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Master Thesis [Behavioural Economics]

The Economic Preference Parameters Risk Attitude and Ambiguity Attitude and Their Association With the Big Five Traits and Facets

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Abstract

Background: Linking personality to various outcomes has a long academic history but is a rather new discipline in economics. Previous research in economics was able to find an association between the Big Five traits Agreeableness and Neuroticism and the economic preference parameter risk attitude. However, no link between personality and the economic preference parameter ambiguity attitude could be established. I evaluated the association between personality and the two economic preference parameters risk attitude and ambiguity attitude. **Methods**: I used the NEO-IPIP-120 to measure the Big Five traits (Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness) and the 30 Big Five facets. Risk attitudes and Ambiguity attitudes were elicited using the design of Borghans et al. (2009). To understand the relationship between personality and the economic preference parameters I used linear regressions, zero-order correlations, and semi-partial correlations. I validated the regressions using the holdout method. **Results**: Data from 237 participants were included in the analysis. The holdout method indicated that the Big Five traits and facets are weak predictors of risk attitudes and ambiguity attitudes, however, the traits and facets still revealed significant directional effects. The regressions showed that the Big Five trait Conscientiousness ($p = 0.03$) is positively related to risk aversion, and the Big Five trait Agreeableness ($p = 0.005$) is positively related to ambiguity aversion. The Big Five facet N4 Self-Consciousness ($p = 0.009$) is negatively related to risk aversion. Furthermore, the Big Five facets provided incremental benefits in estimating risk attitudes: the facet model exhibited a 5 times higher adjusted R^2 compared to the trait model. No incremental benefits were observed when estimating ambiguity attitude with facets. **Conclusion:** Conscientious people tend to be more risk averse, Agreeable people tend to be more ambiguity averse, and Self-Conscious people tend to be more risk seeking. I recommend the usage of the Big Five facets in future studies because of the incremental benefits they can provide.

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1 Introduction

Individual differences define our uniqueness. Dating all the way back to Plato, the study of how alike and how unalike we are is still at the core of today's' behavioural sciences. Modern psychology defined a three pillar approach to individual differences: (1) people vary on numerous attributes, (2) these differences can be measured, and (3) these differences can predict outcomes (Asthon, 2013). In this paper, I make use of one of the most commonly used topic in the study of individual differences: Personality. Personality research has long been prominent in psychology literature and has recently also gained increased attention in economics and outside of academia. In practice, the usage of personality is numerous. Notoriously, Cambridge Analytica used personality characteristics to match people with suited advertisement to swing the election in President Trump's favour (Rosenberg, Confessor, & Cadwalladr, 2018). In the realm of economic academia, the usage of personality research is relatively novel and has not yet been explored to its full potential (Almlund, Duckworth, Heckman, & Kautz, 2011).

At the forefront of a solid theoretical personality framework is the Big Five. The Big Five is mainly characterised by its five large traits: Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism. Recent research in economics has increasingly focused on these Big Five traits thanks to the efforts made by Almlund et al. (2011) and Müller & Schwieren (2017) who advocate the usage of personality in economics. Building on this foundation, I introduce a more comprehensive personality framework to economics: the 30 Big Five facets. The introduction of the Big Five facets to economics constitutes the primary contribution of this paper. The 30 Big Five facets are narrower attributes defining human personality; each Big Five trait is the product of six Big Five facets. Hence, in this personality framework there are the Big Five traits and 30 facets. Psychologists have argued that the Big Five facets could provide incremental benefits in predicting outcomes, compared with using the Big Five traits (e.g. Anglim & Grant, 2014). Therefore, the secondary contribution of this paper is to provide future research with evidence whether these incremental benefits can be observed in economical settings.

To test the incremental effects the Big Five facets may have in the field of economics, I will relate the Big Five framework to economic preference parameters. Two of the most fundamental parameters in economics are risk attitudes and ambiguity attitudes because both parameters help explain economic decision making under uncertainty. More specifically, risk attitudes can account for people's behaviour in situations where all outcomes and their respective probability of occurring are known. For example, risk attitudes can help explain behaviour in bets involving a coin flip. Ambiguity attitudes can account for people's behaviour in situations where all outcomes are known but their respective probability of occurring is not. For example, ambiguity attitudes are partly used to explain trading behaviour, or lack thereof, in the stock market (Dimmock, Kouwenberg, & Wakker, 2016). In short, risk attitudes and ambiguity attitudes are important and well-known parameters in behavioural economics. Previous research was able to establish a relationship between personality and these economic preference parameters: Borghans et al. (2009) found that the Big Five traits Agreeableness and Neuroticism positively relate to risk aversion. However, they were unable to find a relation between the Big Five traits and ambiguity attitude. Though, Borghans et al. (2009) did not measure the 30 Big Five facets. Thus, the tertiary contribution of this paper is to examine whether the missing link between personality and ambiguity can be found with the narrower Big Five facets. Additionally, I test whether I can replicate Borghans et al (2009) Big Five traits findings and whether risk attitudes could be better explained using the Big Five facets.

The remainder of this paper is structured as follows. In the next section, I present the methodological steps applied in personality research: from the selection of the personality framework to the statistical analysis. In section 3, I define the economic preference parameters and describe the elicitation method used. In section 4, I present the hypotheses. In section 5, I present the study design and data collection. In section 6, I present and discuss the results. Section 7 concludes the paper.

2 Personality Research

The study of personality is complex and requires effort and time to understand (Almlund, Ducksworth, Heckman, & Kautz, 2011). Over the past decades, the social sciences have arrived at some consensus regarding the appropriate approach to personality research. This is in stark contrast to economics where the personality methodologies vary. The methodology presented in this paper follows mainly the one found in personality literature. Though, before stating my method, I will summarize the methodological approaches by economists (Figure 1) and social scientists (Figure 2), and then compare them to mine (Figure 3). Figure 3 will additionally serve as a guide for the remainder of this section as each step in the figure has its own sub-chapter. Appendix A features a combined figure which may help guide future researchers.

First, the typical process of an economist (see Figure 1). The first step after starting the research is deciding on a personality framework. Choosing the Big Five framework is often the case, though outdated theories are also being used. Next, the level analyses by economists is generally the Big Five traits. The questionnaires used are often appropriate short-form questionnaires that only measure the Big Five traits and not the Big Five facets. Lastly, the Big Five traits are related to a dependent variable of interest.

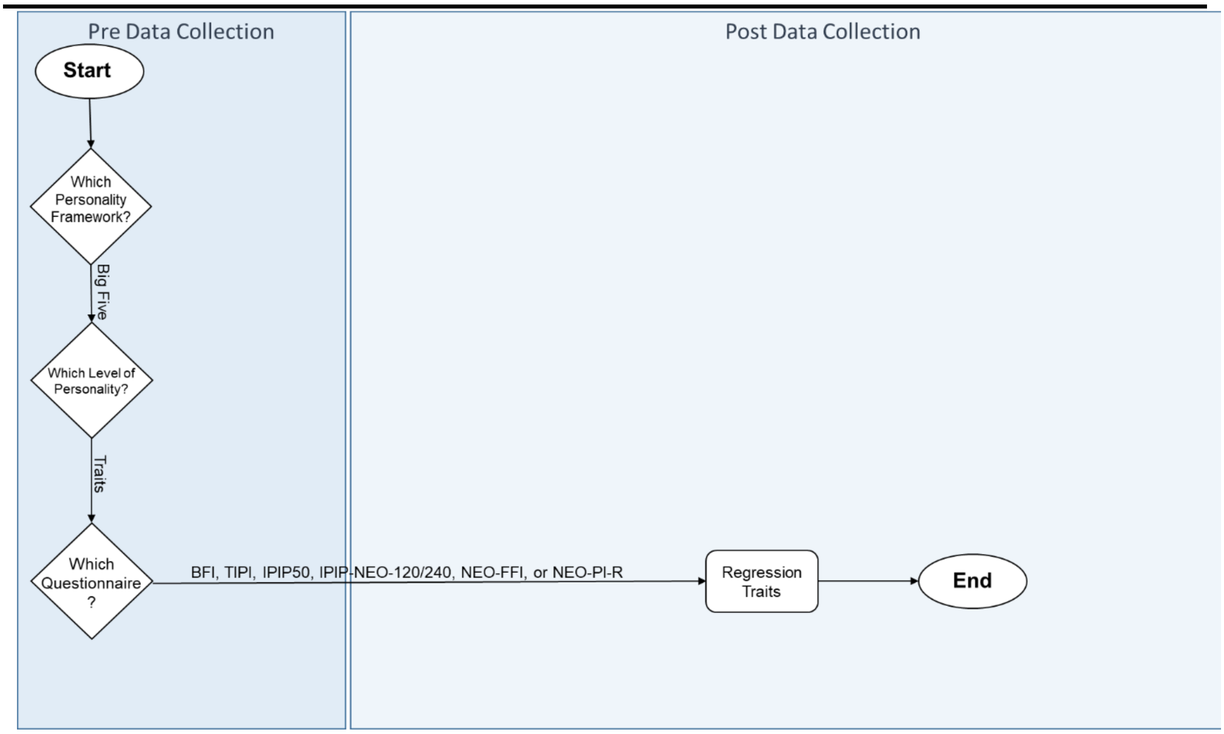

Figure 1. The typical process of an economist when conducting personality research.

The process of social scientists (see Figure 2) is largely the same as that of an economist, with one key difference: often measuring the 30 Big Five facets. In addition to measuring the Big Five traits, social scientists are often interested in the facets because they can provide incremental benefits over the traits. Longer form questionnaires are used to measure the facets; the traits are then calculated on the basis of the facet scores. Two additional smaller differences should be mentioned. First, Cronbach's alpha is calculated to measure the internal consistency of the traits and facets. Second, in addition to regression coefficients, effect sizes are calculated to speak on the strength of the relationship between personality and an outcome.

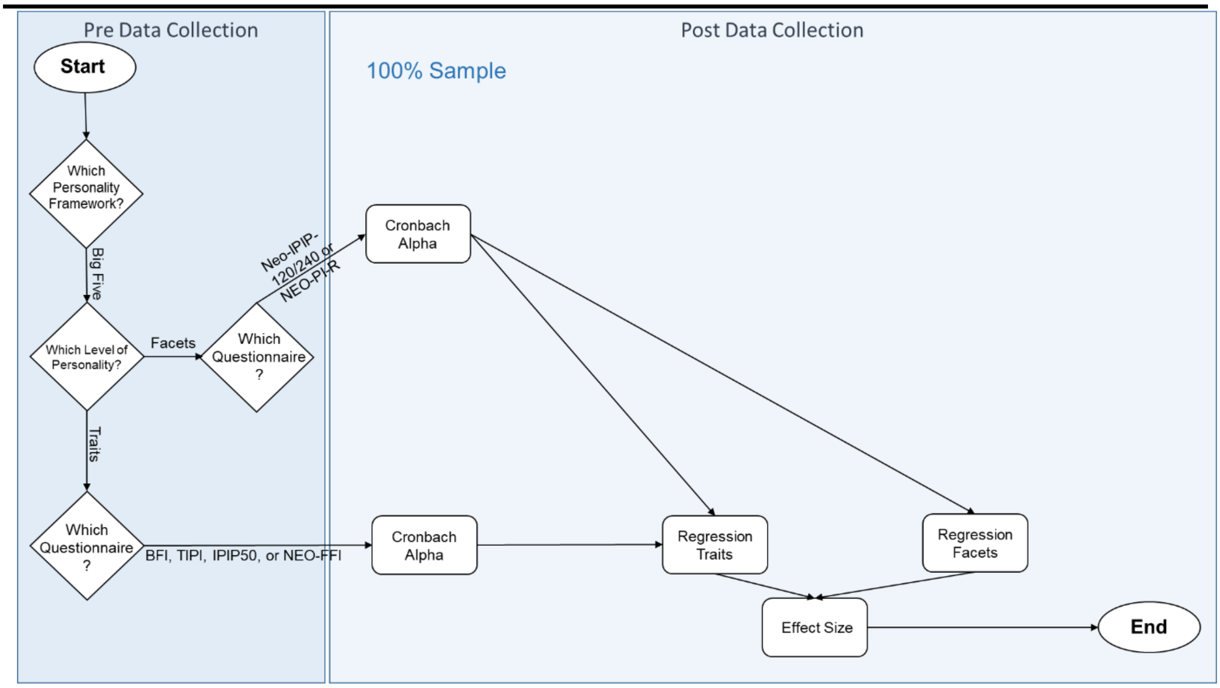

Figure 2. The typical process of a social scientist when conducting personality research.

My methodology (Figure 3) builds on the approach by social scientists, but adds more elements: using the holdout method and reporting semi-partial correlations. The holdout method addresses the problem of over fitting which can occur when fitting a model with multiple variables onto a dataset. Therefore, the dataset is split into two: a training sample (80% of the data) and a testing sample (20% of the data). The model is fit in the training sample and then used to predict the outcomes in the testing sample. Optimally, both models should exhibit low mean squared errors (MSE) to be confident in the predictive power. The semi-partial correlations state the unique contribution to R^2 of a variable and can thus be helpful in determining the strength of a relationship.

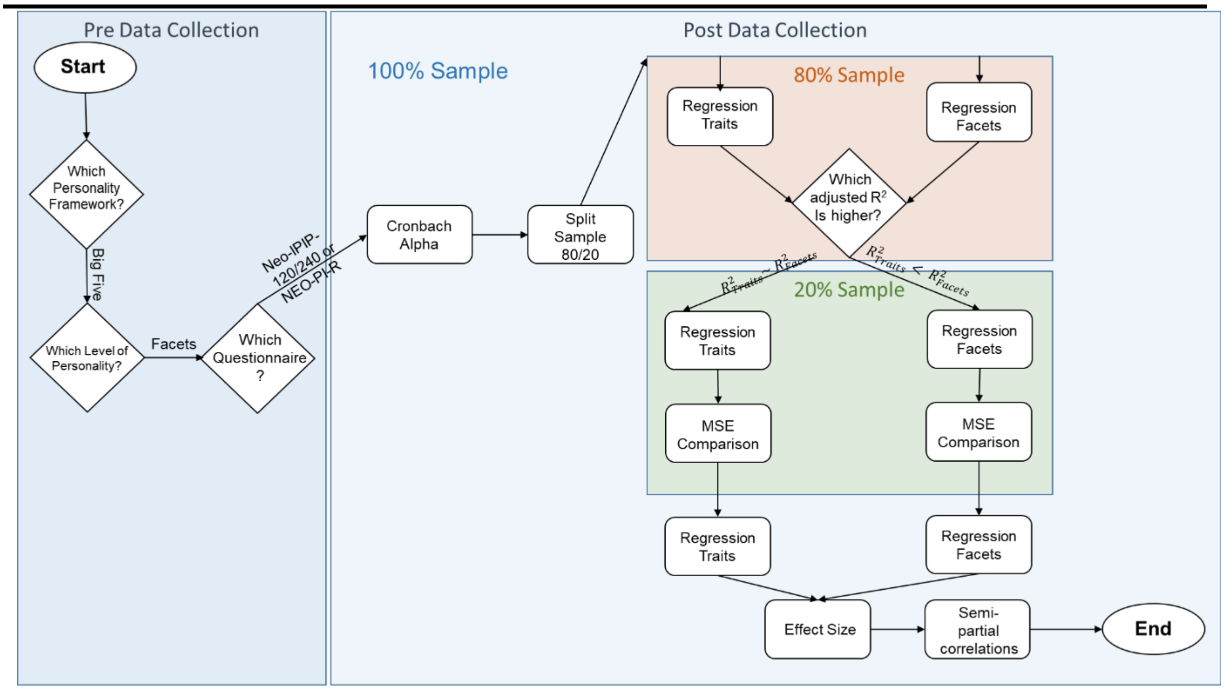

Figure 3. The methodology in my research.

The following section is divided accordingly to the steps in Figure 3, with the two overarching themes pre data-collection procedures and post data-collection procedures. For all steps in the figure I provide argumentations for deciding on a particular direction. The statements made about economists and psychologists/social scientists are mainly based on a self-conducted literature review (see Tables B1, B2, B3 in Appendix B): I collected 22 papers of economists who use personality as an explanatory variable in their models and 19 papers of social scientists who do the same. Then, I excluded papers who did not use a Big Five Test which left 10 papers by economists and 15 papers by social scientists.

2.1 Pre Data Collection

In this chapter, I first discuss the selection of a personality framework, then which levels within this personality framework are analysed, and lastly, which questionnaires are appropriate to measure personality attributes.

2.1.1 The Selection of a Personality Test

Personality has been studied extensively; over time the consensus emerged that the Big Five test is the most reliable and valid method to conceptualise personality (e.g. Almlund, Duckworth, Heckman, & Kautz, 2011; Anglim & Grant, 2014; Goldberg, et al., 2006; McCrae & Costa, 1997). The road to this conclusion was pathed with various other tests that emerged during the 20th century. Because of this large pool of personality tests, it can be confusing for researchers to choose an appropriate one (Almlund, Ducksworth, Heckman, & Kautz, 2011).

