stevenson & Wolfers, 2009). One study on adolescents found no significant difference in life satisfaction between genders (Mahon et al., 2005). Another demographic variable where the effects on happiness are unclear is education. Cuñado and de Gracia (2012) found, contrary to the expression that ignorance is bliss, both direct and indirect positive effects on happiness from education. The indirect effects stem from income increases and labour status while the direct effects imply that having an education has an intrinsic value in itself. However, in a more recent study Brown (2015) found contradicting results and suggested that education may in fact not at all affect happiness more than indirectly.

Frijters and Beatton (2012) have conducted research on the effects of marriage on happiness and found a positive correlation. Stack and Eshleman (1998) found that the relationship between happiness and marriage held with statistical significance for 16 of 17 examined nations. According to findings by Lucas et al. (2003) this effect occurs in the first years of marriage, but in the long run marriage does not affect happiness at all. Recent research however, has found that marriage does in fact have a permanent positive effect on happiness (Qari, 2014; Helliwell & Shawn Grover, 2014). One theory tested by Frey and Stutzer (2006) points to the fact that happier people might simply be more likely to wed, meaning that the validity of insights from previous research is questionable.

Previous research further shows a well-documented negative relationship between subjective well-being and unemployment. Ohtake (2012) found that unemployment decreases happiness even when controlling for income decreases. This is in line with previous findings by Di Tella et al. (2001). Unemployment on a macro-scale is typically dependent on such factors as governmental policies. On this topic, Dreher and Öhler (2011) established that your political opinion has large implications for your happiness levels. They find that "in [...] low- and middle-income countries, left-wing individuals are happier under left-wing governments" and for some samples that "conservative individuals are happier under conservative government". Such a result is very intuitive; the less friction between a respondent's own opinion and policy conducted in her country, the more comfortable life for the individual concerned. Napier and Jost (2008) found a more general result when examining happiness and political opinion in the US; republicans were 68 percent more likely to be "very happy" than were liberal democrats.

It seems that the environment in which people live also impacts their happiness, but it is unclear in what way. The classic urban-rural happiness debate asks whether the convenience of living in a city overrides the calm of the countryside. Previous research is not unanimous, while Gleaser (2011) suggests that city life is superior by all means, findings by Berry and Okulicz-Kozaryn (2011) indicate happiness levels are lowest in urban cities and highest in small towns.

Self-expression variables such as personal projects have also been found to be strongly linked to happiness. For instance, Christiansen (2000) found a strong correlation between self-expression variables such as time spent on personal projects and happiness. He argued this is because of the self-identity factor connected to such projects. Further studies have found that participating in leisure activities of one's own choice impacts happiness and health (Pressman et al., 2009; Kim et al., 2014).

Post (2005) has conducted a thorough review on the effects of altruism on happiness and found that it is indeed good to be good; altruistic people tend to be happier. In a similar paper, Francesca Borgonovi (2008) found a positive effect on happiness from religious volunteering. This is thought to be an effect of voluntary work shifting one's reference points and increasing empathic emotions. There is further an established positive relationship between happiness and religious commitment (Inglehart, 2010). Lim and Putnam (2010) argued this is primarily an effect of the social communities that follow religious practices, e.g. going to church or to the mosque. Results by Jeffrey et al. (2015) suggest that in countries where governmental institutions are strong, religion tends to have a smaller effect on happiness as the support structure of government institutions tends to replace the function of religion. A more general sense of belonging to a community, whether religious or other, has undoubtedly been found to influence happiness (Davidson & Cotter, 1991).

Rothstein (2010) has conducted research on the importance of trust in institutions and welfare systems for happiness. He has established a clear positive relationship between the welfare state and happiness. The welfare state, in turn is strongly connected to corruption and the level of social trust in the country. Such factors involving the state of the country one lives in have often been found to affect happiness. Inglehart (2010) examined ex-communist countries and found that living in such countries was associated with lower happiness levels. This is despite severe economic reforms and in many cases large subsequent growth.[4] Lastly, Inglehart et al. (2008) concluded that the degree to which free choice is allowed in a society is a very important factor affecting happiness.

2.3. Income

Happiness economics is built on a foundation that takes wealth as a granted driver of well-being. This has been proven time and time and again to hold for individuals.[5] Rich people seem to be happier than poor people, which intuitively makes sense because they have access to a higher standard of living. Although the focus of this paper is on the microfoundations of happiness it would be impossible to disregard the debate on macrofoundations spurred by an influential paper by Easterlin (1974). In it, he found that the assumption of a relationship between economic growth and well-being does not hold on a national level for developed countries. He argued that while it is true that a higher income tends to make individuals happier, economic growth does not contribute to increased national happiness over time, creating the famous Easterlin paradox. Even though Easterlin's findings were accepted for a long time – and by many still are – they were met with some credible critique from Stevenson and Wolfers (2008) who claim to have found that across 140 countries the relationship between growth and happiness holds, even when using different datasets. Easterlin et al. (2010) later established that his null relationship holds even for developing countries and claimed that critiques of his paradox are results "either of a statistical artifact or a confusion of the short-term relationship with the long-term one".

Regardless of the above debate, it is safe to say that income and happiness are strongly correlated at least on an individual level. An important aspect of this is the applicability of the law of diminishing marginal utility of income. Stevenson and Wolfers (2008) found that the returns of income on happiness are indeed diminishing. By using the logarithm of income they find that a percentage increase in income generates roughly the same happiness effect across all income levels,

[4] For example, in 2009 Poland's GDP was 189% of that in 1989. This growth is substantially higher than that of other EU countries as well as the US.

[5] See Argyle (1999) for a thorough review.

in line with the Weber-Fechner law.[6] This has become a common way of looking at income increases.[7] Inglehart (2000) found that on a national scale, early phases of GNP growth exhibit great returns in self-reported happiness but that they level off and "eventually reach a point of diminishing returns". In an extension of the law of marginal utility, Nobel laureates Daniel Kahneman and Angus Deaton (2010) found that not only does income exhibit diminishing returns to happiness but that there is also a cut-off point at individual incomes above $75,000 a year, after which further increases show negligible or no effects on happiness.

Some theories further suggest that absolute income might not be the most adequate parameter to explain life satisfaction. Rather, it might be relative income (Layard et al., 2009). The relative income hypothesis states that it is a person's income in relation to others in her surroundings, not the absolute income or abstract standard of living that matters to personal well-being. Intuitively, relative income should have large implications for self-reported happiness, especially in a modern world in which social comparisons are made extremely accessible through constant exposure to the (filtered) life of others creating a severe case of keeping up with the Joneses. On this topic, Stutzer (2004) found in an empirical test that higher individual income aspirations reduce people's utility, *ceteris paribus*. In the same paper, he found that simultaneously, income aspirations increase with income. Knight and Song (2006) have conducted research on social comparison and found that the importance of relative income for happiness is at least twice that of absolute income. This was the case even in poor regions such as rural China. The theory of relative income offers an explanation to the Easterlin paradox; relative income is dependent on some benchmark and happiness levels could be expected to remain constant even with an increasing absolute income as long as the absolute income grows at the same rate as the benchmark (Angeles, 2010).

This is closely related to the concept of the hedonic treadmill which is the tendency of individuals to return to stable happiness levels despite major changes in life. It predicts that an increased income will only lead to new reference points always causing you to want more without being content. At the same time it explains why sudden disabilities and death among relatives for example do not mean permanent unhappiness. It can also be understood as constantly adapting to new reference points. Furthermore, there is evidence that people expect to be happier in the future but think they were less happy in the past (Easterlin, 2001). This could also be seen as a form of adaptation. The tendency to move from measuring happiness dependent on relative rather than absolute terms is much thanks to psychologist Daniel Kahneman's development of prospect theory. The theory is one of behavioural economics and states that rather than making decisions

[6] Stating that the perception of the intensity of a stimulus is proportional to previous levels of the stimulus.

[7] See for example McBride (2001), Boes and Winkelmann (2004, 2006) and Deaton (2008).

based on statistically rational expectancy values, individuals evaluate situations based on gains and losses (Kahneman & Tversky, 1979). This goes against the commonly practiced expected utility model developed in an essay by Swiss 18th century mathematician Daniel Bernoulli.

2.4. Estimating the happiness model

Below we explore how the relationship between happiness and its determinants is typically modelled in happiness economics. We start by reviewing problems involved with the classic linear regression model that uses ordinary least squares estimation and then move on to ordinal regression models and maximum likelihood estimation. We proceed by analysing the proportional odds assumption, alternative models that account for the assumption being violated and examine conclusions previously drawn from those models. While this is a review of econometric methodology, it is not to be mistaken for the methodology used to conduct our analysis which is specified under section 4.

Using linear regression with least squares estimation will most likely give biased and inconsistent estimates when applied to ordinal data (Amemiya, 1977; Horrace & Oaxaca, 2006). This regression model assumes that the data is cardinal and as such treats the distance between the categories of an ordinal dependent variable as constant across all levels. This cardinality assumption need not be true and in fact most likely is not. For instance, suppose your dependent variable is reported on a Likert scale where a level of 1 corresponds to "none", 2 corresponds to "few" and 3 to "many". The "distance" of moving from 1 to 2 need not be the same as moving from 2 to 3 in this scenario. Moreover, what does a decimal number mean in this setting? Such a number has no quantitative meaning as ordinal data essentially is categorical data with an inherent ordering; either one belongs to a category or one does not.

Due to these issues, standard practice in happiness economics is instead to use non-linear, ordinal regression models such as the ordered logistic or probability unit regression,[8] with the former being described as "perhaps the most popular" (Williams, 2016). These models calculate the *probabilities* of being at a certain level of the dependent variable given the various possible levels of the independent variables. While this changes the structural form of the regression model as compared to linear regression and makes the estimated variable betas more difficult to analyse, the general intuition behind the estimated betas is the same for both models. In linear regression, positive betas mean that increases in the independent variables are associated with increases in the dependent variable. For ordinal regression models, positive betas mean that increases in the independent variables are associated with increases in the probability of being at a higher level of the dependent variable. In both linear and ordinal models, larger betas in absolute values are associated with larger marginal effects.

[8] Typically called ordered logit and probit.

For the ordinal regression models, when researchers use the term "effects on happiness", what it means is in fact the effects on the probability of being in a certain category of happiness. It is also worth emphasising that while we speak of "effects", correlation does not necessarily imply causality and happiness economists cannot definitely establish a cause-effect relationship because of the nature of the analysis. There is a risk that an effect occurred before its cause, known as retrocausality. However, for simplicity, we will be using the term "effect" in our analysis but strongly emphasise these semantic shortcomings.

The use of an ordered logistic regression model is appropriate only given that the proportional odds assumption holds. The assumption is illustrated and explained in depth below; for now it is enough to know that it implies constant betas across all levels of the dependent variable. As has been pointed out, it is common practice in econometrics to ignore this assumption, which is inadequate given that it is frequently violated (Long & Freese, 2006; Williams, 2006, 2016). While this widespread negligence is remarkable, it is not very surprising. The use of standard linear regression is extensive and the assumptions and structure of the model are easy to grasp. The proportional odds assumption on the other hand is more complex. The idea of constant betas seems perfectly natural when examined from the point of view of the standard linear regression and thus this mindset is likely to have transferred from linear regression models to non-linear models. This probably stems from an understanding of the non-linear and the linear models as being only marginally different, whereas they actually differ significantly. When the standard linear regression simply maps the dependent variable to the independent variables, the ordinal regression models require a link function to connect the independent variables with the dependent one.[9] Logistic regression uses the logit as its link function, which is the inverse of the logistic function, and probability unit regression uses the probit function, which is the inverse of the cumulative distribution function of the normal distribution. In practice these two link functions produce only marginally different results (Long & Freese, 2006; Agresti, 2010).