For interested readers, I provide an (incomplete) list of past and current alternatives to the Big Five: Rorschach Inkblot Test, Minnesota Multiphasic Personality Inventory, Eysenck Personality Questionnaire, HEXACO, the Dark Triade, and the Myer-Briggs Type Indicator. The *Rorschach Inkblot Test* (Wood, Neyworski, Lilienfield, & Garb, 2016) enjoys features in various movies such as the Watchmen, and its inkblot assessment cards have pop-cultural value. During the personality assessment, subjects reveal what they see in the inkblots. Then, a mix of subjective evaluation and statistical analysis reveals one's personality. Its primary application was in the realm of mental health issues. *The Minnesota Multiphasic Personality Inventory* (Hathaway, 1982) is a questionnaire that has since largely replaced the Rorschach Inkblot Test in mental health facilities. The MMPI measures several scales which provide information on personality aspects and symptoms of clinical disorders. The *Eysenck Personality Questionnaire* (Eysenck & Eysenck, 1975) measures three traits: Extraversion, Neuroticism, and Psychoticism. In addition to introducing the concept of traits, Eysenck also improved the personality literature by introducing the notion that personality may be formed during the developmental stages. Today, it is generally accepted that one’s personality is the result of both nature and nurture (Stangor, 2011).

The *16PF Questionnaire* (Cattell & Mead, 2008) was the first to make use of psychometrics and derive five traits – which are also highly correlated to the Big Five traits.

The main difference between the 16PF and the Big Five questionnaires lies in the way the factor analysis was performed. Cattell, the inventor of 16PF, argued that the factors should be rotated oblique wise. This would allow the five traits to strongly correlate with each other; an assumption that is theoretically supported. However, the inventors of the Big Five Questionnaires rotated the traits orthogonally, thereby restricting the correlation between the traits. This was mainly done to simplify further statistical procedures when using their questionnaire, and is one of the reasons the 16PF has fallen out of favour in the psychology community (Almlund, Ducksworth, Heckman, & Kautz, 2011). *HEXACO* (Ashton & Lee, 2009) is a rather new model and extended the Big Five by adding a 6th factor: Honesty-Humility. It has shown some promising results though further tests and time is needed to assess its reliability and validity fully. Lastly, the *Dark Triad* (Jones & Figuredo, 2012). This personality model consists of 3 negative traits and is used to predict socially undesirable outcomes. Like the HEXACO, the Dark Triad has recently seen an increase in usage in the literature though further evaluations are needed as well. Lastly, the *Myer Briggs Type Indicator (MBTI)*. The MBTI is probably the most well-known personality test, mainly because of its high search engine ranking and usage by companies. However, studies have consistently shown that the MBTI is unreliable and invalid as a personality assessment. It should therefore not be used in serious research (e.g. Carskadon, 1979; Dickson & Kelly, 1985; Pittenger, 1993).

In comparison, the Big Five framework has survived the test of time by exhibiting a high reliability, high validity, solid underlying theoretical framework, and psychometrical support (Almlund, Duckworth, Heckman, & Kautz, 2011; Anglim & Grant, 2014; Goldberg, et al., 2006; McCrae & Costa, 1997). Therefore, researchers should generally use a Big Five questionnaire when assessing personality. However, current scientifically supported alternatives are the HEXACO and Dark Triad. The former may be especially useful in economic trust game settings because of its Honesty-Humility trait.

2.1.2 What level of personality should be analysed?

The Big Five are part of a hierarchy that captures overarching factors as well as underlying facets. The five commonly accepted levels in this hierarchy, are in order from top to bottom, the General Factor of Personality (Musek, 2007; van der Linden, te Nijenhuis, & Bakker, 2010), the Large Two (Digman, 1997), (DeYoung, Peterson, & Higgins, 2002), the Big Five (traits) (Goldberg, 1981; McCrae & Costa, 1987), the DeYoung facets (DeYoung, Quilty, & Peterson, 2007), and the Big Five facets (Goldberg, 1981; McCrae & Costa, 1987). The most commonly studied personality frameworks are the Big Five traits and the Big Five facets (See Appendix C, section: Tenth Page, for the definitions of all Big Five traits and facets). For the purpose of this study, I will focus on these two and aside the other three frameworks. I continue by exploring the advantages and disadvantages of the Big Five traits and the 30 Big Five facets.

The most compelling reason for using the Big Five traits is the statistical principle of parsimony or Occam's razor: parsimony refers to the idea that simpler models are preferred to more complex models, and Occam's razor states that unnecessary assumptions or explanations need to be "shaven" away from a theory or model. Thus, if the variance explained with Big Five traits is virtually the same as in the case when the 30 Big Five facets are used, the model with five factors is always preferred. However, the assumption that the Big Five traits will explain the same as the 30 facets does not always hold. Two scenarios highlight this fact. First, the traits may explain less variance if none of the traits are significantly related to an outcome, but a subset of facets are. Statistically, this can be explained as follows: If within a trait, only one out of the six facets correlates to an outcome, then the trait will most likely be insignificant as a whole and thus not express this relationship. Similarly, if, in the same trait, one facet correlates positively and one facet correlates negatively to an outcome, then the trait will likely show non-significance as well because the facets cancel each other out. Second, even if the traits are significant, the variance explained using facets can be considerably larger compared with using the Big Five traits (e.g. Anglim & Grant, 2014). Both arguments can be condensed into the following equation:

$$\rho^2_{facets} \geq \rho^2_{factors}$$

where ρ corresponds to the explained population variance; usually expressed in an (un)adjusted R^2 form.

Another reason why the Big Five traits are preferred is to avoid statistical difficulties that occur when using the 30 facets. The statistical difficulties can be summarized with two questions: how to address the problem of multiple comparisons and how to address the problem of over fitting? Detailed answers will be provided in the section 2.2.2 and 2.2.3. The third reason for using the Big Five traits is convenience. The questionnaires to measure the Big Five traits are considerably shorter than the ones that measure the 30 Big Five facets. For example, the IPIP50 can be used to measure the Big Five traits and consists of 50 items. The NEO-IPIP-120 can be used to measure the Big Five facets and consists of 120 items. Researchers may, therefore, be inclined to use the shorter questionnaires in anticipation of increasing the likelihood of responses received – as subjects usually prefer less effort to more.

To summarise, facets can provide incremental benefits to traits but require more statistical know-how and longer questionnaires. An overview of the questionnaires is given in the next section.

2.1.3 Which Big Five Questionnaire should be used?

In section 2.1.1 I argued for the usage of the Big Five personality framework and in section 2.1.2 I argued for the incremental benefits of facets. In this third section, I discuss the advantages and disadvantages between questionnaires. Overall, two questionnaires "brands" can be employed to measure the Big Five facets: The NEO-series (Costa & McCrae, 1992) or the IPIP-series (Goldberg, et al., 2006). I will focus on two questionnaires in specific, the NEO-

PI-R (Costa & McCrae, 1992) and the IPIP-NEO-120 (Johnson, 2014) questionnaires. The two questionnaires differentiate themselves in several ways.

First, the NEO-PI-R consists of 240 items and is by many considered the gold standard when measuring personality (Piedmont, 1998). It is the most reliable questionnaire today and provides users with scoring instructions to help evaluate the results, and is thus user-friendly to non-academics too. However, the questionnaire is copyright protected and thus expensive to obtain. Second, the IPIP-NEO-120 consists of 120 items and is highly correlated to the NEO-PI-R. Despite the novelty of the questionnaire, it has quickly gained acceptance in the psychological literature due to it being shorter and not copyright protected. A downside of the IPIP-NEO-120 is the additional psychometrical calculations that are needed to evaluate a person's personality results. Unlike the NEO-PI-R, the IPIP-NEO-120 only provides minimal guidelines and their inventors will not provide any sample means to compare subjects to a general population. Instead, they argue that one's local sample should serve as a base to calculate the percentiles in which each participant belongs to (Goldberg, 2018). Compared with each other, the NEO-PI-R and the IPIP-NEO-120 strongly correlate, indicating that they are measuring the same personality properties. The problem of not measuring the same personality properties can be an issue when using short-form questionnaires which only measure the Big Five traits (e.g. the IPIP50). (See Table 1). In the IPIP50 questionnaire, each trait is the product of 10 items. In the NEO-IPIP-120 questionnaire, each facet is the product of 4 items, and each trait is the product of 24 items (6 facets combined). In the NEO-PI-R questionnaire, each trait is the product of 48 items. Using less items to measure a trait results in an accuracy penalty, as indicated by the lower correlational values.

Table 1. Correlation between two IPIP questionnaires to the NEO-PI-R

Big Five Traits	**IPIP50**	**NEO-IPIP-120**
Extraversion	0.84	0.99
Agreeableness	0.66	0.90
Conscientiousness	0.90	0.92
Neuroticism	0.84	0.97
Openness	0.80	0.96

Note. Source for the data presented in the table is (Johnson, 2014).

Overall, the IPIP-NEO-120 questionnaire is optimal for independent researchers as the questionnaire is free to use and not copy-right protected. For this reason, I will be using the IPIP-NEO-120 to measure the Big Five traits and facets (See Appendix C, Table C1 displays the 120 items and explains how to score the questionnaire). However, given the opportunity to use the NEO-PI-R, I would have opt to do so.

2.2 Post-Data Collection

This section discusses all relevant statistical information regarding my approach to personality research. First, I discuss the usage of Cronbach's Alpha to estimate the internal consistency. Second, I address the problem of multiple comparisons. Third, I address the problem of over fitting and my proposed remedy: the holdout cross validation method. Next, I discuss the statistical procedures in the training and testing sample. Lastly, I present the statistical procedures done with the full sample size.

2.2.1 Cronbach's Alpha

The first statistical procedure that needs to be done with a personality data set is to estimate the internal consistency of each trait and facet. Cronbach's alpha is a standard measure to express internal consistency. The coefficient of Cronbach's alpha ranges from 0 to 1; higher values imply a higher degree of consistency in a trait. In practical terms, we speak of high consistency if all the four items of a facet / 24 items of a trait are highly inter-correlated. In other words, we expect subjects to answer all the items to a relatively similar degree. We have this expectation because the four items of a facet measure virtually the same outcome, the associated questions are just posed in different ways. For example, two items of the N1 Anxiety facet state the following: 1. Worry about things and 2. Fear for the worst. Answering these two questions completely the opposite of each other would pose a threat to the internal consistency of the data because it likely points toward the subjects not reading the questionnaire carefully and just randomly clicking responses.

Mathematically, Cronbach's alpha is expressed in the following formula:

$$\alpha = \frac{n}{n-1} \times \left(1 - \frac{\sum Vi}{Vtest}\right)$$

Where n = number of items within a facet/trait, Vi = sum of score variance of each of the items in a facet/trait, and Vtest = total variance of a facet/trait.

To better understand how consistency is defined, I now explore the two extremes of Cronbach's Alpha: an α of 0 and an α of 1. The former can be created by randomly picking 10 questions, these 10 questions would then form the variable Delta. Because the questions have been randomly chosen, the questions will have no shared variance with each other. Therefore, the sum of the variance of the individual questions will equal to the total variance of Delta.

$$\alpha = \frac{10}{10-1} \times \left(1 - \frac{25}{25}\right) = 0$$

The latter, an α of 1, can be created by asking the same question 10 times, together they would form the variable Gamma. All the 10 questions will have the exact same variance. Hence, the sum of Vi equals 10* Vi and $Vtest$ equals 10^2*Vi.

$$\alpha = \frac{10}{10-1} \times \left(1 - \frac{2.5}{25}\right) = 1$$

Because personality questionnaires do not ask the same exact question, but slightly different versions of the same construct, standard alpha values for facets range from 0.54 – 0.83 and 0.56 – 0.81 for traits (McCrae & Costa, 2010). Conclusions drawn on outcomes which exhibit scores below 0.50 should be cautiously interpreted.

2.2.2 Multiple Comparisons

The problem of multiple comparisons, or also known as the problem of multiple testing and multiplicity problem, occurs when at least two hypotheses are being tested simultaneously (Field, 2013). In practical terms, any regression with two or more explanatory variables suffers from an underestimated Type 1 error, given a certain significance level. For example, if a researcher has a regression with ten explanatory variables and sets the needed significance level to 5%, he should technically not always reject the Null hypothesis if the p-value for a given variable turns out to be slightly below 0.05. Because ten variables are in the equation, the odds of falsely rejecting a true Null hypothesis is no longer 5%, as set out by alpha, but in fact is now 40%[1]. To account for this so called family-wise error rate, the p-values need to be corrected posthoc before drawing conclusions. I expand on several correction methods: Bonferroni correction, Holm-Bonferroni correction, Hommel procedure, Hochberg procedure, Benjamini-Hochberg procedure, and “setting own significance values”. The latter is most prevalent in the literature.

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[1] $1 - (1 - \alpha)^n$ where n = number of explanatory variable and α = significance value

2.2.2.1 Correction methods

Statisticians have provided several solutions to the family-wise error rate; though there is no consensus as to which procedure is best (Blakesley, et al., 2009; Feise, 2002; Lazzeroni & Ray, 2012). A commonly used procedure is the Bonferroni correction (Armstrong, 2014). Its wide usage is mainly due to its simple formula: alpha / k = new alpha. However, this method has received criticism for being too conservative. For example, in personality research, rejecting the Null of a facet-variable would only be possible if its p-value of a facet is below 0.00156 (= 0.05 / 30). A newer model, the Holm-Bonferroni correction, is less restrictive but more complex. Instead of comparing all hypotheses to the same alpha levels, each hypothesis is first ranked from lowest to highest p-value and then compared to an increasing alpha level. This step-down method improves the simple Bonferroni by better rejecting "less significant" hypotheses (Romano, Shaikh, & Wolf, 2010).

Less attention has been given to step-up methods such as the Hommel or Hochberg procedure (Romano, Shaikh, & Wolf, 2010). In contrast to a step-down method, step-up methods give more power to the "more significant" hypothesis. Because of this focus, there is evidence that step-up methods are best suited for sub 0.5 correlations (Blakesley, et al., 2009).

Next, I present the most popular and arguably least scientific method of dealing with multiple comparisons in personality research: setting a lower significance level without using a correction method. A common self-set significance value in personality research, when facets are used, is 0.01 (i.e Chamorro-Premuzic & Furnham, 2002; Chauvin, Hermand, & Mullet, 2007; Ekehammar & Akrami, 2007), though a value of 0.001 has also been observed (Anglim & Grant, 2014). In other cases, the significance value of 5% was not adjusted to avoid type 2 errors (Luchetti, et al., 2018). Nicholson, Soane, Fenton, & Willman (2005), the only economists who reported on facets, also used 5% though they did not report on why they chose this significant value.

I present several reasons as to why most psychological literature choose a significance value of 1%, instead of employing a correction method. First, a simple reduction of the significance value without any of the above mentioned correction methods could be the result of unsophisticated statistical knowledge or convenience. Second, a significance value of 1% may be seen as a compromise between 5% and 0.001% to balance out the occurrence of type 1 and type 2 errors. Third, the following logic may have been applied: if researchers have 5 explanatory variables (e.g. Fama&French Factors or Big Five traits) and set the significance value to 5%, they usually do not consider it a problem of multiple comparisons – even though it technically would be one. If five explanatory variables are present, the chance of "discovering" at least 1 significant value is 22.62%. Therefore, this seems to be an accepted value by the scientific community. Running 30 explanatory variables with a significance value of 1% equates to having a chance of 26.03% to "discover" at least 1 significant value. It could thus be justified to set the significance level at 1% as it imitates the chance of finding at least 1 significant variable in traditional research.

In conclusion, there is no perfect methodological procedure to account for multiple comparisons. This paper will use 1% as a significant value despite its higher allowance for type 1 errors, compared to a Hochberg or Hommel correction. To partialy remedy the issue of type 1 errors, I will additionally use effect sizes to determine the strenght of the significant relationships found (see chapter 2.5).

2.2.3 Over fitting

Over fitting can occur when multiple variables are in a regression. Because of how statistical software packages are set up, it may occur that the regression line "over the top" fits the data points. Visually, a non-linear regression line would then show a high variance in its movements as it crosses through all the points, and overstate effects found. Because these effects are overstated, they may not be found again in a different data set – a problem which affects linear regressions too. Therefore, the model may not be useful for further research as its predictors only work for this one particular dataset where it originated from. To avoid this issue and increase the confidence in the model, I apply the holdout cross validation method.

2.2.3.1 Holdout cross validation method

Cross validation is the umbrella term for methods that aim to evaluate the predictive power of models in a new data set. One such method is the holdout method (Gutierrez-Osuna, 2018; Kohavi, 2001; Reitermanova, 2010). In finance, this is also called in-sample and out-of-sample testing. In this procedure (STATA, 2018), the sample is split into two parts, a training sample and a testing sample. The training set consists of 80% of the data, and the testing sample of the remaining 20% data. Then, all regressions are run in the training set to find the best fit model. In a second step, this best fit model is "tested" in the testing sample to see if it still provides a good fit and thus serves as a reliable prediction model. A good fit is defined as low mean squared errors. A disadvantage of using the holdout method is that it requires a larger sample size compared to "standard" research because the subjects are split into two samples. A more advanced alternative would have been the k-sample cross validation: k refers to the number of times the holdout method was performed. The average values are then taken to validate the regressions. A k of 10 is traditional.

Depending on the dataset, different splitting methods are employed to create a training and testing sample. For a full discussion of which method is optimal for a given dataset, I refer to the works of Reitermanova (2010). The appropriate method for personality data is simple random splitting (SRS). SRS is a standard method in most research and easy to implement with a statistical software such as SPSS. SRS implies that each person in the dataset has an equal probability of being selected for the training and testing sample. A disadvantage of this method is that in any random draw there is a probability of randomly selecting only extreme cases into the testing sample. This would likely increase the probability that the model created in the training sample will not accurately predict the values in the testing sample.

2.3 Statistical procedure in the training sample

Before running any regressions, the personality variables must be properly coded. I used the raw scores for the personality variables. The alternative would have been using percentiles. The advantage of using percentiles is a more natural interpretation of the regression coefficients and having a standardised score; one percentile increase in trait x increases risk aversion by y. The disadvantage of using percentiles is having to create a local sample to determine the percentile scores. This means that the local sample may not be the same as that of the general population, for example, "my" 75th percentile score may in reality only be the 68th percentile score. It would thus cause a false image of which percentile has which predictive power on economic preference parameters. To avoid this issue, I will only speak on the general direction of the effect by using the raw scores; higher scores in trait x predict higher levels of risk aversion. This allows other researchers to replicate my findings without having to worry about how my local sample was created.

Within the training sample, I perform two regressions for each outcome. Model 1 includes the Big Five traits and Model 2 includes the 30 facets. In either model I run all 5 traits or all 30 facets to account for the shared variance between the traits or facets. I am interested in the unique contribution of a trait or facet, while statistically controlling for the other traits or facets. I interpret variables as significant if their significance values are below 0.05 for traits and 0.01 for facets.

Next, we compare the two models with each other to determine the best fit model which is characterised by explaining a larger variance of the economic preference parameters.

However, as a consequence of including 30 facets in Model 2, R^2 artificially increased: mathematically, R^2 will increase with each additional variable even if they do not have a significant effect on the dependent variable. Therefore, a correction method is needed. Two correction methods have shown to be optimal when including facets: The Olkin-Pratt and the Ezekiel Formula (Blakesley, et al., 2009). Both formulas "punish" the inclusion of insignificant variables by correcting R^2 downward. The difference in the outcome between the two formulas is marginal; for convenience I choose to proceed with the Ezekiel Formula as the software IBM SPSS uses the Ezekiel Formula for its adjusted R^2 value (Nimon, Zientrek, & Thompson, 2015). Ezekiel's correction formula is as follows (Ezekiel, 1930):

$$R^2_{adjusted} = 1 - \frac{(N-1)}{(N-p-1)} \times (1 - R^2)$$

where N = sample size and p = number of explanatory variables (excluding the constant term).

If the adjusted R^2 of Model 2 (1) is larger than Model 1 (2), I will proceed with Model 2 (1) as the best fit model because it can explain a higher variance. If the adjusted R^2 value of Model 1 is similar to Model 2, I will continue with Model 1 as the best fit model. The reason for this decision is based on the principle of parsimony, as explained previously.

2.4 Statistical procedure in the testing sample

The best-fit regression model of the training sample predicts the outcome variables in the training and testing sample. To compare the predictive power of the models, the mean squared errors are calculated and compared to each other.

$$Mean\ Squared\ Error = \sqrt{\frac{\sum(\hat{y} - y)^2}{n}}$$

Where $\hat{y}$ is the estimated outcome, y is the actual outcome point, and n is the number of individuals.

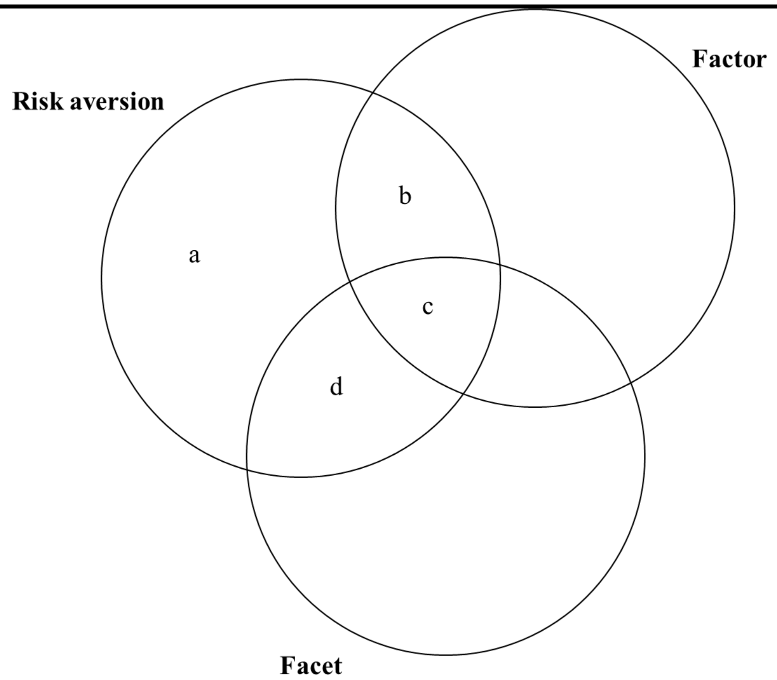
There are four main outcomes that can be expected. First, if both models show a high mean square error, then the model suffers from under fitting. In contrast, the model suffers from over fitting if the testing mean square error is larger than the training mean square error. A good fit is present if both mean square errors are similar and low. Lastly, there is an unknown fit if the mean square error of the testing sample is low and the training sample MSE is high. I expect the problem of over fitting to be the primary concern of the regression because of the inclusions of 30 facets. There are two remedies which help reduce over fitting: a larger sample size could be acquired and predictors could be combined. The former is less realistic in most studies, thus the focus will be on the latter. The latter is realistic if the best fit model happens to be the facet regression, because combining factors can be accomplished by reverting back to the Big Five trait model.

2.5 Final Statistical procedures

Regardless whether the Big Five traits or the Big Five facet model prevailed as the best fit model, the training and testing sample can now be combined into one sample. Within this sample, I run the Big Five trait regression and the Big Five facet regression for both risk attitudes and ambiguity attitudes. In a second step, I add demographic control variables to the regressions to rule out other individual differences which may explain the variance in the economic preference parameters: Gender, naturally, controls for gender differences. While educational attainment can be seen as a rough proxy for intelligence (Hill, et al., 2018).

In addition to measuring the regression coefficients, I measure the effect sizes and semi-partial correlations. The former measures the explanatory contribution of a variable, the latter measures the unique explanatory contribution of a variable. First, I measure the zero-order pairwise Pearson correlation between the Big Five traits and the 30 Big Five facets and the economic preference parameters. Beyond the significance value, the correlational results provide information on the strength of the relationship. For example, regression coefficients can be significant but may have a Pearson r of i.e. 0.04, in which case the variable would not add considerable value to the regression. The Pearson correlation can be squared to determine how much R^2 it can explain. However, alone, zero-order correlations should not determine the strength of the relationship. This is because zero-order correlations do not control for other variables. Hence, it may signal a moderate relationship between a facet and an outcome because of a shared variance with a facet that is truly related to the outcome. To address this problem, I additionally measure the semi-partial correlation to determine the unique contribution of a trait or facet to R^2. The semi-partial correlations will correct for other traits/facets and can provide evidence for incremental benefits above other traits/facets. The squared semi-partial correlation reports how much additional R^2 is explained by a variables unique variance alone.

A visual of the difference between zero-order correlation, semi-partial correlation, and a regression coefficient is displayed in figure 4. In short, the only difference between semi-partial correlations and the regression coefficients are the bounds of values they can take; in statistical tests they will mirror each other's significance value.



$$\text{Zero}-\text{order correlation} = \sqrt{\frac{c+d}{a+b+c+d}}$$

$$\text{Semi}-\text{partial correlation} = \sqrt{\frac{d}{a+b+c+d}}$$

$$\text{beta coefficient} = \sqrt{\frac{d}{a+b+d}}$$

Figure 4. Stylised example for understanding the different types of correlations and regression calculations:
a = unexplained variance of risk aversion, b = unique variance explained by the factor, c = shared variance explained by the factor and the facet, d = unique variance explained by the facet

Zero-order correlations reflects a traits or facets contribution of explaining the variance of the economic preference parameters, not controlling for other traits and facets. They provide information on the strength of the relationship.

Semi-partial correlations reflects a traits or facets unique contribution of explaining the variance of the economic preference parameters, controlling for other traits and facets.

Beta coefficients reflect the unique contribution a trait or facet has, while controlling for other traits / facets. Beta coefficients of the facets and traits serve as predictor values for economic risk preferences.

3 Economic Preference Parameters

For this thesis, I consider two economic preference parameters: risk attitudes and ambiguity attitudes. I first explain the theoretical foundation of each and then describe how they are measured.

3.1 Uncertainty

Economist distinguish between two types of uncertainties: risk and ambiguity (Trautmann & Van den Kuilen, 2015). A risky situation describes any circumstance in which all options and their likelihood of occurring are known. For example, hoping for heads in a coin-toss is risky; the two possible outcomes both occur with a chance of 50%. In contrast, an ambiguous situation is any in which all options are known, but their likelihood of occurring is not precisely known. For example, if you randomly grab into a bag of M&Ms, you will not know the probability of taking out a specific colour. You only know that the colour of the M&M will be red, orange, yellow, green, blue, or brown (=known outcomes). In the real world, ambiguous situations are far more common than risky situations.

3.1.1 Defining Risk Attitudes

Risk attitudes are used to help explain the behaviour of people in situations where they are exposed to risk. Their attitudes – averse, neutral, and seeking – depend on the context of the situation and how they are measured. (Slovic1974; Payne et al. 1980; MacCrimmon and Wehrung 1990; Schoemaker 1990; March and Shapira 1992; Shapira 1997; Payne 1997).

More generally, the following definitions for the three different risk attitudes hold for all economic utility models (Rohde, 2017): Risk seeking is any person who prefers the prospect of a gamble to the expected value of the gamble. Risk neutral is any person who is indifferent between the prospect and the expected value. Risk adverse is any person who prefers the expected value to the prospect. For example, a risk averse person would prefer receiving 1.25 euros (expected value) to playing heads-or-tails where he could win 2.50 euros (prospect). In fact, a risk averse person might accept even a lower sure amount of money. He accepts a "premium" to avoid the risk of receiving nothing from the gamble. This premium is defined and limited, hence at some point, i.e at 80 cent, the person becomes indifferent between playing the gamble and choosing the 80 cents for sure. This point of indifference is also referred to as the certainty equivalent. At any lower amount than the certainty equivalent he will prefer the gamble.

The different risk attitudes can be explained with two approaches: different evaluation of outcomes and different evaluation of probabilities. Independently from each other, we can analyse them for a better understanding. First, a different evaluation of outcomes refers in this context to the utility derived from money. A risk averse person, compared with a risk neutral person, will derive more utility from a sure 200 euros win compared to a coin-flip gamble where she can win 400 euros. Visually, the utility function of a risk averse (seeking) person is concave (convex), compared to linear for risk neutral people. Hence, a risk averse (seeking) person's certainty equivalent is lower (higher) than the expected value of a gamble. Second, instead of evaluating outcomes differently, a person may evaluate probabilities differently. Most people do not process probabilities objectively; they assign a higher probability weight to low probabilities and a lower probability weight to high probabilities, compared to a linear probability weighting function. This is known as "decision weights" and can be visualised as an inverse S-shaped probability weighting function. It may therefore be that subjects just exhibit a different probability weighting function which causes them to evaluate the gamble differently. Compared with a risk neutral person, having a more convex (concave) probability weighting function will increase risk aversion (risk seeking) behaviour. In reality, the evaluation of outcomes and the evaluation of probabilities interact with each other and both are instrumental in determining a subject's risk attitude. For example, a concave utility function can be consistent with a risk seeking attitude if combined with a concave probability function.

3.1.2 Defining Ambiguity Attitudes

Ambiguity attitude is used to help explain the behaviour of people in ambiguous situations. Ambiguity averse people exhibit a preference for risk to ambiguity (Thaler & Sunstein, 2008). Ambiguity neutral people are indifferent between risk and uncertainty. Ambiguity seeking people prefer ambiguity to risk. An example of this can be seen in Ellsberg's experiment. Ellsberg (1961) was one of the pioneers in ambiguity modelling and also showed with his experiments that the above discussed approaches to explaining risk attitudes are not sufficient for explaining ambiguity attitudes. First, I examine Ellsberg's experiment and then argue why subjective evaluations of outcomes and probabilities are not sufficient to explain the Ellsberg paradox.

Ellsberg proposed an experiment involving two urns. Each Urn was filled with 100 marbles. Urn 1 was filled with an unknown ratio of black and red marbles. Urn 2 was filled with exactly 50 black and 50 red marbles. Subjects were then presented a series of gambles. Of these gambles, two, in particular, built the foundation of the Ellsberg Paradox. In each gamble, participants won 100 dollars if they were able to correctly predict the colour that is going to be randomly drawn. In the first of the two gambles, subjects were asked for their betting preference: "Which do you prefer to bet on, that a red marble is drawn from Urn 1 or that a red marble is drawn from urn 2?" Most subjects preferred the bet involving urn 2, the one with the known ratio of black and red balls. The second gamble asked again for their betting preference: "Which do you prefer to bet on, that a black marble is drawn from Urn 1 or that a black marble is drawn from urn 2?". Again, subjects preferred the bet involving urn 2.

This constitutes a paradox because classical economic theory would have expected subjects to pick the bet involving urn 1 in the second gamble. The expectations and assumptions are as follows: The first assumption is that people are probabilistic sophisticated: they attach subjective probabilities to outcomes with unknown probabilities and behave accordingly. The second assumption constitutes that people's choices reveal their preferences and thus their assigned subjective probability. Hence, in the first gamble, the average subject prefers to bet on a red marble being drawn from urn 2. This choice also reveals, according to probabilistic sophistication, that the subject has assigned a probability lower than 50% to a red ball being drawn from urn 1. If he would have thought it is more than 50% likely that a red ball is drawn from urn 1, he would have bet on urn 1. Because of the finite number of outcomes (2 in this case), the Bayesian theorem of additive probabilities should hold: probabilities of all finite, mutually exhaustive and exclusive, outcomes must add up to 100%. In other words, we further gain the knowledge that the subjects judged the probability of a black ball being drawn from urn 1 to be more than 50% (= 100% minus the assigned probability of the red ball being drawn). Therefore, if these assumptions hold, we can derive from the first gamble that the average subject thinks that it is more likely that a black ball is drawn from urn 1. However, contradictory to these expectations, we find that, in the second gamble involving the same urns, the average subject still prefers urn 2 for betting on a black ball being drawn. We must therefore conclude that some of the assumptions are wrong. Namely, no model using additive probabilities can explain the Ellsberg paradox, regardless of the utility or probability weighting function subjects used to assess risky gambles.

However, this "paradox" can be explained if we accept the violation of the additive probability theorem. For example, assume that people do not assign a specific subjective probability to events, rather they are thinking in terms of a range of probabilities. Subjects may rate the "objective" probability of a black / red ball being drawn from urn 1 between 30 – 70%.

Next, for their own cognitive calculations the subjects prefer to use a number near the lower bound of this interval. For example, they make a compromise to enter 40% into their calculations. Hence, it makes sense, for every subjective evaluation of outcome and probability, to choose urn 2 in both gambles.

3.2 Measurement of Risk and Ambiguity Attitudes

In this paper, I elicit risk and ambiguity attitudes using the experimental design by Borghans et al. (2009). Their design is as follows. First, subjects are educated about the principle of a reservation price; the least amount of money they are willing to sell a gamble for. This can be understood as a proxy for the certainty equivalent discussed above. The participants understanding is tested by asking for the reservation price for a 1 euro coin. If they set a price higher than 1 euro or 1.01, they will be re-directed to reread the instructions. Second, a set of urns are introduced. All the urns contain each 10 balls of two different colours. The only difference between the urns lies in the colour distribution of the balls. In the first urn, there are 5 blue and 5 yellow balls. In the second urn, there are between 4 – 6 yellow and blue balls. In the third urn, there are between 2 – 8 yellow and blue balls. In the fourth urn, the number of yellow and blue balls is unknown. Hence, the urns increase in ambiguity. Third, the subjects are informed about the gamble for each urn: "At random, one ball will be drawn from this urn. If you guess the right colour, you'll earn 2 euros. If you are wrong, you'll get nothing." Fourth, for each urn, the subjects are then asked to state their reservation price. The reservations prices for urn 1 and urn 4 provide an indication for the direction of risk aversion and ambiguity aversion.

$$Certainty\ equivalent\ as\ an\ indicator\ for\ risk\ attitudes = RP_{Urn\ 1}$$

The reservation price (in cents) for urn 1 is negatively related to risk aversion. It is important to note that this approach only serves as an indication for the degree of risk aversion as it cannot provide information about the exact degree of risk aversion. Further, subjects can only be described as risk averse if their reservation price is below 1 euro, according to the formal definition of risk aversion. Similarly, we can detect risk neutral and risk seeking individuals by comparing their reservation price to the expected value of the urn gamble (=1 euro), as explained above. In Borghans et al's (2009) study, the average reservation price for urn 1 was 93.2 cents. Hence, subjects were on average risk averse, which is expected. Using the reservation price as the dependent variable gives us an indication about whether the Big Five personality framework can predict how subjects set their reservation price. For example, a negative regression coefficient indicates risk aversion, as with each additional point in a trait or facet, the reservation price would be lowered.

The result of subtracting the reservation price from urn 1 from the reservation price of urn 4 is negatively correlated to ambiguity aversion. The less money subjects accept for selling urn 4, compared to urn 1, the more ambiguity averse they are. Again, this approach only serves as an indication for the degree of ambiguity aversion as it cannot provide information about the exact degree of ambiguity aversion. Further, subjects can only be described as ambiguity averse if their reservation price for urn 4 is below that of urn 1: By comparing the two reservation prices, we can isolate the premium that subjects are willing to pay to avoid ambiguity. In urn 4, subjects pay premium to avoid the risk of receiving nothing and to avoid the ambiguity of the gamble. Hence, if we equate them to each other, we account for the premium paid to avoid risk - only the premium to avoid ambiguity is left. This premium for ambiguity serves as a proxy for ambiguity attitudes. The average premium paid in Borghans et al. (2009) study was 12.4 cents. Hence, subjects were on average ambiguity averse, which is expected. Using the premium to avoid ambiguity as the dependent variable provides us with an indication about whether the Big Five personality framework can predict how much subjects are willing to pay to avoid ambiguity. For example, a negative regression coefficient indicates ambiguity averse behaviour as they are willing to "pay" money to avoid ambiguity with each additional point in a trait / facet.

$$Premium\ to\ avoid\ ambiguity = RP_{Urn\,4} - RP_{Urn\,1}$$

3.2.1 Advantages and Disadvantages of replicating Borghans et al's (2009) study

Borghans et al. (2009) find that the Big Five traits Agreeableness and Neuroticism positively relate to risk aversion. He did not find a relationship between the Big Five traits and ambiguity aversion.