Ordinal regression models do not use least squares estimation (LSE) to regress the dependent variable onto the independent variables, but rather maximum likelihood estimation (MLE) as LSE can give biased estimates for these types of regressions (Greene, 2012). The difference between the two is that MLE calculates estimates based on the likelihood that the estimated parameters produced the observed data and tries to maximise this likelihood iteratively, whereas LSE fits the model to the data to minimise the squared deviations from the estimated model. The benefits of MLE is that you typically get more precise parameter estimations and smaller standard deviations. Myung (2003) points out that alternatives to LSE such as MLE are not

[9] See for instance Long and Freese (2006) or Agresti (2010) for more information about ordered logistic regression.

widely known in the field of psychology which also could explain the aforementioned negligence in the field of happiness economics, it being at the intersection between psychology and economics.

As previously mentioned, the proportional odds assumption implies that variable betas should be constant across all levels of the dependent variable. For an ordered logistic model this means that for a unit increase in an independent variable the probability of being at or below a level of the dependent variable versus being above this level should increase or decrease (depending on the sign of the beta) equally much across all levels of the dependent variable. That is to say that the change in the odds[10] of being in or a below a category of the dependent variable should be equal across all levels of the dependent variable for a unit increase in an independent variable. This translates to the link function, in this case the logit, having a constant slope across all levels of the dependent variable, giving us parallel lines.

Figure 1: The proportional odds assumption holds

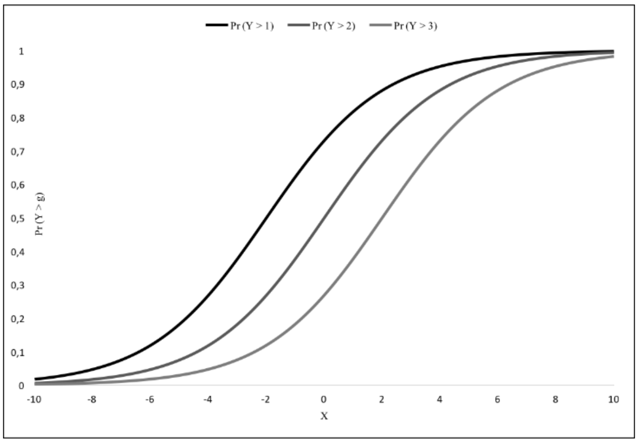
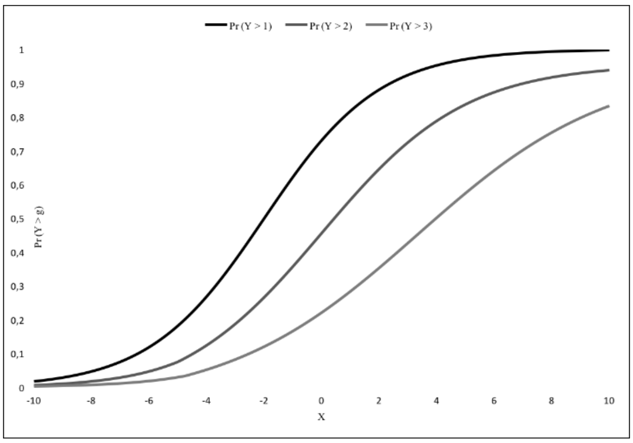


Figure 2: The proportional odds assumption is violated



[10] If the probability of an outcome is *p* the odds of that outcome is defined as *p* / (1 - *p*).

It is important to mention that standard practice in econometrics is to calculate heteroscedasticity-consistent (robust) standard errors for most regressions. This use has been described as "extremely widespread, automatic, and even sometimes unthinking" (King & Roberts, 2014). One can account for heteroscedasticity in a linear regression model by calculating robust standard errors through the use of a covariance matrix. However, this matrix is not applicable for non-linear regression models. Thus, sloppily using robust standard errors to account for heteroscedasticity in non-linear regression models is incorrect and will give inconsistent standard errors. Furthermore, certain forms of heteroscedasticity will cause the proportional odds assumption to break. The fact that all of this receives little attention in the literature (Greene, 2012) further illustrates the current malpractice in the field.

A method of dealing with a potential violation of the proportional odds assumption is to use multinomial logistic regression. This treats all levels of the dependent variable as separate categories and ignores their inherent ordering which allows the betas to vary across all categories. This could potentially result in an abundance of parameters which do not necessarily differ *distinctly* from each other. No appropriate theory exists for why one should treat different happiness levels as separate categories, ignoring their inherent ordering. Examples where multinomial logistic regression is adequate could be if the different levels of the dependent variables correspond to different types of cars, colours or cities, i.e. categorical data. However, treating "very happy" and "happy" as completely different categories and ignoring their ordering makes little intuitive sense.

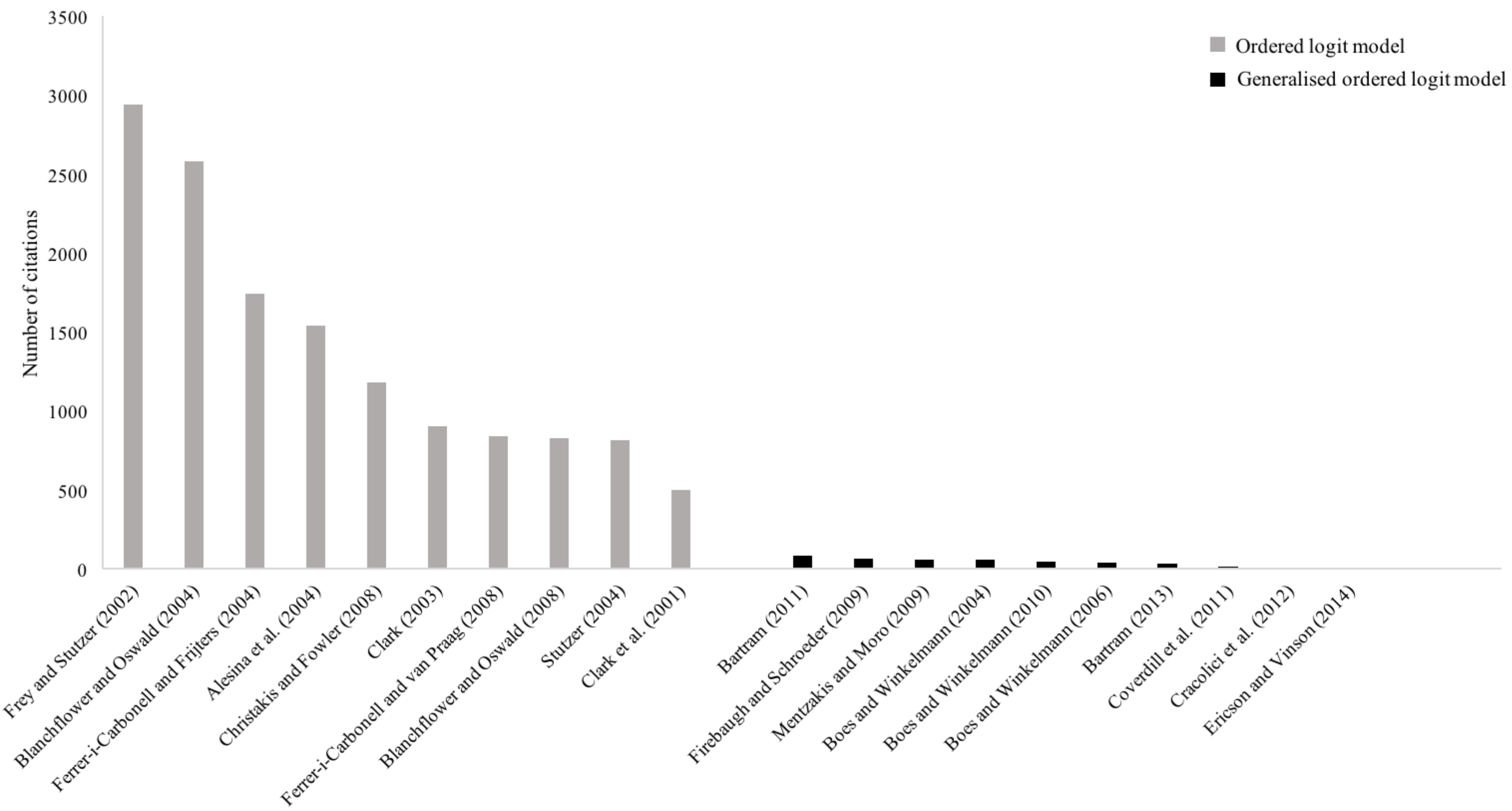
A violation of the proportional odds assumption could also be a sign that a model is misspecified, for instance because of omitted variables or failure to square or logarithmise variables where appropriate. Williams (2016) conducted testing with various different model structures and found that changing the specification of variables or adding variables could heave the violation of the proportional odds assumption. However, this did not account for all cases of violation. Furthermore, this model re-specification needs to be supported by theoretical arguments. Williams also notes that for large sample sizes, even small deviations from the mean could cause the proportional odds assumption to be violated. However, one need only examine the difference in the betas across levels to see if the violation is relevant and significantly large and ignore the violation if its effects are negligible. Another possible explanation could be that there are too few observations in one of the levels of the dependent variable. In those cases a solution could be to dichotomise the outcome variable or alter the scale on which it is reported.

Another way of accounting for the proportional odds assumption being broken is by relaxing the assumption only for the affected variables and thus creating a partial proportional odds model. This model is a form of the generalised ordered logistic regression (gologit). Williams (2016) notes that researchers tend to use the partial proportional odds model because it provides a better fit to the data but that they do not actually explain why that is. That is, use of the partial proportional odds model is typically empirically driven and not based on theory. The risk is that fitting a model to the data gives you information unique to a specific dataset, thus creating a statistically superior model which is invalid from an economic standpoint. Konishi and Kitagawa (2008) point out that "[t]he majority of the problems in statistical inference can be considered to be problems related to statistical modeling". Nevertheless, Williams (2006) argues that one can bypass these issues by testing eventual violations of the proportional odds ratios at strict significance levels.

Use of the partial proportional odds model is supported by theory if and only if there exists an asymmetric relationship between the considered variables. This could very well be the case for happiness economics. Maslow's hierarchy of needs and Hertzberg's two-factor model both support the idea of variables having different importance across motivational levels. It could be that across happiness levels, the importance of certain factors shifts and the determinants that make us happy at one happiness level are no longer important at other levels. The previously mentioned conclusions by Huppert and Whittington also suggest that factors have varying effects on negative and positive well-being. Kahneman and Deaton's findings of a cut-off point for income (above which income no longer has an effect on happiness) discussed above seem to point in this direction as well; once certain needs are satisfied the importance of income drastically shifts downwards. Boes and Winkelmann (2004, 2006, 2010) argue that the life satisfaction scale actually is the composite of two scales: one measure of negative well-being and one of positive well-being. Therefore, it could be that factors that affect the negative part of the scale need not be the same as those that affect the positive part of it. This would be in agreement with the findings of the separation between negative and positive well-being by Huppert and Whittington previously mentioned. Lindeboom and van Doorslaer (2004) further argue that a violation of the proportional odds assumption could be caused by scale of reference bias; what certain subgroups consider as high and low happiness might vary, i.e. varying betas could simply imply that happy people have a different reference point for what happiness is as compared to unhappy people. This is discussed further under the data section in 5.1.

Some research into gologit models that account for the proportional odds assumption has been conducted in happiness economics, but these models are rare and not widely known. To illustrate this we have iterated through the first 1000 articles in Google Scholar using the search terms "happiness" and either "ordered logit" or "ologit". We then selected the ten most cited articles from 2000 and forward that relate to the field of happiness economics. The same process was then repeated with the search criteria of either "happiness", "life satisfaction", or "subjective well-being" combined with either "proportional odds", "parallel lines", "partial proportional odds", or "gologit". We have thus selected recent, highly influential papers in the field of happiness economics that explicitly mention the use of ologit regression and compared these papers with those using more non-traditional regression models. This has resulted in the following diagram:

Figure 3: Citations for ologit and gologit papers



What all the ologit papers have in common is that they make no mention of the proportional odds assumption or any of its alternative formulations. Moreover, many of these are written by either Frey, Stutzer, Blanchflower, Oswald or Clark, who are all highly influential researchers in the field. Notwithstanding the fact that Ferrer-i-Carbonell and Frijters (2004), as well as Ferrer-i-Carbonell and van Praag (2008) both actually cover the topic of methodology in happiness economics specifically and still do not mention the assumption or any of its alternative formulations. Granted, four of these papers use fixed effects models and thus remove the heterogeneity in respondents' answers. However, this ignores the possibility of there being explanatory value in this heterogeneity. Lastly, Stutzer (2004) does not actually use an ologit model but rather a linear one. Nevertheless, he notes that it should provide the same results as the ologit model. As mentioned above, this is not necessarily true.

To find papers focusing on gologit models, we used additional search criteria as compared to the ologit models. The reason for this is that the gologit models simply are so rare that fewer search terms resulted in too few relevant papers. Among the gologit papers, all of them use partial proportional odds models to estimate the relationship between happiness and some variable. While this is by no means an empirical meta study on the field of happiness economics, it serves to illustrate how the proportional odds assumption is commonly not accounted for by the most influential authors. Furthermore, there is significant disparity between citations of influential papers and citations of papers using the gologit models. This seems to point towards that previous research into statistically superior models has had little or no impact on the field of happiness economics. Williams (2016) notes that these models have become more common in recent years, but that the general tendency among researchers is to not motivate their use of the model.

The findings from the gologit papers are generally that there is support for the idea that different factors have varying effects across happiness levels. Ordered logistic regression models do break the proportional odds assumption. For instance, Boes and Winkelmann (2004, 2006) and Mentzakis and Moro (2009) find that while increases in income are associated with higher probabilities of being at higher levels of the well-being scale, this effect decreases across happiness levels. In the 2004 paper this effect is only noticeable for women however and the authors attribute this to men often having the role of primary income earner. Nevertheless, all of the gologit papers have one or several weaknesses in common. They either rely on few data points, use old or country-specific data, or do not examine potential variance inflation from multicollinearity. Furthermore, these papers focus on specific topics such as migration or income and do not look at if this pattern holds for multiple determinants of happiness.

2.5. Contribution to current literature

As should be clear from our review, there is an obvious gap in existing literature. Firstly, there is an inadequate representation of the proportional odds assumption. We contribute to current literature by testing if the negligence with regard to this assumption has any implications for the field of happiness economics. In the case that the assumption is broken, we attempt to provide an answer using our hypothesis of shifting importance of the determinants of happiness. Even though research on gologit models has been conducted, we will examine if these findings hold for the established determinants of happiness across all of Europe, rather than single variables in single countries. We therefore aim to examine if use of the partial proportional odds model adds explanatory power as compared to the standard ordered logistic model, if applied to more recent, multinational data as opposed to the country-specific findings using old data in previous research. Furthermore, in cases of ambiguity regarding the effect of certain variables on happiness, our aim is to clarify these effects.

Improved methodology for the quantification of happiness at an individual level also allows for more correct indices at the macro level. It might be more interesting for governments to examine effects on well-being rather than GDP, as the two are not necessarily correlated. Taxation for the purpose of income equalisation or reducing unemployment might thus be justifiable from a perspective of societal happiness and utility maximisation, rather than for the purpose of increasing growth. This is especially true if we can find support for our hypothesis of shifting importance. By finding determinants that have varying effects on happiness, policy makers can improve societal well-being more efficiently. For instance, identifying a factor that has a larger effect on life satisfaction at lower levels of happiness can facilitate the remedying of imbalances in a population's well-being. If certain factors prove to have constant effects across happiness levels, a general focus on these at the societal level could be warranted. Lastly, improved methodology in the field of happiness economics pushes the field forward by allowing for better quantification of what sums of money are required to neutralise disutility in life across all happiness levels. As such, better models facilitate in the pricing of public goods, such as sustainability. Apart from the obvious fact that understanding human happiness is important, this more policy-related rationale supports our approach to examine economics of happiness from a new perspective.

3. Research question and scope

In this paper we examine if factors affect happiness differently across happiness levels. The mechanism behind this is straightforward. What causes an increase in well-being for a happy person is not necessarily the same as what causes an increase in well-being for an unhappy person. This results in our main hypothesis:

Depending on happiness levels, agents are affected differently by determinants of happiness.

This hypothesis is based on the fact that common practice in happiness economics is to use ordered logistic regression, without testing for the proportional odds assumption. It is possible that this negligence has implications for the validity of insights from previous research into the determinants of happiness. In order to answer above we will therefore examine whether or not the proportional assumption is violated for the most commonly analysed determinants of happiness when modelling their relationship with happiness through ordered logistic regression. We thus formulate a second hypothesis:

The proportional odds assumption is violated when using ordered logistic regression to model the relationship between happiness and its determinants.

If we can support this hypothesis, we will relax the proportional odds assumption for determinants where our analysis shows that the assumption is violated. By doing this we allow their betas to differ across happiness levels and have created a new model in which we have partial proportional odds instead. Although one could test our first hypothesis with the use of quantile regression, applying the partial proportional odds model also allows us to test this second hypothesis and thus examine if the negligence in the field has any implications. We aim to compare the insights provided by our new model to those of the ordered logistic regression model as we believe the partial proportional odds model has greater explanatory power when modelling the relationship between happiness and its determinants. Does it allow us to draw conclusion about the nature of the effects of the determinants of happiness on life satisfaction that the previous model does not?

We want to point out that the aim of this paper is not to find new determinants of happiness, nor is it to question previous findings regarding what the determinants of happiness are. Rather, by applying the partial proportional odds model, we aim to explore if their relationship with happiness actually takes the form that is commonly assumed. We are thus revisiting previous results in the field. Furthermore, we are examining the microfoundations of happiness and not the macroeconomic landscape that makes a country as a whole happy or the constituents of national well-being. Lastly, although our conclusions might have implications for policy debates, we take no normative stance, nor do we provide prescriptive rules. We rather aim to provide empirical data for use in the policy debates.

4. Methodological approach

To model the relationship between happiness and its determinants we use two forms of the generalised ordered logistic regression: standard ordered logistic regression and the partial proportional odds model, the latter of which we develop through the use of Wald tests to examine if the determinants of happiness violate the proportional odds assumption. Below we go through the econometrics of these two models, as well as examine the Wald test and discuss criteria for our modelling to be considered robust.

4.1. The ordered logistic model

The first model we develop is through standard ordered logistic regression. This model is based on the assumption that the ordinal variable happiness y_i has a continuous underlying variable y_i^* such that:

$$y_i^* = \omega_0 + \sum_{k=1}^{K} \omega_k x_{k,i} + \varepsilon_i , \qquad \varepsilon_i \sim \mathrm{i.d.d}(0, \sigma^2)$$

$$y_i = \begin{cases} 1 & \text{if} \quad y_i^* \le \kappa_1 \\ 2 & \text{if} \quad \kappa_1 < y_i^* \le \kappa_2 \\ \vdots & \\ N & \text{if} \quad \kappa_N < y_i^* \end{cases}$$

As such the ordinal scale that happiness is measured on is actually a transformation of an underlying continuous scale. Respondents are either directly or indirectly judging their kappa cut-off levels in the above equation and then decide what level of life satisfaction they are on. These cut-off levels are estimated by the model through maximum likelihood estimation. Note that in the above equation the error terms are independent and identically distributed with a mean of zero and some constant variation. For logistic regression models this variation is fixed at 3.29 which is the variance of the logistic distribution.[11] Instead assuming that the error terms are normally distributed would result in a probit model. As previously mentioned, these two models produce only marginally different results. The logistic regression, however has the benefit of being easier to interpret. Its betas represent constant, logarithmised odds ratios, whereas for the probit model the betas represent changes in z-scores, the effects of which vary depending on the levels of the independent variables.

As mentioned in the theoretical background, these probabilistic regression models use a link function to connect the dependent variable with the independent variables. In the case of ordered logistic regression this link function is the logit, defined as:

$$\mathrm{logit}(p) = \log \frac{p}{1-p}$$

---

[11] $\pi^2 / 3 = 3.29$

In the logit p represents a probability and the probabilities used are the probability of happiness y_i being at or below a level g:

$$p = \Pr(y_i \leq g \mid x_{k,i}), \; g = 1, 2, \dots, N-1$$

The link between the happiness levels and the determinants of happiness $x_{k,i}$ are thus modelled as such:

$$\operatorname{logit}(\Pr(y_i \leq g \mid x_{k,i})) = \log \frac{\Pr(y_i \leq g \mid x_{k,i})}{1 - \Pr(y_i \leq g \mid x_{k,i})} = \log \frac{\Pr(y_i \leq g \mid x_{k,i})}{\Pr(y_i > g \mid x_{k,i})} = \kappa_g - \sum_{k=1}^{K} \beta_k x_{k,i}$$

$$\frac{\Pr(y_i \leq g \mid x_{k,i})}{1 - \Pr(y_i \leq g \mid x_{k,i})} = \frac{\Pr(y_i \leq g \mid x_{k,i})}{\Pr(y_i > g \mid x_{k,i})} = \exp(\kappa_g - \sum_{k=1}^{K} \beta_k x_{k,i})$$

The use of negative betas in the above model is intentional as we want positive beta values to be associated with increased odds of being in higher happiness levels. This makes the intuition behind our model similar to linear regression models. This results in the following cumulative probabilities for the happiness levels:

$$\Pr(y_i \leq g \mid x_{k,i}) = \frac{\exp(\kappa_g - \sum_{k=1}^{K} \beta_k x_{k,i})}{1 + \exp(\kappa_g - \sum_{k=1}^{K} \beta_k x_{k,i})} = \frac{1}{1 + \exp(-\kappa_g + \sum_{k=1}^{K} \beta_k x_{k,i})}$$

$$\Pr(y_i > g \mid x_{k,i}) = \frac{1}{1 + \exp(\kappa_g - \sum_{k=1}^{K} \beta_k x_{k,i})} = \frac{\exp(-\kappa_g + \sum_{k=1}^{K} \beta_k x_{k,i})}{1 + \exp(-\kappa_g + \sum_{k=1}^{K} \beta_k x_{k,i})}$$