For me, the main advantage of using the design of Borghans et al. (2009) is to compare my results with his. First, I can compare whether I can replicate the Big Five trait relationships. Second, I can test whether I find the missing relationship between personality and ambiguity attitudes using the Big Five facets. Lastly, I can examine whether the incremental benefits exists when using the facets. However, to confidently speak about the differences in our personality findings, I must hold the measures of the economic preference parameters constant. If I do not, then differences in our results may be due to the context specificity of economic preference parameters. By closely following the design of Borghans et al. (2009) I eliminate the context specificity factor as an explanation for differences between our approach and state that no other factors could have influenced the differences in our results – with the exception of a different sample and personality questionnaire. The paper of Borghans et al. (2009) is the only study that investigated the relationship between the Big Five traits and economic preference parameters. If there were other options, I would have preferred replicating their elicitation method due to the design limitations in the study of Borghans et al. (2009):

First, using the direct matching approach – directly asking for the reservation price – is easy to understand for subjects but may not always be optimal. Direct matching has been under criticism for two reasons (Glimcher & Fehr, 2013). First, direct matching may give rise to preference reversal: When pricing, subjects may price a “high winning probability, but low pay-out bet” with a lower value compared with a “low winning probability, high pay-out bet”. This is the reversal of when they would simply choose their favourite between the two bets: the subjects would, on average, prefer the “high winning probability, low pay-out bet” – which is the reverse as they would have priced it lower. Second, subjects tend to state lower reservation prices when comparing gambles with different probabilities, compared with comparing gambles with different outcomes. Alternatives to direct matching exist. Other approaches, such as multiple choice lists could help participants to state more accurate reservation prices (Rohde, 2017). Choice lists present participants with a list of binary choices. They force participants to think about several options and can thus guide the participant through several scenarios. Such a mental process is not enforced in the direct matching approach. In choice lists, the reservation price is derived from the switching point between the choice of playing the gamble and taking x amount of money for sure. A disadvantage of using a choice list though is that it can allow for multiple switching points and the answers can be biased towards the middle of the list. The former could be solved by allowing only one switching point and the latter could be solved using a bisectional approach: displaying one binary choice at the time until the switching point is determined. Overall, I proceed with the direct matching approach to elicit the reservation prices, to stay true to the design replication of Borghans et al (2009).

Second, the phrasing of the questions differs from the traditional Ellsberg experiment. Borghans et al. (2009) ask subjects to guess the colour post-draw, while Ellsberg et al. (1961) asked this question pre-draw. The effect of this framing is unknown, potentially it activates a different mental process and thus causes slightly different economic preference values, compared to the traditional Ellsberg method. Hence, the economic preference parameters may capture some noise.

Third, the measures of the economic preference parameters are simple raw values expressed as euro cents. As stated previously, they only give an indication of the degree of risk aversion and ambiguity aversion. Thus, the exact degree of aversion cannot be estimated using the methods of Borghans et al. (2009). However, there are methods to transform the elicited reservation prices into an index to determine the exact degree of risk and ambiguity attitude of subjects. I will perform a robustness check using an index for risk attitude and ambiguity attitude to determine if the relationships to personality remain the same. For this purpose, I borrow the indexes of Sutter et al. (2013). Sutter et al. (2013) use commonly defined index values ranging from 0 to 1 for risk aversion and -1 to 1 for ambiguity aversion. For risk aversion, a score of 1 indicates maximum risk aversion, a score of 0 indicates being maximum risk seeking, and a score of 0.5 equals risk neutral. Similarly, a score of 1 in ambiguity aversion equals maximal ambiguity aversion, while a score of -1 translates to maximum ambiguity seeking. A score of 0 equates to being ambiguity neutral.

The intuition for risk aversion index is as follows: a reservation price of 1 euro should display a risk neutral attitude because it is the expected value of the urn 1 gamble. A reservation price of 2 euros should display a maximum risk-seeking attitude:

$$Risk\ attitude\ r = 1 - \frac{RP_{Urn\ 1}}{2}$$

The intuition for the ambiguity aversion index is as follows. The larger the difference between the reservation prices, the higher the index value should be, capped at max 1. For example, a risk neutral subject would have a $RP_{Urn\ 1}$ of 1. However, assume that he is maximally ambiguity averse, meaning he would accept a large premium when selling the gamble; he is "paying" for not being exposed to ambiguity. In fact, at a price offer of 0, he would be indifferent between the gamble and taking the money. We can thus equate $RP_{Urn\ 4}$ to 0. This results in an ambiguity attitude value of 1, which is indeed maximally ambiguity averse:

$$Ambiguity\ attitude\ a = \frac{(RP_{Urn\ 1} - RP_{Urn\ 4})}{(RP_{Urn\ 1} + RP_{Urn\ 4})}$$

Fourth, 2 euros is a relatively small amount to gamble with. Subjects might not care about 2 euros enough or will not put in enough cognitive resources to really think about their answer and thus exhibit different attitudes with larger sums of money (Slovic1974, Payne et al. 1980, MacCrimmon and Wehrung 1990, Schoemaker 1990, March and Shapira 1992, Shapira 1997, Payne 1997). On the practical side, paying a maximum of 4 euros per subjects allows for a larger subject pool for a given monetary budget, compared to larger pay-outs. Fifth, the values elicited in urn 2 and 3 are merely to measure a directional effect when more ambiguity is introduced. Because I am not interested in the effects of some ambiguity, I will drop these urns from my design.

In sum, I will adopt the identical design of Borghans et al. (2009) – minus the measurement of urn 2 and 3 - to reliably compare the results of the Big Five traits on economic preference parameters.

4 Hypotheses

Borghans et al. (2009) found a positive relationship between personality traits and economic preference parameters. Specifically, they found evidence that the Big Five traits Agreeableness and Neuroticism positively relate to risk aversion. Borghans et al. (2009) did not find a relationship between the Big Five traits and ambiguity aversion. In line with their finding, I hypothesise that I will detect the same relationships on the trait level. Theoretical support for these findings do not exist; because of the numerous adjectives attributed to traits and facets, one could reasonably create a link to virtually any trait and facet. Therefore, my hypotheses are primarily based on the results of Borghans et al. (2009), however, I have also included hypothesis which are based on logical argumentations, which is sub-optimal.

First, I hypothesise that Agreeableness will positively relate to risk aversion but only exhibit a low effect size as I cannot find a strong logical link: The trait agreeableness reflects how an individual interacts with other people, how they cooperate with others, and to what extend they place their self-interest above others. While optimism is also assigned to agreeable people, it is generally meant in the context of evaluating human nature. It is therefore difficult to support the notion that this optimism may also be reflected in how they evaluate the subjective probabilities of winning in a financial gamble – isolated from the human factor. Nevertheless, because of the previous empirical link I have reason to believe that I will replicate this finding.

Second, I hypothesise that neuroticism will positively relate to risk aversion because neurotic people tend to be pessimistic about the future, worried, and anxious. In short, they tend to be pessimistic about life. Therefore, even if they know the exact risks, their subjective winning probability may be worse, causing them to think that they will just end up with the short straw. Consequently, they will avoid risky situations. Similarly, I further hypothesise that neuroticism relates positively to ambiguity aversion because neurotic people feel anxious about uncertainty and over-worry that they will be exposed to adverse outcomes. They will, therefore, tend to avoid ambiguous situations. However, because Borghans et al. (2009) could not find empirical support for this trait relationship, I suspect that at least one facet of Neuroticism will relate to ambiguity aversion. I suspect a similar facet finding for risk aversion.

Hypothesis 1: a) Agreeableness and b) Neuroticism positively relate with risk aversion, but c) Agreeableness and d) Neuroticism are not related to ambiguity attitudes.

Hypothesis 2: At least one facet of Neuroticism relates to a) risk attitude and b) ambiguity attitude.

Conscientiousness is the most "famous" trait in the Big Five framework because of its high predictive power on various outcomes, such as school performance and job performance, slightly below the predictive power of intelligence (e.g. Dumfart & Neubar, 2016, (Chamorro-Premuzic & Furnham, 2002)). People high in conscientiousness exhibit high control over themselves and prefer to plan the future out; they are organised and careful. Because of their inclination to be careful and their tendency to plan the future, I am surprised that it is not related to risk nor ambiguity. I would have expected a positive relationship to both risk aversion and ambiguity aversion. However, because Borghans et al. (2009) has not been able to find empirical evidence to support this argumentation, I instead suspect at least one facet of Conscientiousness will relate to the economic preference parameters.

Hypothesis 3: At least one facet of the trait Conscientiousness relates to a) risk attitudes and b) ambiguity attitudes. The trait itself does not be relate to c) risk attitudes nor b) ambiguity attitudes.

Based on the findings of Borghans et al. (2009), Openness and Extraversion should not be related to risk attitude and ambiguity attitude. Extraversion relates mainly to social activities and energy levels in social situations. Openness (to experience) relates to the cognitive interpretation of the world: creativity, how to think of the arts, finding beauty in the world, and how to form abstractions and prototypes. For neither, I could support logical argumentations as to why they would relate to risk and ambiguity.

Hypothesis 4: a) Openness and b) Extraversion do not relate to risk attitudes.

Hypothesis 5: a) Openness and b) Extraversion do not relate to ambiguity attitudes.

5 Data

In this chapter, I discuss how I collected my data and whether the basic assumptions to perform regressions hold - no serious concerns are reported.

5.1 Data Collection

To collect my data on personality and the economic preference parameter, I created a survey with the online tool Qualtrics. The survey itself consisted of three parts: asking general demographic questions, asking personality related questions, and asking questions to elicit economic preferences (See Appendix C). I distributed the survey using three channels: Facebook, Reddit, and handing-out flyers. On Facebook I made a public post to share the link to my survey. I also shared the link on Facebook groups where students are commonly found, such as the Facebook group of the master “Behavioural Economics” at Erasmus University. On Reddit, I posted my survey on the subreddit r/samplesize. I also printed out flyers with a link to my survey and distributed it on the campus of Erasmus University Rotterdam. The data collection process took place during the time period of the 2nd of June to the 17th of June 2018. In total, 389 people started to take the survey. However, likely due to the length of the survey – a problem discussed in the questionnaire section - only 247 people finished the survey. Out of the 247 people, 9 people failed to understand how to set a reservation price during the practice round of selling 1 euro. Additionally, by one person the reservation price format was not in line with the defined format, despite setting up proper rules in Qualtrics to avoid this issue. These ten people were excluded from the sample, thus the remaining sample used for the data analysis is N = 237.

5.1.1 Incentives

I offered two types of incentives to participants: a non-monetary and monetary reward. The non-monetary reward was in the form of getting to know their personality profile immediately upon filling out the survey. This can be seen as an extrinsic motivator (Sansone & Harackiewicz, 2000). It is reasonable to assume that a subsample of the participants took the survey because they wanted to know their personality, which was the main advertisement message when distributing the survey. Because they were interested in this reward, they were likely to fill out the questionnaire carefully.

In addition to the non-monetary reward, I also used traditional experimental economics incentives: money. The monetary reward is similar to Borghans et al. (2009) pay-out structure where subjects are rewarded according to their choices in the urn gambles 1 and 2. In a first round, a computer will generate a number between 0 and 200 cents, this number is then compared to the subject's reservation price. If the reservation price is lower than the "offer" of the computer, the subject will be paid out the offer price. If the reservation price is higher the gamble will be played. Then, if the subject's colour of choice is picked, he will win 2 euros. If not, he will receive nothing. The subjects who are legible to being paid out must have opted-in. I chose to not automatically force all subjects to play for real money because of privacy reasons. Forcing subjects to state their e-mail address might drive away potential participants because they don't want their personality assessment to be associated with them – a feedback I have received often when explaining my study to people. This sensitivity to personality data may be especially heightened due to the recent issues with Cambridge Analytica and the new European Private Policy laws. Therefore, playing for real money is voluntary.

5.2 Data Validation

Prior to analysing the data I checked basic assumptions of linearity: normality, multicollinearity, and heteroscedasticity. First, I analyse the dependent variables risk attitudes and ambiguity attitudes. The outcome values are non-normally distributed (see Appendix D). For risk attitude, the majority of responses are at 1 euro, followed by a large block of 2 euros responses. Similarly for the ambiguity premium, the largest bar is concentrated at a premium of 0 euros. However, normal probability charts and the residual scatter plots indicate not issue of heteroscedasticity. Second, I analyse the independent personality variables. The personality variables did not pass the Shapiro-Wilk test, however the skewness of the distribution is no greater than 1. Furthermore, the VIF of my independent variables do not exceed 4, most are concentrated around a VIF of 2. The variables which have a value close to 4 were further checked for a high correlation and if their tolerance exceeded 1. Neither was the case. To check for heteroscedasticity, I inspected the residual scatterplot and performed a Koenker test for the various regressions. The Koenker test was not rejected, hence I have reason to believe that heteroscedasticity is not present.

Lastly, the dataset was incomplete because 33 people, out of the 237 people, omitted their age. For the analysis, I replaced these missing ages with the mean age. This single imputation method is recommended for the category age in survey data (Bennet, 2001). Pair-wise and List-wise deletion produce the same results but have less power due to observations missing. The power analysis of including 237 people is as follows: the power of my main trait regression is 0.998 and the power of my main facet regression is 0.776. A power level of 0.80 would have been desirable.

6 Results

The aim of this paper was to 1) introduce the Big Five facets to economics, 2) test the predictive power of personality on the attitudes of risk and ambiguity, 3) test if the missing link between personality and ambiguity can be established using the Big Five facets, and 4) test whether the facets provide incremental benefits compared with the Big Five traits. In addition, I relate the results to the hypotheses made in section 4 and compare them to the study of Borghans et al. (2009).

6.1 Summary Statistics

See Table 2 for a comparison between the summary statistics of Borghans et al. (2009) and mine. The following differences are most striking. The average participant in my sample is risk-seeking and ambiguity averse. In comparison, Borghans et al. (2009) found their sample to be risk-averse, and not risk-seeking. I suspect this difference arose due to the demographical differences in our samples: mine is older and is thus likely to derive less value from 2 euros, compared with teens, because their income is likely higher. Demographically speaking, the average participant in my sample is 25 years old, has a bachelor's degree, and is male. Also, the economic preferences attitudes across education, age, and gender are the same. In contrast, the average participant in Borghans et al.'s (2009) experiment was 15.5 years old, a high school student, and male. Furthermore, in their sample, economic preference parameters differed between genders. Another important difference is the average total experiment time: it took participants 15 minutes to fill out my survey, while participants in the study by Borghans et al. (2009) needed 1.5 hours to fill out all the tasks. This difference likely arose because Borghans et al. (2009) additionally measured IQ and other factors.

In terms of personality scores, the average trait scores in my sample match the general population. The exception to this observation is the trait Extraversion which is lower in my

Table 2. Summary statistic comparison

	Borghans et al (2009)	Brutsch (2018)
N in total	**347**	**237**
Non-voluntary participants	295	0
Voluntary participants	52	237
Average age	**15.5 years old**	**24.82 years old**
N of Women	163	97
N of Men	184	140
Average Total Experiment Time	**1.5 hours**	**15.2 minutes**
Mean reservation price Gamble 1	**93.20 cents**	**117.20 cents**
Mean Ambiguity Premium	12.4 cents	21 cents
Neuroticism	unknown	84.08 points [8.712]
Extraversion	unknown	72.37 points [16.546]
Openness	unknown	84.65 points [11.909]
Agreeableness	unknown	86.09 points [13.532]
Conscientiousness	unknown	81.69 points [14.927]

Note. This table compares the summary statistics between the studies of Borghans et al. (2009) and mine. The main differences are in the number of participants, average age of the participant, average experiment time, and average risk attitudes.

sample. A personality score comparison to Borghans et al.'s (2009) paper is not possible as they did not publish the personality summary statistics and my request for the data has been left unanswered.

6.2 The Predictive Power of Personality

Optimally, the best-fit regression models should be able to predict risk and ambiguity attitudes of people who weren't included in the sample. To test this predictive power, I performed the holdout method: Split the data into an 80% and 20% sample, fitted the regressions to the 80% sample, and with these models I then predicted the economic preference parameters values of the 80% and 20% sample to measure the mean squared errors in both samples.