One can write the specific probabilities of being at a level of happiness as:

$$\Pr(y_i = 1 \mid x_{k,i}) = \frac{1}{1 + \exp(-\kappa_1 + \sum_{k=1}^{K} \beta_k x_{k,i})}$$

$$\Pr(y_i = g \mid x_{k,i}) = \frac{1}{1 + \exp(-\kappa_g + \sum_{k=1}^{K} \beta_k x_{k,i})} - \frac{1}{1 + \exp(-\kappa_{g-1} + \sum_{k=1}^{K} \beta_k x_{k,i})}, \qquad g = 2, \dots, N-1$$

$$\Pr(y_i = N \mid x_{k,i}) = 1 - \frac{1}{1 + \exp(-\kappa_{N-1} + \sum_{k=1}^{K} \beta_k x_{k,i})}$$

4.2. The partial proportional odds model

One can note that in the above model β_k is constant across all happiness levels, i.e. for any given ordinal happiness level $y_i = g$, a determinant of happiness $x_{k,i}$ does not have different $\beta_{k,g}$ but rather constant β_k. Thus, $x_{k,i}$ has a proportional effect on y_i regardless of which level of g we examine, or in other words the proportional odds assumption holds. We can instead relax the proportional odds assumption and allow $\beta_{k,g}$ to vary across happiness levels. This results in the generalised ordered logistic model:

$$\Pr(y_i > g \mid x_{k,i}) = \frac{1}{1 + \exp(\kappa_g - \sum_{k=1}^{K} \beta_{k,g} x_{k,i})} = \frac{\exp(-\kappa_g + \sum_{k=1}^{K} \beta_{k,g} x_{k,i})}{1 + \exp(-\kappa_g + \sum_{k=1}^{K} \beta_{k,g} x_{k,i})}, \qquad g = 1, \dots, N-1$$

We add the following constraint to ensure that the probabilities add up to 1:

$$\kappa_{g-1} - \sum_{k=1}^{K} \beta_{k,g-1}\, x_{k,i} \leq \kappa_g - \sum_{k=1}^{K} \beta_{k,g}\, x_{k,i}$$

In the above model, if at least one beta value varies and at least one is constant across happiness levels, we have created a partial proportional odds model. If not, we will have either estimated a standard ologit or a multinomial logit model. The generalised ordered logistic regression model can thus take the form of any of the standard ordered logit, partial proportional odds, and multinomial logit models. As $\beta_{k,g}$ vary across all levels for the multinomial logit, but β_k do not vary across any happiness level in the standard ologit, the partial proportional odds model could be considered a mix of the two.[12]

To test the proportional odds assumption, we have estimated a multinomial logit model and iteratively tested the assumption for the different beta combinations across all happiness levels. If there is a significant variance between betas across the various levels, this means that an ologit model would have broken the proportional odds assumption. If there is no variance between betas it means that a multinomial logit would have created unnecessary parameters that do not vary significantly. These iterative tests thus serve to find the model best fitted to the data, indirectly also testing the standard ordered logit model for the proportional odds assumption. The test of the assumption is a Wald test, which is asymptotically χ^2-distributed. The null hypothesis of this test is that the coefficients differ across happiness levels, meaning that a significant value and higher Wald statistics show proof that the proportional odds assumption has been violated. While the test uses a 5% significance level by default, we have instead specified a more parsimonious 1% level to ensure that our conclusions have a higher degree of robustness.

4.3. Robustness

Sample sizes need to be large compared to those required by least squares estimation to ensure that ordered logistic models produce unbiased and consistent estimates. Previous research into partial proportional odds models have used between 1,000 and 20,000 observations. Moreover, in order to ensure that the estimates are consistent, it is important that there is an absence of multicollinearity and that there is no clustering in the data causing intraclass correlation. This is further discussed under the data section.

Because ordered logistic regression uses maximum likelihood estimation rather than least squares estimation, the standard R^2 provided by least squares estimation does not exist. However,

[12] An example of the relationship between the three models is provided in appendix table III.

McFadden has developed a different goodness-of-fit statistic called the pseudo R^2 which is calculated as follows:

$$R^2 = 1 - \frac{\ln L(M_{Full})}{\ln L(M_0)}$$

$L(M_{Full})$ is the likelihood function of the estimated model and $L(M_0)$ is the likelihood function of the model without any predictors and thus only an intercept. The interpretation of McFadden's pseudo R^2 is that a value of 0 means that your model provides no explanatory value, whereas a value between 0.2 and 0.4 is considered excellent fit (Hensher & Stopher, 1979).[13]

Moreover, testing that determinants of happiness do not break the proportional odds assumption is in itself a robustness test, giving us an indication that our model does not break any assumptions. However, as noted in the theoretical background, if the assumption is violated, betas need to vary significantly across happiness levels as otherwise the violation is only caused by observations that are outliers from an otherwise well-centred mean. Similarly, if all variables break the proportional odds assumption this could be a sign that the data is faulty, rather than that all of the determinants of happiness have varying effects on life satisfaction across happiness levels.

[13] This was in fact argued by McFadden himself in chapter 15 of the book.

5. Data

Below we review the dataset used for this paper, its methodology for sampling, weighting and translating, as well as the variables under consideration for our analysis.

5.1. European Social Survey

This paper is based on data from the 2012 module of the European Social Survey (ESS) which is a cross-national survey that has been conducted every two years since 2002. The survey is academically driven and states that its main aims are "to chart stability and change in social structure, conditions and attitudes in Europe" and "to introduce soundly-based indicators of national progress, based on citizen's perceptions and judgements of key aspects of their societies" (European Social Survey, 2016). ESS conducts its surveys every other year starting from 2002, meaning that there are seven rounds available, the most recent one conducted in 2014.[14] Our research, however, is based on the round 6 dataset from 2012. This module specialised in life satisfaction and personal well-being and therefore included certain variables unique for that round which were invaluable for our analysis. While we do not believe that the determinants of happiness on a general level have changed significantly since 2012, it is important to acknowledge that an analysis conducted on a single-year dataset could yield a static result and we expose ourselves to the risk that the 2012 module is a statistical outlier and not generally applicable. This risk is reduced somewhat through the multinational nature of our analysis. We base our analysis on 28 countries and have opted to exclude Israel from the original 29 as this is a study on European countries. Our final dataset has 52,165 observations in total, which is considered enough for our sample to be statistically representative and for our ordered logistic models to hold true. A table of the distribution of data across the various countries is provided in appendix table I.

The fact that the data collected by ESS is self-reported results in potential issues. One such issue is that of a potential response bias: a cognitive bias leading respondents to deviate from accurate or true responses. Even though ESS has a very thorough methodology with randomised samples and face-to-face interviews, there is nothing to stop respondents from reporting false information on such things as income, working hours and other socially contingent variables. Another potential problem would occur if respondents quantify their happiness differently. One person's three on a ten-level scale might be another person's six on the very same scale. Thus it could be that people have different reference points for how to collapse their continuous happiness variable into the ordinal.[15] However, as we are discussing *subjective* well-being, differing reference points are actually highly relevant. We could for instance find that happy people tend to define

[14] The 2016 version is currently ongoing at the time of writing.

[15] This is also called state-dependent reporting bias, differential item functioning, heterogeneous reporting behaviour, response category cut-point shift or reporting heterogeneity in the literature (Williams, 2016).

happiness differently from unhappy people. As previously mentioned, this spurs a more philosophical debate. What is more important: how happy an individual think that she is, or what the individual's brain is communicating? One might argue that your perceived happiness is your happiness, *simpliciter*. Again, that is a debate which falls outside the scope of this paper.

ESS samples have a number of rules that each round needs to abide by. The samples "must be representative of all persons aged 15 and over resident within private households in each country, regardless of their nationality, citizenship or language". All individuals in ESS surveys are "selected by strict random probability methods at every stage", i.e. there is no quota sampling. Moreover, all participating countries "must aim for a minimum 'effective achieved sample size' of 1,500 or 800 in countries with ESS populations of less than 2 million after discounting for design effects". All data is collected using face-to-face surveying. The result is a random sample with cross-country data that include some 500 variables.

To ensure that there is no overrepresentation of strata, ESS provides a set of weights for each observation, which account for the likelihood that a certain respondent was to be part of the sample. We use two instruments to weigh our data: post-stratification weights and population size weights. The post-stratification weights serve to reduce errors related to "attempting to measure only a fraction of the population" (sampling errors) and the potential issue of "over- or underrepresentation of respondents with certain characteristics" (non-response bias). The population size weights are necessary when looking at data for combinations of countries, because of differences in population sizes between counties. We use this weight because of the very nature of our analysis; its core is an examination of European countries. If we were to neglect these weights, figures combining data from more than one country might be biased.

As briefly mentioned under theoretical background, previous research within the field of happiness economics has had some problems with semantics. Questions of translation, for example, was an important point in Stevenson and Wolfers' reassessment of the Easterlin paradox. They found that the response categories in certain countries, especially so for Japan, changed over the surveyed years, which had dramatic implications for Easterlin's findings (Stevenson & Wolfers, 2008).[16] This is the result of the severe effects of framing on how respondents decide to answer (see for example Tversky & Kahneman, 1981). To avoid such problems, the ESS survey is translated from English for each surveyed nation. They require "[translations] for each language used as a first language by 5 per cent or more of the population". The formulations of questions are also held constant over the years (European Social Survey, 2016).

[16] The highest happiness category was changed from "Although I am not innumerably satisfied, I am generally satisfied with life now" to "Completely satisfied" causing an obvious shift in reference points.

5.2. Variables under consideration

The variables we use in our analysis are based on previously established determinants of happiness explained in the theoretical background. We elaborate further on certain variables below and explain our transformations, discuss what they are proxies for and the potential weaknesses of our assumptions. It should be acknowledged that ESS has used all of the variables below for analysing happiness.

Table 1: Explanation of variable names

Variable	Definition	Scale
Happiness	Satisfaction with life as a whole	Extremely dissatisfied (0) - Extremely satisfied (4)
Logincome	Natural logarithm of respondent’s decile income	Income in deciles 1 - 10
Age	Respondent’s age	15 - 103
Agesq	Age to the second power	225 - 10609
Health	Subjective general health	Very bad (0) - Very good (4)
Male	Being male	Dummy
Tertiaryeducation	Having a tertiary education equivalent to at least a Bachelor’s degree	Dummy
Married	Being legally married or in a legally registered civil union	Dummy
Unemployed	Having been unemployed during the last seven days	Dummy
Lrscale	Placement on the political left-right scale	Left (0) - Right (10)
Urban	Living in an urban environment such as a big city or suburbs to a big city	Dummy
Providehelp	Provide help and support to people you are close to	Not at all (0) - Completely (6)
Religion	Belonging to a particular religion or denomination	Dummy
Minority	Belonging to a minority ethnic group in country	Dummy
Closepeople	Feel close to the people in local area	Disagree strongly (0) - Agree strongly (4)
Trustpeople	Most people can be trusted or you can’t be too careful	You can’t be too careful (0) - Most people can be trusted (10)
Respect	Feel people treat you with respect	Not at all (0) - A great deal (6)
Receivehelp	Receive help and support from people you are close to	Not at all (0) - Completely (6)
Direction	Have a sense of direction in your life	Not at all (0) - Completely (10)
Accomplishment	Feel accomplishment from what I do	Disagree strongly (0) - Agree strongly (4)
Freedomdecide	Free to decide how to live my life	Disagree strongly (0) - Agree strongly (4)
Timeinterests	Make time to do things you really want to do	Not at all (0) - Completely (10)
Trustlegal	Trust in the legal system	No trust at all (0) - Complete trust (10)
Stfgov	How satisfied with the national government	Extremely dissatisfied (0) - Extremely satisfied (10)
Excommunist	Living in a formerly communistic country	Dummy
Werehappy	How often were you happy past week	None or almost none of the time (0) - All or almost all of the time (3)

We have transformed the *happiness* variable from the initial eleven-step scale (0-10) provided in the dataset to a more compact five step ranking (0-4). Compressing the scale in such a manner is common within happiness economics.[17] An illustration of our transformation can be found in appendix table II. This transformation results in a merging of groups, allowing us to account for the underrepresentation of people who rank their life satisfaction on low levels. We further argue that this makes answers less arbitrary as it is easier to distinguish between categories on a more compact scale. While this makes the proportional odds assumption less likely to be violated due to the grouping of potentially differing variances in larger groups, if there is still evidence of such a violation it would only serve to strengthen our results. After transforming the data, we can see that approximately 12% of respondents rank their happiness in the two lowest categories:

Table 2: Distribution of observations across happiness levels

Happiness	Frequency	Percent	Cumulative
0	2015	3.89	3.89
1	3980	7.67	11.56
2	13653	26.32	37.88
3	19820	38.22	76.10
4	12396	23.90	100.00
Total	51864	100	

The income variable is divided into deciles rather than absolute numbers to account for differences in income between countries. For instance, a high income in one country could be a low income in another, but by placing people in income deciles this is accounted for. This results in ten different income groups. We have further transformed it by using the logarithm of income to account for the empirically proven diminishing returns to happiness of moving between income groups. While there are some controversies in transforming ordinal data as if it was continuous, this is mainly an issue for ordinal scales that do not represent some underlying data. Income deciles has an obvious underlying continuous scale that allows for such a measure. For a further discussion on this, see Rhemtulla et al. (2012).

We consider *providehelp* a proxy for altruistic behaviour, which has been found to have a positive effect on happiness as established in the theoretical background. An issue with this proxy is that providing help and support to people one is close to need not be truly altruistic. It might as well be a measurement for how close one is to people or how needy one's friends are. Nevertheless, as that would constitute a measurement of community and social life, both of which also are positively correlated with happiness, we argue for the inclusion of this variable, but urge caution.

[17] See for example MacKerron (2012) and Vinson and Ericson (2014).

Religion, *minority*, *closepeople*, *respect*, *receivehelp* and *trustpeople* are variables that represent different forms of social community. We argue that these are all different indicators of the quality of a social community as well as social life. By controlling for other measures of community than religion we eliminate the problem of distinguishing between the effects of the religious community and the actual belief in something. The *minority* variable is a proxy for alienation and the level of social inclusion. Unfortunately, this is a clear disadvantage as compared to a variable that actually measures these things directly as being a minority does not necessarily provide a good approximation for lack of social inclusion.

The variables *direction*, *accomplishment*, *freedomdecide* and *timeinterests* are all measures of different aspects of personal fulfilment and self-expression. A potential weakness could be that these variables do not provide a sufficiently accurate approximation. One could further argue that they are too similar to justify the split into several variables. Ideally, we would like to have access to a variable that more accurately and directly measures self-expression and personal fulfilment. We generally consider all variables necessary as well as good proxies of the different aspects of personal fulfilment, but note that they in aggregate need not fully represent the full concept.

To describe the state of the country we use the variables *trustlegal*, *stfgov* and *excommunist* and argue that these are all different measures of the functioning of a country. A potential issue here is overlap between the variables. The trust in a country's legal system and one's satisfaction with the government could reasonably be assumed to correlate rather strongly, even if this need not always be the case. In nations which have developed and sophisticated political systems, the trust in these institutions could well be expected to remain strong even if certain individuals are unhappy with the current ruling government. The *excommunist*[18] dummy controls for differences between countries in the data since as these nations tend to exhibit lower happiness levels (see discussion under section 2.2).

5.3. Extended analysis

We utilise an additional variable, *werehappy*, to control for possible reference bias in our model. In a famous experiment by Kahneman and Frederick (2002) related to happiness, respondents were asked about how happy they were with their life in general followed by a question about how many dates they had been on the past month. Answers to the two questions correlated imperceptibly when asked in the above order, but exhibited a staggering correlation of 0.66 when switching the order. It is obvious that such effects of attribute substitution (replacing a difficult question with an

[18] Our analysis includes Poland, Slovenia, Cyprus, Slovakia, Czech Republic, Estonia, Kosovo, Lithuania, Russia, Albania, Hungary, Ukraine and Bulgaria. These countries have either been openly communist or part of communist unions.

easier, more accessible one) causes a bias towards a certain stimuli which has large impacts on results and should therefore be controlled for. Our variable *werehappy*, being a measure of how happy one has been the past seven days, should adequately control for these reference biases.

To account for potential multicollinearity among the above variables we have created a correlation matrix (using Spearman's rank coefficient due to much of our data being ordinal). *Receivehelp* and *providehelp*, as well as *trustlegal* and *stfgov*, seem to have a high correlation. We also provide a table of variance inflation factors in which we can notice that the degree of variance inflation is low. We can therefore argue for the inclusion of all four of these variables. We argue that they measure different things and also do not inflate variance significantly. Both the correlation matrix and the table of variance inflation can be found in appendix tables IV and V.

Due to the fact that people within countries could show a tendency to agree with each other to a larger extent than between countries, we are aware that our data could show signs of intraclass correlation. In a report by Jeffrey et al. (2015) it was found that a great degree of variance in subjective well-being is explained by intra-country variance. By performing an ANOVA analysis of happiness across countries we find that approximately 13% of the variance in our happiness variable is explained within country. We thus opt to use cluster-robust standard errors to account for within-country variance. The ANOVA analysis can also be found in the appendix VI.

6. Results and analysis

Below we present our empirical results and analysis. We first produce descriptive statistics of the determinants of happiness and our tests of whether or not these violate the proportional odds assumption. As we find strong support that the proportional odds assumption is violated, we develop the partial proportional odds model and analyse the implications of it.

6.1. Empirical results

Table 3: Descriptive statistics of variables

Variable	Obs	Min	Mean	Max	Std. Dev.
Happiness	51864	0	2.706	4	1.036
Logincome	42312	0	1.415	2.303	0.706
Age	52050	15	48.492	103	18.546
Agesq	52050	225	2695.413	10609	1857.932
Health	52069	0	2.735	4	0.932
Male	52148	0	0.456	1	0.498
Tertiaryeducation	51991	0	0.292	1	0.455
Married	51548	0	0.511	1	0.500
Unemployed	52165	0	0.088	1	0.284
Lrscale	44178	0	5.182	10	2.304
Urban	35652	0	0.473	1	0.499
Providehelp	51662	0	5.127	6	1.088
Religion	51725	0	0.604	1	0.489
Minority	51534	0	0.065	1	0.247
Closepeople	51604	0	2.607	4	0.953
Trustpeople	51961	0	4.906	10	2.494
Respect	51341	0	4.471	6	1.214
Receivehelp	51688	0	4.958	6	1.251
Direction	51201	0	6.986	10	2.186
Accomplishment	51647	0	2.755	4	0.855
Freedomdecide	51921	0	3.004	4	0.901
Timeinterests	51605	0	6.619	10	2.216
Trustlegal	50725	0	4.692	10	2.825
Stfgov	50683	0	3.956	10	2.580
Excommunist	50320	0	0.478	1	0.500
Werehappy	51497	0	1.887	3	0.821

Table 4: Testing the proportional odds assumption

Variable	Wald	Violated
Logincome	0.00420	Yes
Age	0.0547	No
Agesq	0.3491	No
Health	0.00204	Yes
Male	0.0982	No
Tertiaryeducation	0.00195	Yes
Married	0.00001	Yes
Unemployed	0.00006	Yes
Lrscale	0.9414	No
Urban	0.4908	No
Providehelp	0.00363	Yes
Religion	0.0335	No
Minority	0.00000	Yes
Closepeople	0.3717	No
Trustpeople	0.0943	No
Respect	0.2008	No
Receivehelp	0.5111	No
Direction	0.00000	Yes
Accomplishment	0.0408	No
Freedomdecide	0.5816	No
Timeinterests	0.00010	Yes
Trustlegal	0.0658	No
Stfgov	0.00000	Yes
Excommunist	0.00000	Yes
Werehappy	0.3249	No

Numbers given for $p > \chi^2$
A significant test statistic provides evidence that the proportional odds assumption has been violated

The table shows a clear indication that the proportional odds assumption is violated for 11 out of 25 determinants of happiness at a 1% significance level. For many variables the significance goes well below that. What we find is that 11 out of 25 determinants of happiness violate the assumption and thus have varying betas across happiness levels. A table sorted by determinants that have varying or constant betas can be found in appendix table VII. This strongly supports our second hypothesis; the proportional odds assumption is violated and to account for this we develop a partial proportional odds model and compare it to the ologit model on the following page.