The results are summarised in Table 3. The facet regression outperformed the trait regression when estimating risk attitudes. Conversely, the trait regression outperformed the facet regression when estimating ambiguity attitudes. Though, none of the four regressions

Table 3. Holdout method output

		Risk attitude		Ambiguity Attitude	
		Traits	Facets	Traits	Facets
n = 193	Root MSE	50.05	54.11	62.30	66.41
	Min_predicted	90.22	41.83	-44.86	-77.43
	Max_predicted	143.71	178.40	10.46	10.46
	R^2	1.63%	7.46%	1.82%	0.00%
	F-test	1.78	1.52	1.72	0.91
n = 44	Root MSE	55.89	50.19	54.78	51.83
	Min_predicted	92.02	63.53	-40.13	-59.63
	Max_predicted	139.83	186.90	9.89	16.02

Note. The table shows the estimated values based on 4 regression models fitted in the training sample (n = 193). The testing sample (n = 44) shows equally high mean squared errors, indicative of model under fitting.

models were significant. The (root) mean squared errors (MSE) were also high for all four regressions models and in both training and testing sample. This is an indication for under fitting – contrary to the expectation that the Big Five facet models will suffer from over fitting. Under fitting implies that the models do not fit the data and other variables are needed to explain risk and ambiguity attitudes more effectively. The inaccuracy of the predicted values is also highlighted by its lowest and highest estimates. For example, when estimating risk attitude, the predictions of the facet regression range from 41.83 to 186.90 cents. The actual values range from 0 to 200 cents (see Appendix D), in fact, around 30% of the actual values are outside the predicted range.

In conclusions, the high MSE, the low R squared, and the inability to predict small and large values point towards a low predictive power of personality. Personality variables are not good predictors of the economic preference parameters risk attitude and ambiguity attitude, but may provide directional effects.

6.3 The Relationships between Personality and Economic Preference Parameters

To examine the relationship between personality and the economic preference parameters, I combined the previously split samples into one sample (N = 237). A detailed description of why the following analyses were performed can be found in the Section 2.5. In short, I ran a total of four regressions for each economic preference parameter. These four regressions were divided into two Big Five traits models and two Big Five facets models; one model including only the personality variables and the other model including the covariates gender and education. In addition, I report the zero-order correlations and the semi-partial correlations.

6.3.1 Risk Attitude

First, I ran the two Big Five trait models to predict risk attitudes (see Table 5). In model 1, the Big Five trait Conscientiousness ($p = 0.03$) was positively related to risk aversion: more conscientious people tend to be more risk averse. The relationship remained significant when controlling for gender and educational attainment. However, the strength of this relationship was minimal; the zero-order correlation was not significant, whereas the semi-partial correlation was significant but small. The squared semi-partial correlation of a variable expresses the incremental benefit in R^2 of including that variable in the model. Controlled for the other traits, the Big Five trait Conscientiousness could explain 2% of the variance in risk attitudes. Based on these findings, I have evidence to reject hypothesis 3c which stated that Conscientiousness is not related to risk attitudes.

Additionally, the analyses displayed in Table 4 provide evidence to answer hypothesis 1a, 1b, 4a, and 4b which reflect the results from Borghans et al. (2009). Hypothesis 1 stated that a) Neuroticism and b) Agreeableness positively relate to risk aversion. Based on my results, I do not have evidence to support these hypotheses: neither trait was significant at a 5% significance level. However, the Big Five trait Agreeableness ($p = 0.051$) would have likely

Table 4. Risk attitude: Big Five traits

Variable	Model 1	Model 2	Pearson Correlations	Semi-Partial Correlations
Constant	**111.597****	**120.311****		
	[48.378]	[53.563]		
Neuroticism	0.032	-0.003	-0.004	0.008
	[0.268]	[0.283]		
Extraversion	0.438	0.463	0.070	0.103
	[0.278]	[0.287]		
Openness	-0.340	-0.323	0.003	-0.064
	[0.374]	[0.353]		
Agreeableness	0.576	0.561	0.091	0.128
	[0.294]	[0.307]		
Conscientiousness	**-0.606****	**-0.703****	-0.097	**-0.143****
	[0.276]	[0.284]		
Age		0.387		
		[0.487]		
Female		1.329		
		[8.855]		
High school Degree		-16.686		
		[12.813]		
Bachelor's Degree		-8.708		
		[12.955]		
Master's Degree		-15.895		
		[14.091]		
PhD		31.176		
		[28.290]		
Adjusted R Square	0.016	0.018		
F-test	1.781	1.388		

Note. The Big Five trait models estimated the reservation price in urn gamble 1. The Big Five trait Conscientiousness is negatively related to the reservation price in both regression models as well as the semi-partial correlation, at a 5% significance level. A negative coefficient is indicative of a risk averse attitude. The constant coefficient of more than 1 euro is in line with the risk-seeking attitude of the sample. Neither of the regression models reported a significant F-test, as is also evident by the low adjusted R square.
** p < 5%; *** p < 1%

become significant with higher statistical power in my analysis. Therefore, Borghans et al.'s (2009) larger sample size could explain why he found Agreeableness to be related to risk attitude, while I did not find such a relationship. Another explanation, which may also explain why Neuroticism was not significant in my analysis, refers to the selection of questionnaires. Borghans et al. (2009) used the IPIP-50 questionnaire, while I used the NEO-IPIP-120 questionnaire to measure personality. Correlating both questionnaires to the NEO-PI-R questionnaire, the golden standard in personality assessment, we find the following relationship (see Table 1 in section 2.1): For the IPIP50 questionnaire, Agreeableness correlates with 0.66 and for the NEO-IPIP-120 questionnaire with 0.90, to the NEO-PI-R. Neuroticism correlates with 0.84 and 0.97, respectively. This indicates that the two personality traits, Agreeableness and Neuroticism, reflect slightly different properties depending on the questionnaires used. In addition to this difference between our studies, one other factor could be responsible. Borghans et al's (2009) experiment took on average 1.5 hours while my survey took on average only 15.2 minutes to complete. A longer survey time may put the participants in a hot state due to exhaustion, boredom, or, in their case, because they felt forced to participate to pass their course. This, in turn, may have overwritten their "natural" economic preferences and personality characteristics, thus introducing noise in the measurement of the data. Though, post-hoc, there is no method to test this assumption. Hence, these differences (larger sample size, different questionnaire, and cold/hot state) may have caused our conflicting results. Hypothesis 4 stated that a) Openness and b) Extraversion are not related to risk attitude. The hypotheses are supported by my results as neither of the traits were significant in my regression. This is consistent with Borghans et al. (2009) study.

Second, I ran the two Big Five facet models to predict risk attitude (see Table 5). In model 1, the Big Five facet N4 Self-Consciousness ($p = 0.009$) was negatively related to risk aversion: more self-conscious people tend to be more risk seeking. The relationship remained significant when controlling for gender and educational attainment. However, the strength of this relationship was minimal; the zero-order correlation was not significant, whereas the semi-partial correlation was significant but small. Controlled for the other facets, the Big Five facet

N4 Self-Consciousness could explain 2.66% of the variance in risk attitude. Based on these findings, I have evidence to support hypothesis 2a: at least one facet of Neuroticism relates to risk attitude. The analyses displayed in Table 5 further provides evidence to answer hypothesis 3a: at least one facet of the trait Conscientiousness will relate to risk attitude. Neither regression model 1 nor model 2 found a significant relationship. However, the zero-order correlation shows that C6 Cautiousness positively correlates with risk aversion. Not controlled for other facets, C6 Cautiousness can explain 3.8% of the variance in risk attitude. However, a single zero-order correlation is too little support to speak in favour of hypothesis 3a. I therefore have too little evidence to reject the null hypothesis of 3a. Lastly, an unexpected result is the positive relationship of A5 Modesty to risk aversion, if controlled for demographic variables. Though, this may lend partial support to the previous finding of Borghans et al. (2009) that the construct Agreeableness is related to risk attitudes.

Table 5. Risk attitude: Big Five facets

Variable	Model 1	Model 2	Pearson Correlations	Semi-Partial Correlations
Constant	66.415 [63.656]	73.310 [68.040]		
<u>Neuroticism</u>				
N1 Anxiety	0.833 [1.738]	0.358 [1.762]	-0.019	0.029
N2 Anger	1.363 [1.114]	1.213 [1.121]	0.045	0.076
N3 Depression	-1.948 [1.633]	-1.911 [1.675]	-0.031	-0.074
N4 Self-Consciousness	**4.310***** [1.640]	**4.446***** [1.650]	0.024	**0.163*****
N5 Immoderation	-0.560 [1.309]	-0.364 [1.334]	0.024	-0.026
N6 Vulnerability	-3.422** [1.610]	-3.441** [1.636]	-0.056	-0.132**
<u>Extraversion</u>				
E1 Friendliness	3.148** [1.578]	3.995** [1.590]	0.079	0.124**
E2 Gregariousness	0.361 [1.459]	0.580 [1.466]	0.043	0.015

Variable	Model 1	Model 2	Pearson Correlations	Semi-Partial Correlations
E3 Assertiveness	3.022**	2.931	0.078	0.123**
	[1.522]	[1.522]		
E4 Activity Level	1.699	1.549	0.046	0.066
	[1.596]	[1.644]		
E5 Excitement-Seeking	-0.540	-0.275	0.055	-0.021
	[1.559]	[1.592]		
E6 Cheerfulness	-2.113	-2.536	0.005	-0.081
	[1.611]	[1.630]		
Openness				
O1 Imagination	2.371	2.605	0.042	0.105
	[1.398]	[1.409]		
O2 Artistic Interests	-0.512	-0.890	-0.013	-0.025
	[1.239]	[1.310]		
O3 Emotionality	-0.866	-0.760	-0.045	-0.036
	[1.495]	[1.512]		
O4 Adventurousness	0.309	0.551	0.064	0.012
	[1.515]	[1.519]		
O5 Intellect	-2.998	-2.786	-0.111	-0.120
	[1.559]	[1.592]		
O6 Liberalism	0.463	0.112	0.073	0.020
	[1.412]	[1.440]		
Agreeableness				
A1 Trust	-1.099	-1.476	0.045	-0.058
	[1.172]	[1.181]		
A2 Morality	0.722	0.559	0.027	0.029
	[1.546]	[1.545]		
A3 Altruism	-1.785	-1.645	0.008	0.059
	[1.859]	[1.875]		
A4 Cooperation	2.612	2.793	0.075	0.106
	[1.529]	[1.532]		
A5 Modesty	3.356**	**3.536*** **	0.126	0.155**
	[1.347]	[1.348]		
A6 Sympathy	1.386	1.125	0.068	0.049
	[1.742]	[1.767]		
Conscientiousness				
C1 Self-Efficacy	1.212	0.871	0.040	0.040
	[1.865]	[1.890]		
C2 Orderliness	-0.640	-0.641	-0.092	-0.042
	[0.949]	[0.961]		
C3 Dutifulness	-3.684**	-3.634**	-0.116	-0.128**
	[1.789]	[1.804]		
C4 Achievement-Striving	-0.001	-0.080	-0.009	-0.000
	[1.461]	[1.459]		
C5 Self-Discipline	-0.155	-0.071	-0.009	-0.005

Variable	Model 1	Model 2	Pearson Correlations	Semi-Partial Correlations
	[1.937]	[1.945]		
C6 Cautiousness	-2.350**	-2.482**	**-0.181*****	-0.139**
	[1.052]	[1.060]		
<u>Control variables</u>				
Age		0.451		
		[0.525]		
Female		5.492		
		[8.648]		
High school Degree		-12.554		
		[12.822]		
Bachelor's Degree		-4.339		
		[12.822]		
Master's Degree		-9.781		
		[14.177]		
PhD		43.569		
		[28.979]		
Adjusted R Square	0.081	0.088		
F-test	**1.696****	**1.634****		

Note. The Big Five facet models estimated the reservation price in urn gamble 1. The Big Five facet N4 Self-Consciousness is positively related to the reservation price in both regression models as well as the semi-partial correlation, at a 1% significance level. A positive coefficient is indicative of a risk seeking attitude.
** p < 5%; *** p < 1%

6.3.2 Ambiguity Attitude

First, I ran the two Big Five trait models to predict ambiguity attitudes (see Table 6). In model 1, the Big Five trait Agreeableness (p = 0.005) was positively related to ambiguity aversion: more agreeable people tend to be more ambiguity averse. The relationship remained significant when controlling for gender and educational attainment. However, the strength of this relationship was minimal; both the zero-order correlation and the semi-partial correlation were significant but small. Controlled for the other traits, the Big Five trait Agreeableness could explain 3.39% of the variance in ambiguity attitude. Based on these findings alone, I have strong evidence to reject hypothesis 1c which stated that Agreeableness is not related to ambiguity attitudes. However, this finding is in stark contrast to Borghans et al. (2009) as they

Table 6. Ambiguity attitude: Big Five traits

Variable	Model 1	Model 2	Pearson Correlations	Semi-Partial Correlation
Constant	28.356	25.988		
	[49.550]	[54.769]		
Neuroticism	0.112	0.062	0.084	0.027
	[0.274]	[0.290]		
Extraversion	-0.433	-0.417	**-0.129****	-0.100
	[0.284]	[0.294]		
Openness	0.150	0.211	-0.078	0.028
	[0.355]	[0.391]		
Agreeableness	**-0.858*****	**-0.955*****	**-0.188*****	**-0.184*****
	[0.301]	[0.314]		
Conscientiousness	0.421	0.549*	0.006	0.097
	[0.283]	[0.291]		
Age		-0.154		
		[0.498]		
Female		9.548		
		[8.367]		
High school Degree		10.260		
		[13.101]		
Bachelor's Degree		-4.718		
		[14.339]		
Master's Degree		-12.399		
		[14.409]		
PhD		-33.201		
		[28.927]		
Adjusted R Square	0.034	0.039		
F-test	**2.676****	**1.870****		

Note. The Big Five trait models estimated the differences in the reservation prices between urn gamble 1 and 2. The Big Five trait Agreeableness is positively related to the difference in reservation prices in both regression models as well as the zero-order and semi-partial correlation, at a 1% significance level. A negative coefficient is indicative of an ambiguity averse attitude. Both regression models reported a significant F-test.
** p < 5%; *** p < 1%

did not find a relationship between the Big Five traits and ambiguity attitudes. As a potential explanation for the difference between our results, I refer back to differences mentioned in 6.3.1: usage of a different questionnaire being the main suspect.

The analyses displayed in Table 6 also provides evidence to answer the hypotheses 1d. 3b, 5a, and 5b, which are based on the results of Borghans et al. (2009). Hypothesis 1d predicted no relationship between Neuroticism and ambiguity attitudes, hypothesis 3b predicted no relationship between Conscientiousness and ambiguity attitudes, and hypothesis 5a stated that no relationship between Openness and ambiguity attitudes will be found. My results support these hypotheses as no significant relationships were found. Hypothesis 5b predicted no relationship between Extraversion and ambiguity attitudes. Neither regression model 1 nor model 2 showed a significant relationship. However, the zero-order correlation showed that Extraversion positively correlated with ambiguity aversion. Not controlled for other traits, Extraversion could explain 1.66% of the variance in ambiguity attitudes. However, a single zero-order correlation only provides weak support against hypothesis 5b, thus I do not reject its prediction.

Second, I ran the two Big Five facet models to predict ambiguity attitudes (see Table 7). The analyses displayed in Table 7 provides evidence to answer hypothesis 2b and 3c. Hypothesis 2b stated that at least one facet of Neuroticism will relate to ambiguity attitudes. I do not have evidence to support this hypothesis as I found no significant relationship. Hypothesis 3c stated that at least one facet of Conscientiousness is related to ambiguity attitude. Again, I do not have evidence to support this hypothesis; no regression coefficient was significant in either model. However, the zero-order correlation of E1 Friendliness and E2 Gregariousness was significant, though small. Not corrected for other facets, they could explain 2.86% and 2.99% of the variance in ambiguity attitude, respectively, which is an unexpected finding.

Table 7. Ambiguity attitude: Big Five facets

Variable	Model 1	Model 2	Pearson Correlations	Semi-Partial Correlations
Constant	41.959	31.960		
	[68.222]	[73.078]		
Neuroticism				
N1 Anxiety	-1.284	-1.119	0.066	-0.044
	[1.863]	[1.892]		
N2 Anger	-1.788	-1.715	0.010	-0.096
	[1.194]	[1.203]		
N3 Depression	1.088	1.200	0.112	0.040
	[1.750]	[1.799]		
N4 Self-Consciousness	-3.054	-3.208	0.056	-0.112
	[1.758]	[1.772]		
N5 Immoderation	1.767	1.659	0.040	0.081
	[1.403]	[1.432]		
N6 Vulnerability	2.584	2.437	0.080	0.096
	[1.726]	[1.758]		
Extraversion				
E1 Friendliness	-1.467	-1.747	**-0.169*** **	-0.056
	[1.691]	[1.709]		
E2 Gregariousness	-2.888	-2.997	**-0.173*** **	-0.119
	[1.564]	[1.575]		
E3 Assertiveness	0.326	0.618	-0.040	0.012
	[1.631]	[1.635]		
E4 Activity Level	-0.198	0.075	-0.067	-0.007
	[1.710]	[1.766]		
E5 Excitement-Seeking	1.008	0.814	-0.018	0.039
	[1.671]	[1.709]		
E6 Cheerfulness	1.059	1.586	-0.083	0.039
	[1.727]	[1.750]		
Openness				
O1 Imagination	2.044	1.859	0.120	0.088
	[1.498]	[1.513]		
O2 Artistic Interests	0.797	0.661	-0.021	0.038
	[1.328]	[1.407]		
O3 Emotionality	-1.408	-1.304	-0.092	-0.056
	[1.602]	[1.624]		
O4 Adventurousness	-2.001	-2.187	-0.150**	-0.079
	[1.624]	[1.632]		
O5 Intellect	-1.394	-0.858	-0.061	-0.053
	[1.671]	[1.709]		
O6 Liberalism	0.181	0.699	-0.082	0.007
	[1.514]	[1.546]		
Agreeableness				

Variable	Model 1	Model 2	Pearson Correlations	Semi-Partial Correlations
A1 Trust	-1.113	-0.925	-0.158**	-0.057
	[1.256]	[1.268]		
A2 Morality	1.220	1.242	-0.105	0.047
	[1.657]	[1.659]		
A3 Altruism	1.135	0.797	-0.136**	0.036
	[1.992]	[2.014]		
A4 Cooperation	-2.710	-2.838	-0.126	-0.107
	[1.639]	[1.645]		
A5 Modesty	-0.156	-0.289	-0.061	-0.007
	[1.444]	[1.448]		
A6 Sympathy	-1.836	-1.928	-0.154**	-0.063
	[1.867]	[1.898]		
Conscientiousness				
C1 Self-Efficacy	-0.401	0.055	-0.029	-0.013
	[1.998]	[2.029]		
C2 Orderliness	0.759	0.915	0.045	0.048
	[1.018]	[1.032]		
C3 Dutifulness	-0.666	-0.717	-0.049	-0.022
	[1.918]	[1.937]		
C4 Achievement-Striving	-0.062	-0.214	-0.042	-0.002
	[1.566]	[1.567]		
C5 Self-Discipline	1.862	1.768	-0.011	0.058
	[2.076]	[2.089]		
C6 Cautiousness	1.624	1.747	-0.074	0.093
	[1.127]	[1.138]		
Control variables				
Age		-0.064		
		[0.564]		
Female		8.491		
		[9.288]		
High school Degree		5.496		
		[13.772]		
Bachelor’s Degree		-9.480		
		[13.879]		
Master’s Degree		-15.506		
		[15.227]		
PhD		-47.712		
		[31.124]		
Adjusted R Square	0.012	0.016		
F-test	1.099	1.104		

Note. The Big Five facet models estimated the differences in the reservation prices between gamble 1 and 2. No regression coefficients were significant at 1%.
** p < 5%; *** p < 1%

Table 8. Result comparison between Borghans et al. (2009) and Brütsch (2018)

	Borghans et al (2009)	Brütsch (2018)
Significant Traits related to Risk attitude	Agreeableness and Neuroticism	Conscientiousness
Significant Traits related to Ambiguity attitude	None	Agreeableness
Significant Facets related to Risk attitude	Not measured	N4 Self-consciousness
Significant Facets related to Ambiguity attitude	Not measured	None

Note. Summary of the results of Borghans et al. (2009) and mine. The Big Five traits were significant at 5%, the Big Five facets were significant at 1%.