Table 5: Estimation of the happiness models

Variables	**Ordered logit** Happiness	**Partial Proportional Odds** 0	1	2	3
Logincome	0.321***	0.641***	0.381***	0.408***	0.173**
	(0.0643)	(0.119)	(0.0811)	(0.0824)	(0.0724)
Age	-0.0437***	-0.0416***	-0.0416***	-0.0416***	-0.0416***
	(0.00769)	(0.00848)	(0.00848)	(0.00848)	(0.00848)
Agesq	0.000431***	0.000407***	0.000407***	0.000407***	0.000407***
	(6.59e-05)	(7.13e-05)	(7.13e-05)	(7.13e-05)	(7.13e-05)
Health	0.313***	0.455***	0.395***	0.356***	0.241***
	(0.0437)	(0.0655)	(0.0679)	(0.0600)	(0.0377)
Male	-0.0586	-0.0520	-0.0520	-0.0520	-0.0520
	(0.0366)	(0.0366)	(0.0366)	(0.0366)	(0.0366)
Tertiaryeducation	-0.0772	0.0741	-0.0832	0.0188	-0.187**
	(0.0661)	(0.160)	(0.130)	(0.0822)	(0.0774)
Married	0.344***	0.450**	0.278***	0.243***	0.484***
	(0.0678)	(0.186)	(0.0677)	(0.0591)	(0.103)
Unemployed	-0.684***	-0.609***	-0.691***	-0.745***	-0.430**
	(0.117)	(0.0995)	(0.148)	(0.0981)	(0.195)
Lrscale	0.0571***	0.0569***	0.0569***	0.0569***	0.0569***
	(0.0159)	(0.0157)	(0.0157)	(0.0157)	(0.0157)
Urban	-0.0301	-0.0341	-0.0341	-0.0341	-0.0341
	(0.0504)	(0.0473)	(0.0473)	(0.0473)	(0.0473)
Providehelp	-0.0120	-0.217***	-0.122**	-0.0404	0.149***
	(0.0242)	(0.0792)	(0.0488)	(0.0278)	(0.0540)
Religion	0.00235	0.0165	0.0165	0.0165	0.0165
	(0.0623)	(0.0604)	(0.0604)	(0.0604)	(0.0604)
Minority	-0.322***	-0.962***	-0.485***	-0.456***	0.0175
	(0.116)	(0.144)	(0.179)	(0.0978)	(0.174)
Closepeople	-0.0115	-0.0102	-0.0102	-0.0102	-0.0102
	(0.0472)	(0.0481)	(0.0481)	(0.0481)	(0.0481)
Trustpeople	0.0721***	0.0726***	0.0726***	0.0726***	0.0726***
	(0.0124)	(0.0122)	(0.0122)	(0.0122)	(0.0122)
Respect	0.0654*	0.0651*	0.0651*	0.0651*	0.0651*
	(0.0381)	(0.0368)	(0.0368)	(0.0368)	(0.0368)
Receivehelp	0.145***	0.150***	0.150***	0.150***	0.150***
	(0.0265)	(0.0292)	(0.0292)	(0.0292)	(0.0292)
Direction	0.114***	0.0319	0.118***	0.122***	0.113***
	(0.0201)	(0.0281)	(0.0290)	(0.0270)	(0.0323)
Accomplishment	0.248***	0.249***	0.249***	0.249***	0.249***
	(0.0528)	(0.0545)	(0.0545)	(0.0545)	(0.0545)
Freedomdecide	0.136***	0.140***	0.140***	0.140***	0.140***
	(0.0476)	(0.0458)	(0.0458)	(0.0458)	(0.0458)
Timeinterests	0.125***	0.0855**	0.0578***	0.131***	0.156***
	(0.0179)	(0.0365)	(0.0195)	(0.0219)	(0.0193)
Trustlegal	0.0434**	0.0461***	0.0461***	0.0461***	0.0461***
	(0.0189)	(0.0173)	(0.0173)	(0.0173)	(0.0173)
Stfgov	0.129***	0.377***	0.238***	0.151***	0.0753***
	(0.0220)	(0.0772)	(0.0329)	(0.0236)	(0.0180)
Excommunist	-0.831***	-0.711***	-0.821***	-1.066***	-0.599***
	(0.251)	(0.204)	(0.253)	(0.281)	(0.217)
Werehappy	0.464***	0.463***	0.463***	0.463***	0.463***
	(0.0477)	(0.0437)	(0.0437)	(0.0437)	(0.0437)
Constant	-1.456***	-1.208***	-2.808***	-5.533***	-8.197***
	(0.405)	(0.369)	(0.284)	(0.517)	(0.469)
Observations	22,103	22,103	22,103	22,103	22,103
Pseudo R^2	0.1656	0.1800	0.1800	0.1800	0.1800

Standard errors clustered by country in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In the above table one can see that the number of observations on which we were able to run the regressions is 22,103, which is enough to ensure statistical representation. McFadden's pseudo R^2 is higher for the partial proportional odds model at 0.1800 than for the ordered logit model at 0.1656. This also shows good fit, given that a McFadden pseudo R^2 of 0.2-0.4 is considered excellent, as explained under section 4. A majority of our betas are significant at the 1% level. We also see that the *providehelp* variable is statistically insignificant when using the ologit model, but significant for the proportional odds model. For both models, unemployment and living in an ex-communist country have large negative impact on happiness and we see large positive effects on happiness from income, health and marriage. The largest positive effect comes from our control variable, *werehappy*. If a person has been happy in the last seven days has a huge impact on how that person measures her general level of life satisfaction. Accounting for this allows us to remove some of the risks of attribute substitution bias.

We can categorise our findings into two groups: determinants of happiness with constant betas and determinants that have shifting betas across different happiness levels. This split is interesting. It seems to suggest that some determinants are equally important regardless of a respondent's self-reported well-being, which is in line with previous research using ordered logit methods that ignore the proportional odds assumption. However, some determinants have shifting betas meaning that, in line with our initial hypothesis, their importance for happiness shifts across happiness levels. The determinants with constant betas are mainly the community variables, i.e. how close a respondent feels to those around her, and partly proxies of self-expression such as one's freedom to decide and sense of accomplishment from what they do, as well as some demographic factors. Determinants that exhibit differing betas are for instance income and having time for your interests, which does make intuitive sense. As you get happier, you derive less pleasure from income and more pleasure from having time to do what you are interested in. Interestingly, some of these determinants, such as a respondent's satisfaction with government and the respondent's subjective health also vary significantly across happiness levels. We cautiously conclude that the differing betas of these variables seem to imply that these determinants of happiness have a varying important for life satisfaction across happiness levels.

Of the betas that vary across happiness levels, every single one does so to a large extent, apart from sense of direction in life. It varies only very marginally (but with a high degree of statistical significance) across the three highest happiness levels, but has a much lower and statistically insignificant beta coefficient for the lowest happiness level. This could be an effect of most data being closely centred around the mean and that certain outliers cause a violation of the proportional odds assumption. Alternatively, it could mean that having a sense of direction in life is simply not important for your well-being when you are unhappy, but that it becomes important as you get happier.

6.2. Determinants with constant betas

Firstly, we observe that although the beta values for *male*, *urban*, *religion* and *closepeople* are constant across happiness levels, they are not statistically significant. Since we control for many other factors, it could be that the effects that these four variables have on happiness are simply included in the other factors. For instance, when controlling for community factors the effect of *religion* is statistically insignificant. This seems to suggest that it is the community component of religion that affects happiness, rather than being religious. Further, the previously found correlation between high happiness levels and living in an urban environment could be explained by the access to high-paid jobs, accounted for with our income variable. *Closepeople* being insignificant could in turn be explained by the fact that it is a measurement of how close a respondent is to people in her local area, which is not necessarily the same as feeling close to people in general nor is it a measurement of her social life and belonging to her community. It might simply be that on average, how close one is to people locally does not correlate with happiness levels. Two of our other community variables are measures of the degree of a respondent's trust in people and how respected she feels by people generally. Another is how often she receives help from people close to her. We argue these are all better estimators for the extent to which one feels belonging to a community than how close one feels to people in the local area.

Our results can confirm that when plotting happiness against age it returns a U-shaped curve, meaning that people are generally happiest during adolescence and after retirement, reaching its minima during midlife. Previous research has suggested that this minima is an effect of how responsibilities are many and the amount own-time is low at this point in life. As we control for this factor through the time for interests variable and find that the effect of age on happiness is still significant, we would like to offer an alternative explanation for the U-shaped curve. We believe this effect in part could be explained by deviations between how societal norms expect an individual to act at certain points in life and how the individual actually does act and has accomplished at these points. Simply, people feel they have not accomplished what is expected of them; or as previous research has suggested, that they are forced to give up the unattainable dreams of their youth.

We find evidence that people who sympathise with right-wing politics are generally happier than those further left on the political spectrum. It is difficult to determine if this supports the finding in previous literature that a respondent is more likely to be happy if the ruling government's politics consorts with her own; it would be very arbitrary to establish the aggregate of every ruling government's average placement on a left-right scale for all of Europe. It does however, to some extent confirm the findings conducted on happiness levels for republicans and liberal democrats in the United States and suggests the same relationship to be true for Europeans. We believe this to be an effect of right-wing conservatives being more prone to connive societal injustices, or conversely that left-wing sympathisers have a tendency to see them where they might not exist. Such a distinction cannot be established with the current data.

The variables that measure social communities and their importance all exhibit constant effects, except for the minority variable which could be an inadequate proxy for sense of belonging in a community since being a minority incorporates various other aspects. Further, this variable is not statistically significant at the highest happiness level. The other results seem to imply that the importance of human interaction does not change; specifically the value of feeling respected, being able to trust those around you and receiving help when needed. The same is true for the variables used a proxies for the degree of personal fulfilment. A sense of accomplishment and the freedom to decide how to live your own life both exhibit statistically significant, constant effect across all levels. The same intuition is applicable – these things seem to activate basic human reward systems whose utility is not altered depending on current happiness levels. Granted, it seems that there are no diminishing returns to hormonal rewards.

Interestingly, although the effect of trust in the legal system is constant, satisfaction with government is not. This is likely due to the sense of satisfaction correlating with the respondent's current state of mind and mood, whereas trust is a more deep-seated feeling detached from current mood (c.f. the *trustpeople* variable). However, both variables are subject to bias through attribute substitution, i.e. they are likely to be evaluated based on recent happenings such as what the respondent has seen in the news lately. The answers could then be weighted disproportionately towards that stimuli.

6.3. Determinants with varying betas

While we note that the betas of the education variable vary across happiness levels, we find no statistically significant results for this effect except for the highest happiness level. We cannot draw any conclusions regarding this variable's effect on happiness and will return to this issue in 7.2.

Unsurprisingly, we find that the income variable has a significant positive effect on happiness and can thus reconfirm previous research. Although the effect of income is always positive, this effect is drastically decreased when moving across happiness levels. This gives support to the notion that money can buy off unhappiness more efficiently than it buys happiness, again drawing on the separation of happiness into two scales. Perhaps you can buy a higher standard of living but not happiness, or it could be that it is the safety in income that is valued, but not what income can buy. The data points towards a trend of a diminishing effect of income on happiness *depending on current happiness levels*. It is important to note that this is separated from the traditional concept of diminishing returns of an increased income. This should be rather intuitive and is in line with need theories, borrowing from psychology. Once a person sees herself as happy, material wealth is overridden by personal fulfilment factors. In the light of this, the ordered logit model which suggests a constant effect across all levels seems to offer insufficient explanatory power.

The results that health yields are rather peculiar. While it would make intuitive sense that a respondent values her health equally across happiness levels, it seems it is not so. We do see a positive effect on happiness, but it decreases across happiness levels. As happiness increases, the importance of good subjective health decreases indicating that happiness is partly detached from physical conditions given that one is already happy.

We find statistically significant evidence that marriage positively affects happiness, in line with previous findings. We can establish that very unhappy as well as very happy people have much to gain from marriage whilst middle-category respondents are not affected as much. Any conclusions drawn from this result should be used with caution and incorporate a discussion on retrocausality. It might be that people at the ends of the happiness scale on both sides simply are more likely to wed.

Unemployment has a strict negative influence on happiness. In fact, it is one of the strongest effects of all our analysed variables. This puts further pressure on constructing policies aimed at fighting unemployment on a national scale as it seems to be one of the factors impacting unhappiness the most. Interestingly, the effect is increasingly negative up until the highest happiness level where it drops to about 60 percent of the effect found on the next highest level, remaining negative however. This fits with the finding that income becomes less important at higher happiness levels, resulting in less importance of employment. Further, people who exhibit such high happiness levels are likely to have found ways to assign meaning to their life and are thus not as concerned with employment. The preceding decrease seems to suggest that people at moderate happiness levels find a large portion of their meaning and happiness from their employment.

Providehelp demonstrates a shift from a negative effect on the lowest levels of happiness to a positive effect on happiness on higher levels. This shift is interesting. We argue it is an effect of that providing help to someone can have different meanings. For unhappy people it looks as if it is merely a burden and perhaps not voluntary whereas happy people might participate in such activities of sheer benevolence. Perhaps *providehelp* is best seen as a proxy for altruism only for people who are already happy. Again we would like to raise the issue of retrocausality; there is no way of telling if happy people simply are more altruistic than their less happy counterparts.

The *minority* variable has a remarkably strong negative effect on happiness, especially at the lowest level of happiness. This indicates an unfortunate result; an unhappy person belonging to a minority is likely to remain unhappy. For the highest level the effect cannot be established with statistical significance. This could imply that a member of a minority who considers herself happy might not be affected by – or perhaps even subject to – alienation and other factors causing unhappiness among other minority members. The general negative effect from being a minority is substantially smaller for the ologit model.

The time available for respondents to spend on interests has a positive effect across all levels. However, while it decreases between the lowest to the second-lowest level, it reaches a turning point and increases between the two highest levels. For everyone, spending time doing what one is interested in is a key to happiness, and more so for very happy people who derive the greatest pleasure from these leisure activities. This is consistent with a theory of shifting importance and that unhappiness can, or might even need to, be bought off whereas happiness is obtained from personal fulfilment.

The results from the *excommunist* variable are somewhat puzzling at first glimpse. The effect on happiness of living in an ex-communist country is negative, and increasingly so up until the highest level of subjective well-being. At this point the effect is actually closer to zero. It seems as if some kind of "happiness elite" in ex-communist countries are less affected than others. Despite, or perhaps because of, severe economic reform, happiness levels are generally lower in ex-communist European countries than other European countries. Many of the Eastern European states still struggle in many aspects and lag behind its Western counterparts. We hypothesise that this is closely tied to the functioning of a country's government. Indeed, when examining our dataset we find that ex-communist countries exhibit about 20 percent lower average satisfaction with government than do non ex-communist countries, standard deviations being roughly the same. The level of satisfaction with government is positively linked to happiness across all levels, however becoming gradually less important as happiness increases.

7. Discussion

Below we answer our research question, review additional insights from our model and discuss the robustness and limitations of our findings.

7.1. Answering our research question

We find strong evidence that the proportional odds assumption is violated. Subsequent econometric analysis clearly points towards the fact that several determinants of happiness differ in effect when moving across happiness levels. In particular, we show that even when controlling for diminishing marginal returns of income to happiness, income still has a distinctly lower effect on life satisfaction at higher happiness levels. This goes against the current understanding of the income-happiness relationship where it often is assumed that the lower effect of income on life satisfaction as happiness increases is purely due to it being a logarithmic function of income. Instead, our results suggest that being on a higher happiness level in itself causes people to value income less.

It is worth noting that there is a trade-off between the added complexity of the proportional odds model and the gains in terms of estimation quality. We argue that the use of the partial proportional odds model is warranted and adequate as we find such a distinct shift in importance for the determinants of happiness. Moreover, one of the variables that had a statistically insignificant effect on happiness in the ologit model was significant at a 1% level in the gologit model. Assuming that the proportional odds assumption holds is an assumption that the betas of the determinants of happiness are constant. It has the effect of the implicit assumption that the effects of the determinants of happiness are symmetric across all happiness levels. There is a clear indication from our paper that this need not be the case. Unless researchers actively assume that there is no shifting importance for the determinants of happiness and thus ignore the proportional odds assumption due to the added complexity of alternative models, they need to account for it in their models. Current practice is flawed and could potentially inhibit progress within the field of happiness economics.

7.2. Additional insights

There is clear support for the idea of shifting importance when examining determinants such as income or having time to spend on what you are interested in; their beta values vary significantly and one could reasonably explain why that is. However, some findings are peculiar. Why is the effect of having a tertiary education insignificant across all happiness levels except the highest one, where it has a significant and distinctly negative effect on happiness? This illustrates a weakness in the idea of shifting importance. It does not specify why some variables have constant betas and some vary, nor does it reasonably explain why some factors are insignificant at certain happiness levels, but not at others. It is as such hard to distinguish between what effects are artefacts of the data and more generally applicable results. Thus, more research needs to be conducted on other datasets to see if the proportional odds assumption is consistently broken and if determinants have distinctly varying effects across happiness levels. This would support the idea that there is an underlying theory explaining these violations of the proportional odds assumption, either ours or a different one.

One pattern among the variables is that the effect on happiness of belonging to a community seems to be constant across all happiness levels. This indicates that some determinants of happiness simply are not dependent on current happiness levels. An explanation of this could be that the value of social exchange and sense of safety from belonging to a community simply is independent from one's current well-being. Certain variables, such as sense of accomplishment and the freedom to decide how to live your life, also exhibit statistically significant, constant effects across all levels. It could be that these determinants trigger our biological reward systems and that we simply are wired to derive equally much life satisfaction across all levels of happiness from presence of these variables. Our current level of well-being does seem to affect the amount of happiness we can derive from other determinants of happiness. The question is if this is due to people actively shifting priorities or if it rather is a subconscious act? For instance, are the positive effects of income derived from an increased feeling of safety, which diminishes across happiness levels, or is it mainly the increased supply of available goods that comes with increased income that is important, which you value less when you are happy?

7.3. Robustness and limitations

The high pseudo R^2 of our model shows that it fits the data well, better than the ologit model. Combined with a vast sample size, this points in the direction that our results are robust. Furthermore, testing the proportional odds assumption and accounting for it is in itself an indicator of robustness. We conducted this test at the low significance level of 1%. In addition to this, as we transformed our happiness variable and split it into smaller groups, the proportional odds assumption should be less likely to be violated due to the grouping of potentially differing variances in larger groups. Despite these statistically conservative measures, we find that the ologit model still violates the proportional odds assumption, and for many determinants the violation of the assumption has a significance level of well below 1%. We also test for multicollinearity and find no evidence of there being variance inflation, which typically is neglected in gologit papers.

Even if the proportional odds assumption is violated, betas need to *distinctly* vary across levels of the happiness variable. Otherwise the model returns an abundance of parameters showing similar importance across happiness levels and this is more likely to be a function of the data, rather than an actual asymmetric relationship between happiness and its determinants. When examined we found that only one variable shows signs of this: sense of direction. What is peculiar about this determinant is that it seems to be insignificant at the lowest level of happiness, whereas it has a significant, but seemingly constant effect at the next three happiness levels. Whether this is an artefact of the data or an actual relationship is difficult to say and we recommend exercising caution when drawing conclusions from our results. For the remaining variables, there is a distinct shift in importance of betas across happiness levels.

As noted in section 2, a violation of the proportional odds assumption could be due to model misspecification. There are many different potential transformations of variables that could be made and tested for. Omitted variable bias and thus endogeneity is a common problem in economics, and happiness economics is certainly no exception; there are many determinants of happiness that we have not examined. However, the introduction of other variables or transforming our current variables has to be backed by theory. Using the partial proportional odds model to account for a violation of the assumption is actually based on our hypothesis; there is *shifting importance* of the determinants of happiness.

We do control for a certain amount of omitted variable bias and reference bias in the form of our *werehappy* variable, showing us that how happy one has been recently, significantly impacts how one ranks current levels of general life satisfaction. This illustrates the issues of self-reported data well. There is a risk of our data being biased in one direction. Perhaps people have a tendency to rank their happiness higher on questionnaires than they actually feel, due to pride or cultural reasons. Moreover, there are issues with our dataset being a cross-country study. Our ambition was indeed to analyse Europe as a whole, but there is a risk that cultural and language differences cause this aggregation of data to be faulty. The definition of "life satisfaction" could differ across European countries. By using the *excommunist* variable we account for some of this bias and clustering our standard errors at the country level accounts for inconsistent standard errors. The risk of endogeneity problems are thus reduced, but we still urge caution when analysing our model due to these bias risks. Regarding our use of dataset, there is also the risk that by examining only the 2012 data set, we expose ourselves to the risk that our observations on aggregate is a statistical outlier in comparison to other years and not generally applicable.

Further, it is of great importance to discuss the possibility that our findings suffer from retrocausality. If this is the case, variables that have been found to affect happiness might in fact have an inverse relationship – happier people might simply tend to do certain things rather than actually becoming happy from them. It is hard to prove that an increased income makes people happier as opposed to that happier people might simply make more money. While some of these inverse relationships might be counter-intuitive they could still hold true. Such could be the case for marriage for example. Marriage could be expected to increase happiness by many but it might simply be that happier people are more likely to wed. With varying betas, retrocausality becomes harder to argue for. One has to show not only that being happy causes the effects we see in the determinants of happiness, but also why this effect varies across happiness levels.

There is also the issue of simultaneity to address. Chances are that factors such as satisfaction with the government, trust or how close one feels to people are variables that do affect life satisfaction, but that life satisfaction in turn affects these variables once more. It is closely related to the concept of retrocausality mentioned above, but differs in the sense that happiness would create a "feedback loop" in which it is dependent on itself. Happiness thus breeds more happiness. Although this potential endogeneity problem is an issue for most models using happiness as their dependent variable, we still urge caution when analysing our estimated beta values as they could be biased.

A benefit of our methodology and approach is that it has high replicability and thus the prospects for testing external validity are good. It should be possible to conduct the same analysis on a different dataset in a replication study and get the same results, or build on our research to further examine the nature of the relationship between happiness and its determinants. Although we have accounted for many common problems in econometrics and statistics, such as multicollinearity, clustered standard errors and potential sampling biases, there are still uncertainties with regard to potential retrocausality, simultaneity, biases due to our dataset being based on single year data and the varying interpretations of what "life satisfaction" means across languages and cultures. The main question with regard to internal validity is why certain factors vary across happiness levels and some do not. Not being able to provide the answer to this makes it difficult to distinguish between statistical artefacts and actual causal connections. This is certainly an interesting area for future research.

8. Concluding remarks

In this paper, we have tested the idea that the effects of the determinants of happiness vary in importance depending on happiness levels. We conducted econometric analysis on a vast cross-sectional dataset from 2012 covering the majority of European countries and found strong indications that many of the determinants of happiness violate the proportional odds assumption when used in an ordered logistic regression model. By subsequently applying the more sophisticated partial proportional odds model instead we find that certain variables do in fact distinctly vary across happiness levels. We have established that assuming proportional odds for a statistical model indirectly has the implication of falsely assuming that factors affect happiness symmetrically across all happiness levels. Our results regarding violations of the proportional odds assumption are robust and statistically significant with very low alpha values and our regression yields a high pseudo R^2, suggesting good fit to the data.