In summary, the key relationships across the Big Five traits and facet models were as follows: The Big Five trait Conscientiousness ($p = 0.03$) was positively related to risk aversion and the Big Five trait Agreeableness ($p = 0.005$) was positively related to ambiguity aversion. Further, the Big Five facet N4 Self-Consciousness ($p = 0.009$) was negatively related to risk aversion and the Big Five facet A5 Modesty ($p = 0.009$) was also negatively related to risk aversion, if controlled for demographic variables. These findings are in stark contrast to the results of Borghans et al. (2009) who only reported a relationship between the Big Five traits Agreeableness and Neuroticism and the economic preference parameter risk attitude (see Table 8).

6.4 Incremental Benefits of the Big Five Facets

To test the incremental benefits, I compared the Big Five trait and facet regression models in section 6.3 with each other: the Big Five facets provided large incremental benefits when estimating risk attitude. The Big Five trait model could explain 1.6% and the Big Five facets could explain 8.1% of the variance in risk attitude; the Big Five facets were able to explain 5 times more variance than the Big Five traits could. An increase this high in adjusted R^2 is extremely uncommon; previous literature has shown average increases of around 0.35 times the adjusted R^2 (e.g. Anglim & Grant, 2014; Quevedo & Abella, 2011). No incremental benefits were observed when estimating the ambiguity premium.

I believe these observations are a strong indication for the potential benefits the Big Five facets can provide in explaining economic related constructs. Because of the large increase in incremental benefits observed when estimating risk attitude, I recommend future researchers to measure the Big Five facets and implement them into their models.

6.5 Robustness Check

To test whether the relationship between personality and the economic preference parameters would change under different expressions of risk attitudes and ambiguity attitudes, I rerun the four model 1 regressions with the parameter definitions by Sutter et al (2013) (see Appendix E). The estimated results are in line with the findings previously presented. The coefficient values differ because of the transformation of the economic preference parameters into an index, but the significant personality relationships remain the same.

7 Discussion

This paper investigated the relationship between personality and the economic preference parameters risk attitude and ambiguity attitude. Conscientious people were found to be more risk averse, and Agreeable people were found to be more ambiguity averse. This paper contributed to the field behavioural economics in several ways.

First, this paper contributed to the behavioural economic field by introducing the Big Five facets. Previous literature introducing personality to economics have not mentioned this construct (Almlund, Duckworth, Heckman, & Kautz, 2011; Müller & Schwieren, 2017). The Big Five facets are easy to implement and can help improve models because of incremental benefits. Furthermore, personality research may benefit from employing cross validation methods. The holdout method was used in this paper, providing evidence that the personality models are not reliable as sole predictors of the economic preference parameters risk and ambiguity attitudes.

Second, this study was the first to relate the Big Five facets to risk and ambiguity attitudes, providing a better understanding to which degree personality relates to economic preference parameters. Incremental benefits of the Big Five facets were observed when estimating risk attitudes. At most, personality can explain 8.1% of the variance in risk attitudes, leading to a further question of how risk and ambiguity attitudes can be explained. Because these attitudes differ among individuals, it would seem likely that they are related to other individual differences. The three major areas of interest in individual differences studies are: gender, intelligence, and personality. Past research which incorporated one or more of these areas, and this study, could not explain risk attitude nor ambiguity attitude to a satisfactory degree using these three explanatory variables (e.g. (Borghans et al., 2009; Brütsch, 2018; (Eugeni, 2016; Ramdjanamsingh, 2017). Because of that, I hypothesise that past life experiences may contribute to forming risk and ambiguity attitudes. I propose that future research should examine when these attitudes are formed and how stable they are throughout life. Optimally, a longitudinal twin study should be performed, starting from an early age. Monozygotic and dizygotic twins should be recruited to measure if the attitudes are derived from a genetic component, shared environment experience (evidence that the attitudes are formed at an early age), or personal environment experience (evidence that these attitudes are formed at an older age).

Third, this paper may serve as a guide for future economists who would like to incorporate personality as an explanatory variable or researchers who want to further study the association between personality and economic preference parameters. For example, this study could be enriched by using different contextual definitions of risk attitude and ambiguity attitudes. Furthermore, a-insensitivity could be related to personality. A-insensitive (Tversky and Fox, 1995) refers to the struggle to discriminate between different levels of unknown probabilities; how a person perceives the level of ambiguity. This parameter has recently gained more attention and improved our understanding of decision making under ambiguity. The relationships related to these constructs may be different from this research. Among the traits, Agreeableness seems to be promising because Borghans et al. (2009) found it to be significantly related to risk attitude, while I found a significant relationship with ambiguity attitude. Among the facets, there are several facets which were significant at the 5% significance level and might become significant under different definitions of risk and ambiguity attitudes. Therefore, future hypotheses, regarding the relationship to different contextual definitions of risk attitudes and ambiguity attitudes, or a-insensitivity, could be based on these traits and facets.

7.1 Limitations and Conclusions

This study has several limitations. First, the limitations regarding Borghans et al (2009) measurement of risk and ambiguity attitudes have been discussed in the chapter 3.2.1 and will not be repeated in detail here. In summary, the risk and ambiguity attitudes measurements are context specific, therefore the results of this study may not be generalizable to other definitions of risk and ambiguity attitudes. Second, self-selection of participants, recruitment through the internet, and self-report questionnaires can have adverse effects, though in personality research it is generally is unproblematic (Gosling, Vazire, & John, 2004). Third, a larger sample size would have given more power to my analyses, which may have allowed partial replication of Borghans et al. (2009) findings, specifically finding a significant relationship between Agreeableness and risk attitudes.

In conclusion, this paper provided evidence towards an association between personality and attitudes of risk and ambiguity. The latter is a link which previously was not found. Additionally, this paper showed that the Big Five facets had incremental benefits over the Big

Five traits when explaining risk attitudes. Together, this empirical evidence is supportive of including the comprehensive Big Five personality framework when estimating behavioural outcomes in economic situations.

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Appendices

Appendix A – FlowChart Personality Research

Figure A1 may aid interested readers in conducting their own personality research.

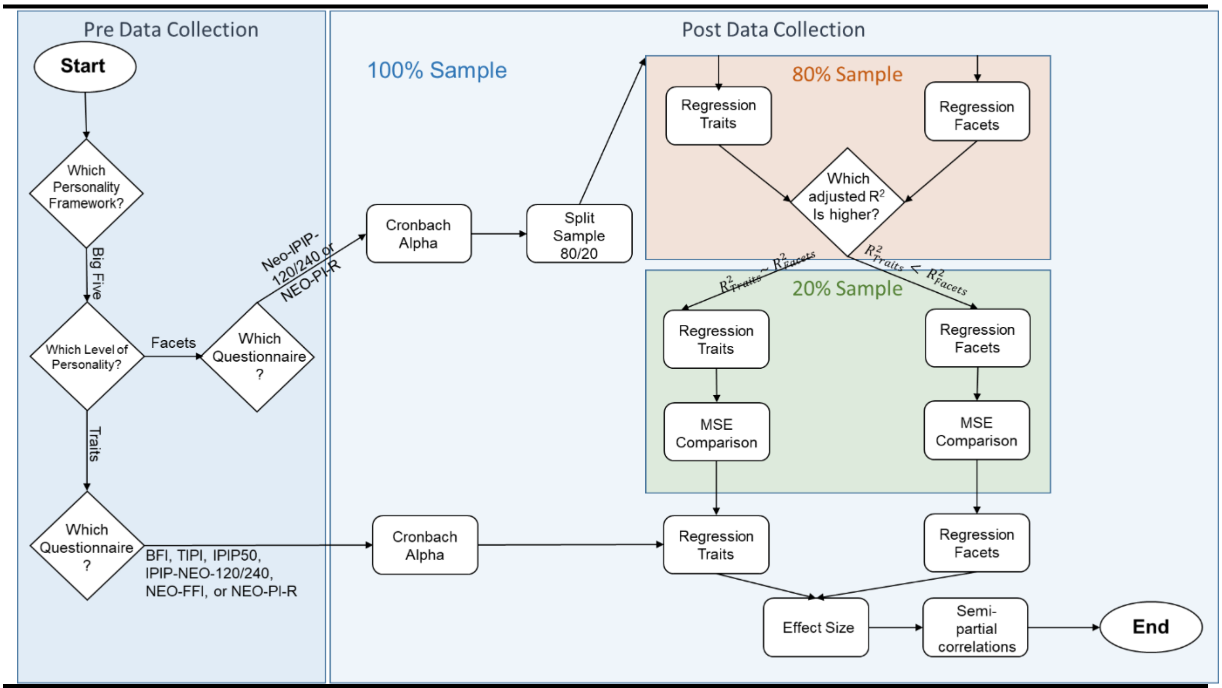


Figure A1. FlowChart Personality Research

Appendix B – Literature Review

Table B1. Social Science Papers which used the Big Five traits and facets

	Personality Test	Level of Personality	Sample Size	Significance value	Statistical Test	Topic
(Chamorro-Premuzic & Furnham, 2002)	Big Five	Facets (NEO-PI-R)	247	0.01	Correlation and multiple regression.	Academic success
(Graham & Lachman, 2014)	Big Five	Facets (NEO-PI-R)	154	0.05	hierarchical multiple regression	Cognitive Performance
(Hayward, Taylor, Smoski, Steffens, & Payne, 2013)	Big Five	Facets (NEO-PI-R)	216	0.001	Linear and logistic regression	Depression
(Luchetti, et al., 2018)	Big Five	Facets (NEO-PI-R)	5380	0.05 but comparison of results with theory and previous studies	Multinomial regressions	Alcohol consumption
(Cerasa, et al., 2016)	Big Five	Facets (NEO-PI-R)	714	0.01	ANCOVA and Cohen’s d	Similarities between priests
(Chauvin, Hermand, & Mullet, 2007)	Big Five	Facets (Modified IPIP-120)	795	0.01	Correlation and Step-wise regression	Risk perception
(Ekehammar & Akrami, 2007)	Big Five	Facets (NEO-PI-R)	408	0.01	Step-wise regression	Prejudice
(Jourdy & Petot, 2017)	Big Five	Facets (NEO-PI-R)	58	Bonferroni correction; translates to 0.0016	Zero-order Correlation (Pearson r)	Depression
(Marrero & Abella, 2011)	Big Five	Facets (NEO-PI-R)	554	0.01	Multiple regression, Step-wise regression, and Zero-order correlation (Pearson r)	Well-being

Note. This table shows that the average social scientists uses the NEO-PI-R questionnaire and consideres facet signiciant at a 1% level. The median sample size is 408 participants.

Table B2. Social Science Papers which used the Big Five traits

	Personality Test	Level of Personality	Sample Size	Significance value	Statistical Test	Topic
(Chapman, et al., 2012)	Big Five	Traits (NEO-FFI)	602	0.05	random effects linear regressions	Cognitive Functioning
(Koorevaar, et al., 2013)	Big Five	Traits (NEO-FFI)	447	0.05	Logistic regression	Depression diagnosis
(Busic-Sontic, Czap, & Fuerst, 2017)	Big Five	Traits (NEO-FFI)	6044	0.05	Logistic regression	Green decision-making
(Hammond & Morrill, 2016)	Big Five	Traits (BFI)	81	0.05	Probit model	bidding behavior in competing auctions
(Le Vigouroux, Scola, Raes, Mikolajczak, & Roskam, 2017)	Big Five	Traits (TIPI)	1723	0.05	Generalized Additive Models	Parental burnout
(Dewberry, Juanchinch, & Narendran, 2013)	Big Five	Traits (IPIP50)	355	0.05	Correlation and Hierarchical regression	Competence in Decision-making

Note. This table shows that the average social scientists uses the NEO-FFI questionnaire and consideres traits signiciant at a 5% level. The median sample size is 524 participants.

Table B3. Economic Papers which used a Big Five personality test

	Personality Test	Level of Personality	Sample Size	Significance value	Statistical Test	Topic
(Müller & Schwieren, 2017)	Big Five	Traits (NEO-PI-R)	138	Bonferroni, 0.02	Correlation and multiple regression	Trust Games
(Brandstätter & Königstein, 2001)	Cattell's 16PF	Traits (16PA)	43	0.05	Multiple regression	Ultimatum Bargaining Decisions
(Ben-Ner, Putterman, Kong, & Magan, 2004)	Big Five	Traits (NEO-FFI)	100	0.10	multivariate regression analysis	Dictator Game
(Swope, Cardigan, Schmitt, & Shupp, 2008)	MBTI	Types	233	0.10	Multiple regression	Laboratory Economic Games
(Filbeck, Hatfield, & Horvath, 2005)	MBTI	Types	68	0.10	Multiple regression	Risk aversion
(Mayfield, Perdue, & Wooten, 2008)	Big Five	Traits (NEO-FFI)	194	0.05	Correlation and multiple regression	Investment style
(Viinikainen & Kokko, 2012)	Big Five	Traits (NEO-FFI)	151	0.10	Correlation and Probit Model	Unemployment
(Borghans, Golsteyn, Heckman, & Meijers, 2009)	Big Five	Traits (BFI)	347	0.10	Multiple regression	Risk aversion and Ambiguity
(Dohmen, Falk, Huffman, & Sunde, 2010)	Big Five	Traits (BFI)	1012	0.10	Multiple regression	Risk aversion
(Baert & Decuypere, 2014)	Big Five	Traits (TIPI)	159	0.10	Multiple Regression	Hiring Decisions
(Nicholson, Soane, Fenton, & Willman, 2005)	Big Five	Facets (NEO-PI-R)	1638	0.05	Stepwise regression	Risk-taking
(Lo, Repin, & Steenbarger, 2005)	Big Five	Traits (IPIP-NEO-120)	80	0.10	Correlation §wanted to find similar result to priest, shared personality%	Trading performance
(Durand, Newby, Tant, & Trepongkaruna, 2013)	Big Five	Traits (NEO-FFI)	61	0.10	Tobit	Overconfidence

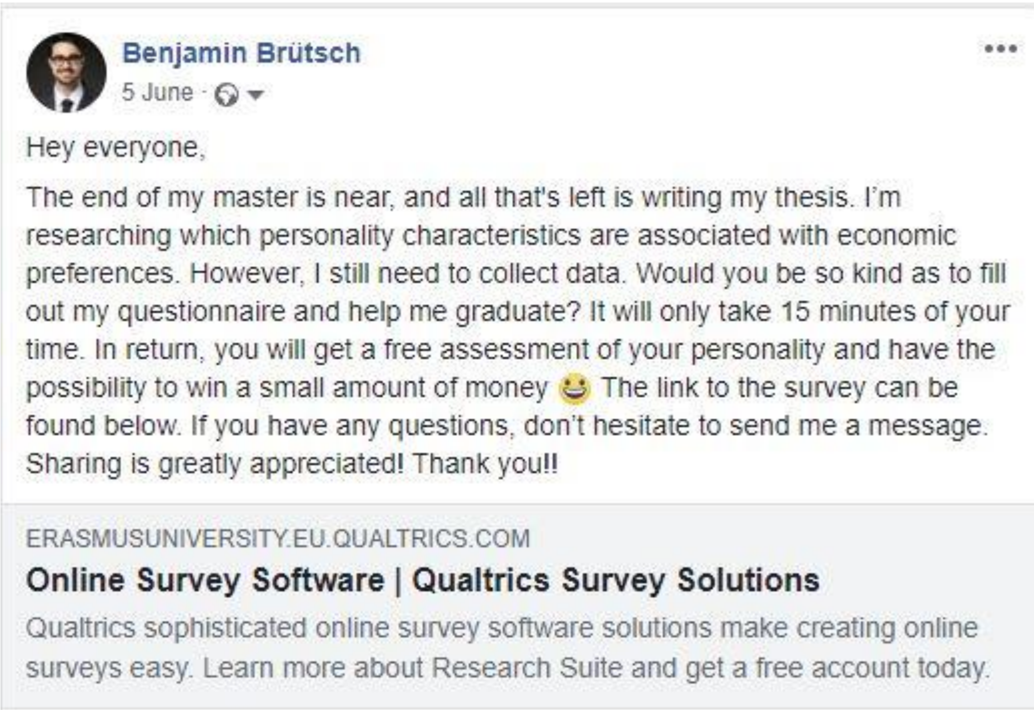
Note. This table shows a largely heterogeneic image of the methodologies employed by economists. The MBTI was used sometimes, sometimes facets were measured but not reported on, and the accepted significance values are often 10%. The median sample size is 151 participants.