Our contribution to the current state of knowledge can be split into two. Firstly, we show that the negligence in testing the proportional odds assumption common in previous research has severe implications for the results of econometric analysis of happiness and the interpretation of the results. This implicit assumption of symmetrical relationships between happiness and its determinants is potentially inhibiting progress within the field of happiness economics. Secondly, we show that the determinants of happiness have a different effect on happiness depending on one's current position on the happiness scale. While previous research using partial proportional odds models for examining happiness exists, it does not examine multiple determinants of happiness, but rather specific variables. Moreover its representativeness is questionable because it uses old, country-specific datasets with small sample sizes. Our research uses recent data with a large sample size, examines Europe as a whole, and looks at the effects of all the most commonly examined determinants of happiness. This fills at least two important gaps in the field of happiness economics.

Future research should further examine what violations of the proportional odds assumption implies. Our findings should be reconfirmed using a different dataset to reassure no loss of generality, or build on the results to find what it is that causes the importance of certain variables to shift across happiness levels. Are the effects caused by an active prioritisation of certain determinants, or is a more subtle relationship involved, such as dormant emotional factors or evolutionary reasons? Furthermore, one could examine if certain transformations of variables result in that the assumption holds and examine the validity of these transformations. Lastly, as we have examined the microfoundations of happiness, a potential future research area could be to examine the effects of external, macroeconomic factors on happiness and whether these too vary across happiness levels. Such measures could include interest rates, stock market performance or GDP growth.

The policy implications for our findings are substantial. If one can distinguish the factors that help unhappy individuals in society the most, it goes a long way to maximise the utility of a population. Perhaps this is a more modern and adequate approach to policymaking than economic growth. For instance, in order to minimise utility loss and maximise utility gains for unhappy people, policy should address unemployment and issues revolving around being a minority in a country, as well as try to improve people's general health. As the income variable we use is measured in deciles and there is a highly significant, positive relationship between being in higher income categories and happiness, this poses a problem for policy makers. People seem to measure their happiness in relation to other, higher income categories. Thus, if income is increased for the general population, certain groups will still be poor in relationship to others, leaving the current disparity in life satisfaction unchanged. Unless income is perfectly equal across populations, someone always has to be in the lowest income bracket. This means that in order to increase happiness, policy makers would have to focus on the other determinants of happiness rather than income.

Moreover, better models allow us to price determinants of happiness more efficiently. It is possible to calculate how much income is required to neutralise the disutility of bad factors across all happiness levels, or alternatively examine how much people derive pleasure from factors such as sustainability and compare it to how much income is required to accomplish the same effects. By doing so, better quantification of happiness can help by pricing for example sustainability or pollution. Such experiments of pricing sustainability have previously been conducted but are very much still in their infancy. Lastly, as most macroeconomic indices such as HDI and GNH are based upon individual measures of happiness, showing that determinants of happiness have a varying effect on happiness across happiness levels allows for index makers to account for this in their weightings to give more accurate representation of countries.

To conclude, we have offered new insights into how the importance of the determinants of happiness might change as happiness increases. These results are robust and significant. In spite of this, we find it necessary to mention that ultimately, happiness is in its nature dependent on innumerable variables and conditions. While quantifying happiness does offer a valuable glimpse into what we as humans value and what makes us appreciate life, we can probably never establish a secret recipe or combination of variables that result in pure happiness. Perhaps this is the very charm of the pursuit of happiness. We believe this is a lesson to be learned, not by means of economic sciences, but through life itself.

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Appendix

Table I: Distribution of observations across European countries

Country	Frequency	Percent	Cumulative
Albania (AL)	1201	2.30	2.30
Belgium (BE)	1869	3.58	5.89
Bulgaria (BG)	2260	4.33	10.22
Switzerland (CH)	1493	2.86	13.08
Cyprus (CY)	1116	2.14	15.22
Czech Republic (CZ)	2009	3.85	19.07
Germany (DE)	2958	5.67	24.74
Denmark (DK)	1650	3.16	27.90
Estonia (EE)	2380	4.56	32.47
Spain (ES)	1889	3.62	36.09
Finland (FI)	2197	4.21	40.30
France (FR)	1968	3.77	44.07
United Kingdom (GB)	2286	4.38	48.45
Hungary (HU)	2014	3.86	52.31
Ireland (IE)	2628	5.04	57.35
Iceland (IS)	752	1.44	58.79
Italy (IT)	960	1.84	60.63
Lithuania (LT)	2109	4.04	64.68
Netherlands (NL)	1845	3.54	68.21
Norway (NO)	1624	3.11	71.33
Poland (PL)	1898	3.64	74.97
Portugal (PT)	2151	4.12	79.09
Russia (RU)	2484	4.76	83.85
Sweden (SE)	1847	3.54	87.39
Slovenia (SI)	1257	2.41	89.80
Slovakia (SK)	1847	3.54	93.34
Ukraine (UA)	2178	4.18	97.52
Kosovo (XK)	1295	2.48	100.00
Total	52165	100.00	

Table II: Transformation of happiness scale

Old	0	1	2	3	4	5	6	7	8	9	10
New	0		1		2			3		4	

Table III: Various forms of generalised ordered logistic regression

Ordered logistic model			
Variable	Level 1	Level 2	Level 3
X_1	0.634		
X_2	0.121		

Partial proportional odds model			
Variable	Level 1	Level 2	Level 3
X_1	0.716	0.658	0.544
X_2	0.119		

Multinomial logistic model			
Variable	Level 1	Level 2	Level 3
X_1	0.687	0.645	0.569
X_2	0.175	0.144	0.075

Examples of beta coefficients for two independent variables X_1 and X_2 across four levels of an ordinal dependent variable.

Table IV: Correlation matrix (Spearman)

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.
1. Happiness	1																								
2. Logincome	0.25	1																							
3. Age	-0.07	-0.20	1																						
4. Health	0.33	0.24	-0.42	1																					
5. Male	0.03	0.10	-0.04	0.08	1																				
6. Tertiaryeduaction	0.08	0.32	-0.07	0.11	-0.03	1																			
7. Married	0.07	0.25	0.24	-0.04	0.06	0.06	1																		
8. Unemployed	-0.15	-0.21	-0.15	0.01	0.03	-0.07	-0.05	1																	
9. Lrscale	0.14	0.07	0.00	0.07	0.03	0.00	0.03	-0.04	1																
10. Urban	-0.03	0.12	-0.06	0.03	-0.02	0.19	-0.08	-0.02	-0.03	1															
11. Providehelp	0.18	0.03	0.02	0.10	-0.08	0.00	0.09	-0.02	0.02	-0.02	1														
12. Religion	-0.04	-0.11	0.15	-0.07	-0.09	-0.04	0.10	0.00	0.09	-0.08	0.05	1													
13. Minority	-0.09	-0.05	-0.04	-0.04	0.00	0.00	0.00	0.06	-0.05	0.05	-0.02	0.07	1												
14. Closepeople	0.09	-0.06	0.14	0.00	-0.01	-0.08	0.10	-0.01	0.04	-0.20	0.16	0.12	-0.03	1											
15. Trustpeople	0.29	0.19	-0.03	0.17	0.03	0.15	0.01	-0.08	0.03	0.03	0.03	-0.08	-0.04	0.03	1										
16. Respect	0.25	0.04	0.09	0.11	-0.02	0.04	0.07	-0.06	0.05	-0.04	0.31	0.08	-0.04	0.29	0.15	1									
17. Receivehelp	0.25	0.08	-0.02	0.14	-0.05	0.02	0.04	-0.06	0.03	-0.02	0.62	0.04	-0.04	0.16	0.11	0.32	1								
18. Direction	0.36	0.17	-0.05	0.23	0.03	0.11	0.08	-0.10	0.10	0.01	0.29	0.03	-0.04	0.14	0.13	0.29	0.30	1							
19. Accomplishment	0.30	0.14	-0.03	0.21	0.03	0.07	0.08	-0.11	0.06	-0.02	0.23	0.01	-0.05	0.18	0.10	0.26	0.22	0.35	1						
20. Freedomdecide	0.25	0.05	-0.01	0.17	0.04	0.05	-0.03	-0.05	0.07	0.02	0.18	-0.03	-0.04	0.12	0.08	0.23	0.18	0.26	0.35	1					
21. Timeinterests	0.27	0.01	0.07	0.12	0.04	-0.01	-0.03	-0.03	0.06	-0.02	0.21	0.01	-0.04	0.14	0.11	0.23	0.23	0.32	0.23	0.22	1				
22. Trustlegal	0.35	0.16	-0.04	0.18	0.03	0.11	-0.01	-0.08	0.07	0.02	0.03	-0.07	-0.04	0.01	0.37	0.16	0.11	0.15	0.12	0.11	0.12	1			
23. Stfgov	0.35	0.17	-0.01	0.13	0.02	0.10	0.01	-0.11	0.16	0.01	-0.01	-0.04	-0.01	0.02	0.30	0.10	0.06	0.16	0.11	0.10	0.12	0.49	1		
24. Excommunist	-0.29	-0.03	-0.02	-0.16	-0.05	-0.01	0.01	0.03	0.04	0.01	-0.06	0.09	0.09	0.01	-0.22	-0.16	-0.10	-0.01	-0.11	-0.11	0.01	-0.36	-0.18	1	
25. Werehappy	0.40	0.17	-0.13	0.30	0.03	0.06	0.07	-0.08	0.08	-0.02	0.19	-0.03	-0.06	0.10	0.13	0.21	0.23	0.29	0.30	0.24	0.20	0.13	0.12	-0.12	1

Table V: Testing variance inflation

Variable	VIF	1/VIF
Providehelp	1.54	0.648815
Receivehelp	1.49	0.670960
Trustlegal	1.49	0.671385
Age	1.45	0.687635
Logincome	1.37	0.730976
Health	1.37	0.731926
Excommunist	1.35	0.742011
Stfgov	1.33	0.752325
Respect	1.30	0.770844
Direction	1.29	0.772946
Accomplishment	1.29	0.775153
Married	1.23	0.814932
Werehappy	1.23	0.815866
Freedomdecide	1.21	0.824409
Timeinterests	1.20	0.833820
Tertiaryeducation	1.19	0.840296
Closepeople	1.18	0.844346
Trustpeople	1.17	0.856764
Urban	1.11	0.899091
Unemployed	1.10	0.906031
Religion	1.09	0.917619
Lrscale	1.07	0.936535
Minority	1.04	0.958660
Male	1.04	0.965447
Mean VIF	1.26	

Table VI: Testing intraclass correlation

Source	SS	df	MS	F	Prob > F
Between country	6721.1023	27	248.92972	272.440	0.0000
Within country	47363.076	51836	0.91371009		
Total	54084.179	51863	1.0428278		

Number of obs	51864
R-squared	0.1243
ICC	0.12773
Est. reliability of a country mean	0.99633

Table VII: Varying and constant betas

Variable	Beta coefficient
Logincome	Varying
Health	Varying
Tertiaryeducation	Varying
Married	Varying
Unemployed	Varying
Providehelp	Varying
Minority	Varying
Direction	Varying
Timeinterests	Varying
Stfgov	Varying
Excommunist	Varying
Age	Constant
Agesq	Constant
Male	Constant
Lrscale	Constant
Urban	Constant
Religion	Constant
Closepeople	Constant
Trustpeople	Constant
Respect	Constant
Receivehelp	Constant
Accomplishment	Constant
Freedomdecide	Constant
Trustlegal	Constant
Werehappy	Constant
Amount varying	11
Amount constant	14
Total	25