Appendix C – Survey Elements

Introduction Message

Reddit:

Facebook:



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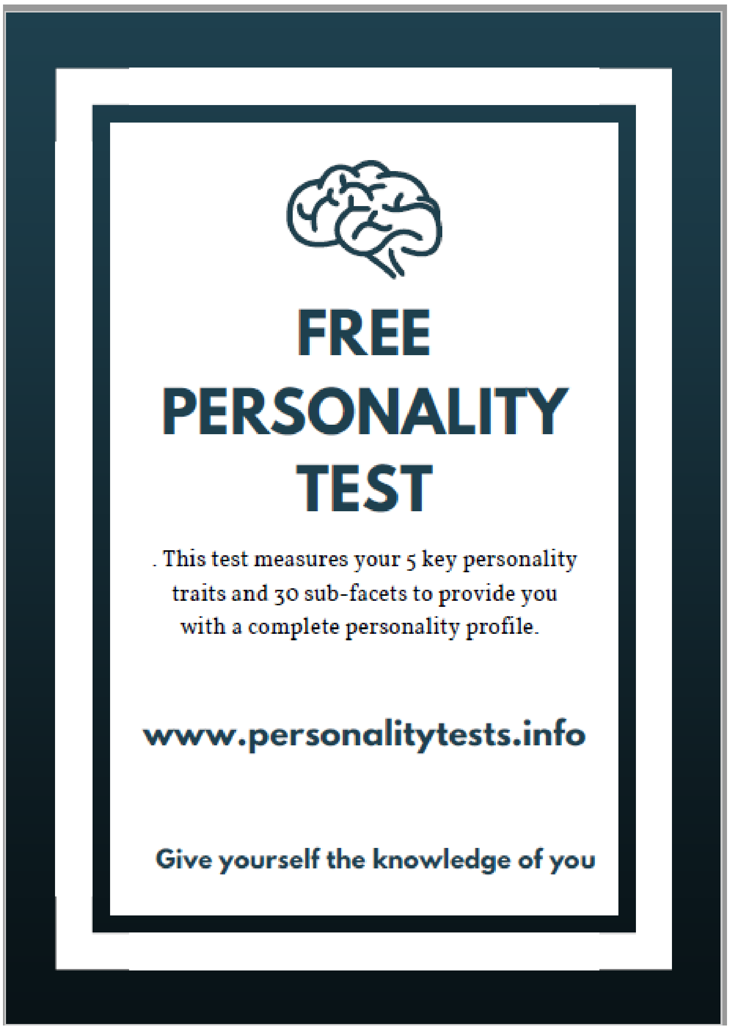
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First Page – Demographic variables

What is your age?

What is your gender?

- Male
- Female

What is your level of education?

- Less than a high school diploma
- High school degree or equivalent (e.g. GED)
- Bachelor’s degree (e.g. BA, BS)
- Master’s degree (e.g. MA, MS, MEd)
- Doctorate (e.g. PhD, EdD)

Age was coded as a continuous variable. Gender was coded as male = 0 and female = 1. Male was omitted from the regressions. Education values for individuals were coded as 0 or 1, less than a high school diploma was omitted from the regression.

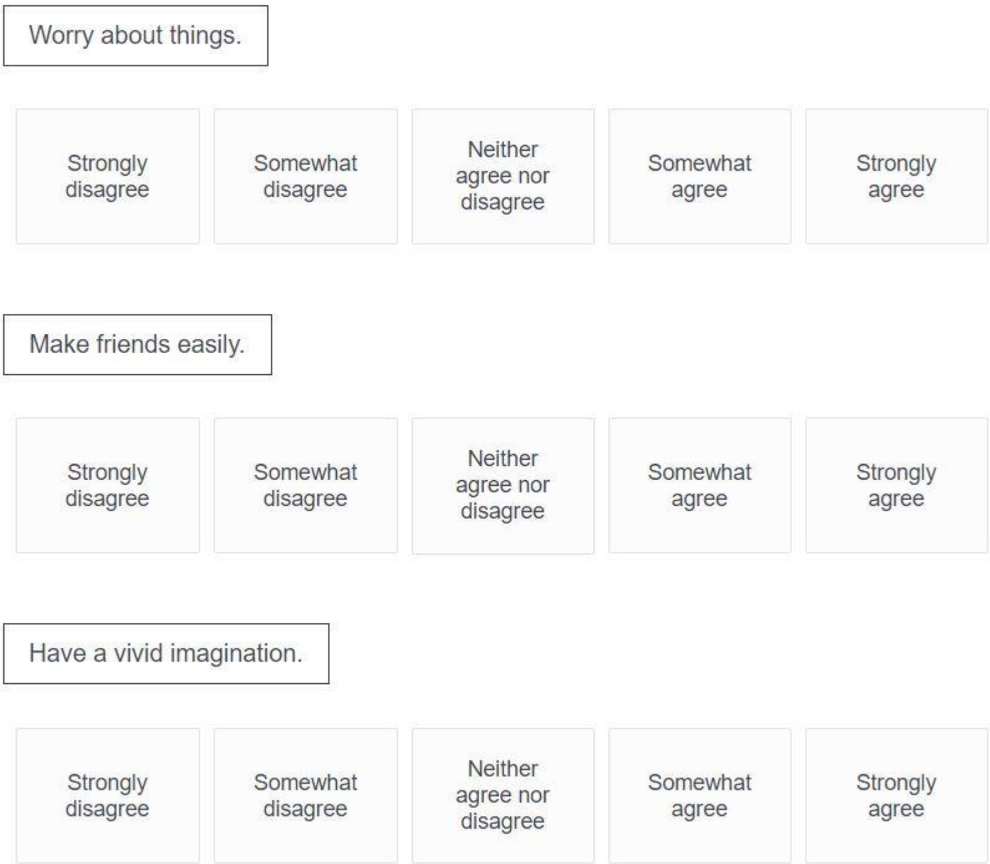
Second Page – Personality Intro

The following pages contain phrases describing people's behaviours. Please use the rating scale next to each phrase to describe how accurately each statement describes you. Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. Your responses will be kept in absolute confidence and cannot be associated with you as an individual.

→

Third Page – Personality Questionnaire

The 120 items of the NEO-IPIP-120 were presented in the layout below. For space reasons, only 3 questions are shown. The 5-point Likert scale values range from 1 (=Strongly disagree) to 5(= strongly agree)



In Table C1, all 120 items are listed, including their scoring keys. For readers unfamiliar with personality questionnaires, I provided an example of how to calculate the facets. For example, to calculate N2 Anger, we need the answers for the items no. 6, 36, 66, and 96. Assume that their answer scores are 5, 4, 4, and 1, respectively. Before calculating the facet score, the scoring key needs to be applied. A+ indicates no change in the variable, A– calls for the 'inverse' of the number: a 1 should be transformed to a 5, a 2 should be transformed to a 4, a 3 remains the same, a 4 should be transformed to a 2, and a 5 should be transformed to a 1.

In this example case, the 1 of question no. 96 is transformed into a 5. Hence, the total score of N2 Anger is 5+4+4+5 = 18. The total trait score is the summation of its facet scores.

Table C1 – Big Five Facet items and scoring

Big Five Traita	Domain scales, facet scales, and items	Facet key and Scoring	IPIP-120 item no.
Neuroticism			
	N1 Anxiety		
	Worry about things	+N1	1
	Fear for the worst	+N1	31
	Am afraid of many things	+N1	61
	Get stressed out easily	+N1	91
	N2 Anger		
	Get angry easily	+N2	6
	Get irritated easily	+N2	36
	Lose my temper	+N2	66
	Am not easily annoyed	−N2	96
	N3 Depression		
	Often feel blue	+N3	11
	Dislike myself	+N3	41
	Am often down in the dumps	+N3	71
	Feel comfortable with myself	−N3	101
	N4 Self-Consciousness		
	Find it difficult to approach others	+N4	16
	Am afraid to draw attention to myself	+N4	46
	Only feel comfortable with friends	+N4	76
	Am not bothered by difficult social situations	−N4	106
	N5 Immoderation		
	Go on binges	+N5	21
	Rarely overindulge	−N5	51
	Easily resist temptations	−N5	81
	Am able to control my cravings	−N5	111
	N6 Vulnerability		
	Panic easily	+N6	26
	Become overwhelmed by events	+N6	56
	Feel that I’m unable to deal with things	+N6	86

Big Five Traita	Domain scales, facet scales, and items	Facet key and Scoring	IPIP-120 item no.
	Remain calm under pressure	−N6	116
Extraversion			
	E1 Friendliness		
	Make friends easily	+E1	2
	Feel comfortable around people	+E1	32
	Avoid contacts with others	−E1	62
	Keep others at a distance	−E1	92
	E2 Gregariousness		
	Love large parties	+E2	7
	Talk to a lot of different people at parties	+E2	37
	Prefer to be alone	−E2	67
	Avoid crowds	−E2	97
	E3 Assertiveness		
	Take charge	+E3	12
	Try to lead others	+E3	42
	Take control of things	+E3	72
	Wait for others to lead the way	−E3	102
	E4 Activity level		
	Am always busy	+E4	17
	Am always on the go	+E4	47
	Do a lot in my spare time	+E4	77
	Like to take it easy	−E4	107
	E5 Excitement Seeking		
	Love excitement	+E5	22
	Seek adventure	+E5	52
	Enjoy being reckless	+E5	82
	Act wild and crazy	+E5	112
	E6 Cheerfulness		
	Radiate joy	+E6	27
	Have a lot of fun	+E6	57
	Love life	+E6	87
	Look at the bright side of life	+E6	117
Openness			
	O1 Imagination		
	Have a vivid imagination	+O1	3

Big Five Traita	Domain scales, facet scales, and items	Facet key and Scoring	IPIP-120 item no.
	Enjoy wild flights of fantasy	+O1	33
	Love to daydream	+O1	63
	Like to get lost in thought	+O1	93
	O2 Artistic interests		
	Believe in the importance of art	+O2	8
	See beauty in things that others might not notice	+O2	38
	Do not like poetry	−O2	68
	Do not enjoy going to art museums	−O2	98
	O3 Emotionality		
	Experience my emotions intensely	+O3	13
	Feel others' emotions	+O3	43
	Rarely notice my emotional reactions	−O3	73
	Don't understand people who get emotional	−O3	103
	O4 Adventurousness		
	Prefer variety to routine	+O4	18
	Prefer to stick with things that I know	−O4	48
	Dislike changes	−O4	78
	Am attached to conventional ways	−O4	108
	O5 Intellect		
	Love to read challenging material	+O5	23
	Avoid philosophical discussions	−O5	53
	Have difficulty understanding abstract ideas	−O5	83
	Am not interested in theoretical discussions	−O5	113
	O6 Liberalism		
	Tend to vote for liberal political candidates	+O6	28
	Believe that there is no absolute right or wrong	+O6	58
	Tend to vote for conservative political candidates	−O6	88
	Believe that we should be tough on crime	−O6	118
Agreeableness			
	A1 Trust		
	Trust others	+A1	4
	Believe that others have good intentions	+A1	34
	Trust what people say	+A1	64
	Distrust people	−A1	94
	A2 Morality		

Big Five Traita	Domain scales, facet scales, and items	Facet key and Scoring	IPIP-120 item no.
	Use others for my own ends	−A2	9
	Cheat to get ahead	−A2	39
	Take advantage of others	−A2	69
	Obstruct others' plans	−A2	99
	A3 Altruism		
	Love to help others	+A3	14
	Am concerned about others	+A3	44
	Am indifferent to the feelings of others	−A3	74
	Take no time for others	−A3	104
	A4 Cooperation		
	Love a good fight	−A4	19
	Yell at people	−A4	49
	Insult people	−A4	79
	Get back at others	−A4	109
	A5 Modesty		
	Believe that I am better than others	−A5	24
	Think highly of myself	−A5	54
	Have a high opinion of myself	−A5	84
	Boast about my virtues	−A5	114
	A6 Sympathy		
	Sympathize with the homeless	+A6	29
	Feel sympathy for those who are worse off than myself	+A6	59
	Am not interested in other people's problems	−A6	89
	Try not to think about the needy	−A6	119
Conscientiousness			
	C1 Self-Efficacy		
	Complete tasks successfully	+C1	5
	Excel in what I do	+C1	35
	Handle tasks smoothly	+C1	65
	Know how to get things done	+C1	95
	C2 Orderliness		
	Like to tidy up	+C2	10
	Often forget to put things back in their proper place	−C2	40
	Leave a mess in my room	−C2	70

Big Five Traita	Domain scales, facet scales, and items	Facet key and Scoring	IPIP-120 item no.
	Leave my belongings around	−C2	100
	C3 Dutifulness		
	Keep my promises	+C3	15
	Tell the truth	+C3	45
	Break rules	−C3	75
	Break my promises	−C3	105
	C4 Achievement-striving		
	Work hard	+C4	20
	Do more than what's expected of me	+C4	50
	Do just enough work to get by	−C4	80
	Put little time and effort into my work	−C4	110
	C5 Self-Discipline		
	Am always prepared	+C5	25
	Carry out my plans	+C5	55
	Waste my time	−C5	85
	Have difficulty starting tasks	−C5	115
	C6 Cautiousness		
	Jump into things without thinking	−C6	30
	Make rash decisions	−C6	60
	Rush into things	−C6	90
	Act without thinking	−C6	120

Fourth Page – Testing the subjects understanding of a reservation price

In this short, last part of the questionnaire, you will be playing two gambles (= winning money with a certain probability). We will introduce the two gambles in the next step. For each of the two gambles, you are asked to give the minimum price at which you would be willing to sell the respective gamble. You have the option to play for real money in these two gambles and be paid out accordingly (more information on how to get paid out after you played the gambles).

The possible payouts are coming from either winning the gamble or selling the gamble. You can imagine the following scenario: Person A is giving you a gamble you can play. Person B wants to play the gamble and is willing to buy the gamble from you. The trading process is as follows: both of you write down a number on a piece of paper and then reveal it to each other at the same time. If the number person B wrote down is larger than your number, he will pay you the amount of money he wrote down. If the number he wrote down is smaller than the number you wrote down, you will be playing the gamble instead because he is not willing to pay you as much as you wanted.
Keep in mind that person B's process of writing down a number is equivalent to that of a computer. It randomly generates a number; there are no tricks or tactics involved in person B's number generation. It is completely random.

To test your understanding of how to arrive at the best selling price for yourself, imagine the following: Instead of a gamble, Person A gives you a 1 euro coin. Again, you have the possibility to trade with Person B. What number are you writing down on your piece of paper? In other words, what would be the minimum price at which you would be willing to sell 1 euros? (Answer format: x.xx euros, hence if you would like to sell for 1 cent, you would type in 0.01)

Fifth Page

If the subjects would like more information on how to set the reservation price, they are forwarded to the sixth page. If they understood the price setting, they are forwarded to the seventh page.

The optimal answers are 1 euro or 1.01 euros as the minimum amount at which you should be willing to sell a 1 euro coin. If you are selling a 1 euro coin below the price of 1 euro, you would make a loss. If you set the price e.g. at 1.50 euros, you would be making a loss if you were offered 1.20 euros (loss of 20 cents because you could have traded the 1 euro coin for 1.20 euros).

I understand how to effectively set a minimum selling price and would like to move on to the real gamble

I would like more information on how to set the minimum selling price

→

Conditional Sixth Page

If subjects still did not understand how to set a reservation price, the survey would automatically end and skip to the tenth page.

To better understand how much to sell a 1 euro coin for, we can consider all the extreme cases.

You wouldn’t want to sell 1 euro for free because you would lose 1 euro.

You wouldn’t want to sell 1 euro for 0.99 euros because you would be losing 1 cent.

You **would** want to sell 1 euro for 1 euro because it is of equivalent value.

You **would** want to sell 1 euro for 1.01 euros because that would be a gain of 1 cent, and there would be no loss for you if the offer of Person B is 1 euro.

You wouldn’t want to sell 1 euro for 1.02 euros because you would miss out on a gain of 1 cent if the offer of Person B is 1.01 euros. (1.01 – 1 euros = 1 cent).

You wouldn’t want to sell 1 euro for 2 euros because you would miss out on a gain of 99 cents if the offer of Person B is 1.99 euros. (1.99 – 1 euros = 99 cents)

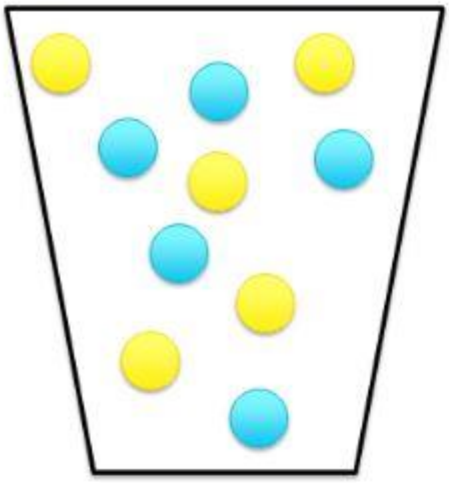
I understand

I don't understand

Seventh Page – Eliciting Risk attitudes

We will now move on to the first gamble:

Imagine the following gamble: there is a bag filled with 5 blue and 5 yellow balls.



At random, one ball will be drawn from this bag. You then have the chance to guess the colour of the drawn ball. If you guess the right colour, you'll earn 2 euros. If you are wrong, you'll get nothing.

What is the minimum price you are willing to sell this gamble? *Just to remind you, the offer of person B will be randomly generated by a computer. The computer will randomly select a value between 0 and 200 cents (= 2 euros).* (Answer format: x.xx euros)

If the randomly generated number is above your minimum price, you will get paid what the computer offered you. If the randomly generated number is below your minimum price, you will be playing the gamble. For this purpose, please indicate which colour you are betting on if you were playing the gamble?

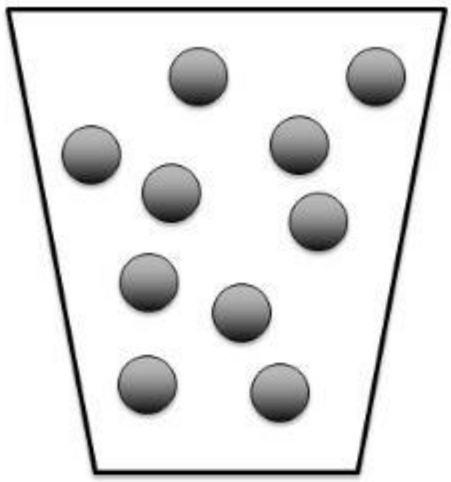
Blue

Yellow

Eight Page – Eliciting Ambiguity attitudes

We will now move on to the second gamble:

Imagine the following gamble: there is a bag filled with **10 blue and yellow balls. The colour distribution is unknown; there may be between 0 – 10 blue or yellow balls.** (black balls to illustrate the unknown colour distribution of the blue and yellow balls)



At random, one ball will be drawn from this bag. You then have the chance to guess the colour of the drawn ball. If you guess the right colour, you'll earn 2 euros. If you are wrong, you'll get nothing.

What is the minimum price you are willing to sell this gamble? *Just to remind you, the offer of person B will be randomly generated by a computer. The computer will randomly select a value between 0 and 200 cents (= 2 euros).* (Answer format: x.xx euros)

If the randomly generated number is above your minimum price, you will get paid what the computer offered you. If the randomly generated number is below your minimum price, you will be playing the gamble. For this purpose, please indicate which colour you are betting on if you were playing the gamble?

Yellow

Blue

Ninth Page – Optional pay-out option

The previous situations will be played out as described: an offer is being made that is compared to your selling price, if the offer is higher, you get paid the offer price. If the offer price is lower, you will play the gamble. If your colour is drawn, you will win 2 euros. If not, you will win nothing.

A number of lucky participants will be paid according to their outcomes. If you want to have a chance to be one of these lucky participants, you may state your email address. We will contact you if you happen to be picked and communicate the monetary amount you won. (you can leave the field empty if you don't wish to participate).

Tenth Page – Personality Report

Having filled out the survey completely, the participants immediately received their personality profile. The participants do not see the calculations displayed after every trait and facet, they would only see the respective results, expressed as percentile.

Also, this report shows the definitions of the Big Five traits and the 30 Big Five facets.

Personalised Report

To understand your individual scores, your answers are compared to other people. In science, this is expressed in terms of percentiles. For each Personality characteristic we will display the percentile you belong to. See the chart below to understand what it means to be in a certain percentile range.

Percentile Chart

Percentile Rank	>4	4 - 10	11 - 22	23 - 39	40 - 59	60 - 76	77 - 88	89 - 95	95<
Meaning	extremely low	very low	below average	slightly below average	Average	slightly above average	above average	very high	extremely high

Print this page or save as PDF (🡐 *a button participants could click*)

Neuroticism

Your raw score on Neuroticism: $e{round (gr://SC_cu8ouYosrqkNswZ/Score + gr://SC_bCswNXfNIBlTvvL/Score + gr://SC_6heZzo7fOKq6i2N/Score + gr://SC_dg7FUapO1Xoh92J/Score + gr://SC_1LL3CxiiowPUlZr/Score + gr://SC_88kDFu5HGeJhtf7/Score) }

Percentile Rank	>4	4 - 10	11 - 22	23 - 39	40 - 59	60 - 76	77 - 88	89 - 95	95<
Raw Score	>43	44 - 49	50 - 57	58 - 65	66 - 76	78 - 80	81 - 87	88 - 95	96<

Neuroticism is the one Big Five factor in which a high score indicates more negative traits. Neuroticism is not a factor of meanness or incompetence, but one of confidence and being comfortable in one's own skin. It encompasses one's emotional stability and general temper. Those high in neuroticism are generally given to anxiety, sadness, worry, and low self-esteem. They may be temperamental or easily angered, and they tend to be self-conscious and unsure of themselves. Individuals who score on the low end of neuroticism are more likely to feel confident, sure of themselves, and adventurous. They may also be brave and unencumbered by worry or self-doubt.

Your Neuroticism facet percentile scores:

N1 Anxiety: $e{round (-0.0497 * (gr://SC_cu8ouYosrqkNswZ/Score ^ 3) + 1.8455 *

(gr://SC_cu8ouYosrqkNswZ/Score ^ 2) - 13.536 * gr://SC_cu8ouYosrqkNswZ/Score + 29.034, 1)} percentile
Anxious people are shy, fearful, nervous, tensed and restless. This scale does not measure specific fears or phobias, but high scorers are more likely to have such fears, as well as free-floating anxiety. On the other hand, low scorers are calm and relaxed.

N2 Anger: $e{round (-0.0359 * (gr://SC_bCswNXfNIBlTvvL/Score ^ 3) + 1.3088 * (gr://SC_bCswNXfNIBlTvvL/Score ^ 2) - 7.5428 * gr://SC_bCswNXfNIBlTvvL/Score + 12.893, 1)} percentile
This facet represents the tendency to experience anger and negative emotions, such as frustration and bitterness. This scale measures the individual's readiness to experience anger. Its expression depends upon individual's level of Agreeableness. Disagreeable persons often score high on this scale. Low scorers are easy going and slow to anger.

N3 Depression: $e{round (-0.0404 * (gr://SC_6heZzo7fOKq6i2N/Score ^ 3) + 1.2394 * (gr://SC_6heZzo7fOKq6i2N/Score ^ 2) - 3.9859 * gr://SC_6heZzo7fOKq6i2N/Score + 4.3585, 1)} percentile
This scale measures normal individual differences in the tendency to experience depressive affect. High scorers are prone to feelings of guilt, sadness, hopelessness, and loneliness. They are easily discouraged and often dejected. Low scorers rarely experience such emotions, but they are not necessarily cheerful and lighthearted as these positive characteristics being associated instead with Extraversion.

N4 Self-Consciousness: $e{round (-0.0541 * (gr://SC_dg7FUapO1Xoh92J/Score ^ 3) + 1.9402 * (gr://SC_dg7FUapO1Xoh92J/Score ^ 2) - 13.626 * gr://SC_dg7FUapO1Xoh92J/Score + 27.978, 1)} percentile
The emotions of shame and embarrassment form the core of this facet. Self-conscious individuals are uncomfortable around others, sensitive to ridicule, and prone to feelings of inferiority. Self-consciousness is akin to shyness and social anxiety. Low scorers do not necessarily have poise or good social skills, but they are simply less disturbed by awkward social situations.

N5 Immoderation: $e{round (-0.0669 * (gr://SC_1LL3CxiiowPUlZr/Score ^ 3) + 2.4601 * (gr://SC_1LL3CxiiowPUlZr/Score ^ 2) - 19.882 * gr://SC_1LL3CxiiowPUlZr/Score + 47.247, 1)} percentile
Immoderation refers to the inability to control cravings and urges. Desires or yearnings (for food, cigarettes, possessions, a.s.o) are perceived by the high scorers as being so strong that the individual cannot resist them, although he or she may later regret the behavior. Low scorers find it easier to resist such temptations, having a high tolerance for frustration and the capacity to easier postpone gratifications.

N6 Vulnerability: $e{round (-0.056 * (gr://SC_88kDFu5HGeJhtf7/Score ^ 3) + 1.7644 * (gr://SC_88kDFu5HGeJhtf7/Score ^ 2) - 8.8293 * gr://SC_88kDFu5HGeJhtf7/Score + 13.095, 1)} percentile
The final facet of Neuroticism is vulnerability to stress. Individuals who score high on this scale feel unable to cope with stress, becoming dependent, hopeless, or panicked when facing emergency situations. Low scorers perceive themselves as capable of handling themselves in difficult situations and often have a healthy feeling of trust in their adaptive abilities.

Conscientiousness

Your raw score on Conscientiousness: $e{round (gr://SC_07LSk3nArQjFUDH/Score + gr://SC_3t3CjORj8baRddP/Score + gr://SC_0ufCCUIDHvjNuh7/Score + gr://SC_8cwPkYYyhslgKTb/Score + gr://SC_0qeowOoSy5jEi6p/Score + gr://SC_bjcxQYpPbYmP7x3/Score) }

Percentile Rank	>4	4 - 10	11 - 22	23 - 39	40 - 59	60 - 76	77 - 88	89 - 95	95<
Score	>58	59 - 66	67 - 72	73 - 79	80 - 88	89 - 96	97 - 102	103 - 108	109<

Conscientiousness is a trait that can be described as the tendency to control impulses and act in socially acceptable ways, behaviors that facilitate goal-directed behavior. Conscientious people excel in their ability to delay gratification, work within the rules, and plan and organize effectively. Someone who is high in conscientiousness is likely to be successful in school and in their career, to excel in leadership positions, and to doggedly pursue their goals with determination and forethought. A person who is low in conscientiousness is much more likely to procrastinate, to be flighty, impetuous, and impulsive.

Your Conscientiousness facet percentile scores:

C1 Self-efficacy: $e{round (-0.1413 * (gr://SC_07LSk3nArQjFUDH/Score ^ 3) + 6.6407 * (gr://SC_07LSk3nArQjFUDH/Score ^ 2) - 90.87 * gr://SC_07LSk3nArQjFUDH/Score + 386.88, 1)} percentile
Self-efficacy refers to the sense that one is capable, sensible, prudent, and effective. High scorers on this scale feel well-prepared to deal with life. Low scorers have a lower opinion of their abilities and admit that they are often unprepared and inept. Self-efficacy is most highly associated with self-esteem and internal focus of control.

C2 Orderliness: $e{round (-0.0321 * (gr://SC_3t3CjORj8baRddP/Score ^ 3) + 1.1545 * (gr://SC_3t3CjORj8baRddP/Score ^ 2) - 5.7998 * gr://SC_3t3CjORj8baRddP/Score + 8.8571, 1)} percentile
High scorers on this scale are neat, tidy, and well-organized. They keep things in their proper places. Low scorers are unable to get organized and describe themselves as unmethodical. Carried to an extreme, high Orderliness might contribute to a Compulsive Personality Disorder.

C3 Dutifulness: $e{round (-0.121 * (gr://SC_0ufCCUIDHvjNuh7/Score ^ 3) + 5.6698 * (gr://SC_0ufCCUIDHvjNuh7/Score ^ 2) - 76.029 * gr://SC_0ufCCUIDHvjNuh7/Score + 315.41, 1)} percentile
High scorers on this scale adhere strictly to their ethical principles and scrupulously fulfill their moral obligations. Low scorers are more casual about such matters and may be somewhat undependable or unreliable.

C4 Achievement-striving: $e{round (-0.0652 * (gr://SC_8cwPkYYyhslgKTb/Score ^ 3) + 2.9525 * (gr://SC_8cwPkYYyhslgKTb/Score ^ 2) - 34.401 *

gr://SC_8cwPkYYyhslgKTb/Score + 120.6, 1)} percentile
Individuals who score high on this facet have high aspiration levels and work hard to achieve their goals. They are diligent and purposeful and have a sense of direction in life. Very high scorers, however, may invest too much in their careers and become workaholics. Low scorers are lackadaisical and perhaps even lazy. They are not driven to succeed. They lack ambition and may seem aimless, but they are often perfectly content with their low levels of achievement.

C5 Self-discipline: $e{round (-0.0795 * (gr://SC_0qeowOoSy5jEi6p/Score ^ 3) + 3.1672 * (gr://SC_0qeowOoSy5jEi6p/Score ^ 2) - 31.177 * gr://SC_0qeowOoSy5jEi6p/Score + 91.63, 1)} percentile
Self-Discipline means the ability to begin tasks and carry them through completion despite boredom and other distraction. High scorers have the ability to motivate themselves to get the job done. Low scorers procrastinate in beginning chores and are easily discouraged and eager to quit.

C6 Cautiousness: $e{round (-0.0347 * (gr://SC_bjcxQYpPbYmP7x3/Score ^ 3) + 1.3055 * (gr://SC_bjcxQYpPbYmP7x3/Score ^ 2) - 8.095 * gr://SC_bjcxQYpPbYmP7x3/Score + 14.806, 1)} percentile
The final facet is Cautiousness, that is the tendency to think carefully before acting. High scorers on this facet are cautious and deliberate. Low scorers are hasty and often speak or act without considering the consequences. At best, low scorers are spontaneous and able to make snap decisions when necessary.

Extraversion

Your raw score on Extraversion: $e{round (gr://SC_0whu4DZQjdNjWWp/Score + gr://SC_a9x4tWbtqd0ehqB/Score + gr://SC_dnDj7hNBqf9eEAd/Score + gr://SC_9NxLWXPoXo1vOkJ/Score + gr://SC_2mMx8UwDCtvGaDb/Score + gr://SC_9NzC6dfb34jsN3n/Score) }

Percentile Rank	>4	4 - 10	11 - 22	23 - 39	40 - 59	60 - 76	77 - 88	89 - 95	95<
Score	>55	56 - 62	63 -69	70 - 76	77 - 85	86 - 92	93 - 99	100 - 105	106<

This factor has two familiar ends of the spectrum: extroversion and introversion. It concerns where an individual draws their energy and how they interact with others. In general, extroverts draw energy or “recharge” from interacting with others, while introverts get tired from interacting with others and replenish their energy from solitude. People high in extroversion tend to seek out opportunities for social interaction, where they are often the “life of the party.” They are comfortable with others, gregarious, and prone to action rather than contemplation. People low in extroversion are more likely to be people “of few words,” people who are quiet, introspective, reserved, and thoughtful.

Your Extraversion facet percentile scores:

E1 Friendliness: $e{round (-0.0529 * (gr://SC_0whu4DZQjdNjWWp/Score ^ 3) + 2.2433 *

(gr://SC_0whu4DZQjdNjWWp/Score ^ 2) - 22.21 * gr://SC_0whu4DZQjdNjWWp/Score + 65.088, 1)} percentile
Friendliness is the facet of Extraversion most relevant to issues of interpersonal intimacy. Friendly people are affectionate and warm. They genuinely like people and easily form close attachments to others. Low scorers are neither hostile nor necessarily lacking in compassion, but they are more formal, reserved, and distant in manner than high scorers. Friendliness is the facet of Extraversion that is closest to Agreeableness in interpersonal space, but it is distinguished by a cordiality and heartiness that is not part of Agreeableness.

E2 Gregariousness: $e{round (-0.0394 * (gr://SC_a9x4tWbtqd0ehqB/Score ^ 3) + 1.4599 * (gr://SC_a9x4tWbtqd0ehqB/Score ^ 2) - 9.4115 * gr://SC_a9x4tWbtqd0ehqB/Score + 17.807, 1)} percentile
The second aspect of Extraversion is gregariousness, that is the preference for other people's company. Gregarious people enjoy the company of others, and the more the merrier. Low scorers on this scale tend to be loners who do not seek, or even actively avoid social stimulation.

E3 Assertiveness: $e{round (-0.057 * (gr://SC_dnDj7hNBqf9eEAd/Score ^ 3) + 2.3957 * (gr://SC_dnDj7hNBqf9eEAd/Score ^ 2) - 23.843 * gr://SC_dnDj7hNBqf9eEAd/Score + 70.369, 1)} percentile
High scorers on this scale are dominant, forceful, and socially ascendant. They speak without hesitation and often become group leaders. Low scorers prefer to keep in the background and let others do the talking, come-up with ideas and propositions, assign tasks and lead group projects.

E4 Activity level: $e{round (-0.0816 * (gr://SC_9NxLWXPoXo1vOkJ/Score ^ 3) + 3.0139 * (gr://SC_9NxLWXPoXo1vOkJ/Score ^ 2) - 26.119 * gr://SC_9NxLWXPoXo1vOkJ/Score + 67.045, 1)} percentile
High scorers are characteristic of people who have a rapid tempo in life. These persons are vigorous, energetic and need to be always busy. Active people lead fast-paced lives. Low scorers are more leisurely and relaxed intempo, although they are not necessarily sluggish or lazy.

E5 Excitement-seeking: $e{round (-0.0626 * (gr://SC_2mMx8UwDCtvGaDb/Score ^ 3) + 2.4764 * (gr://SC_2mMx8UwDCtvGaDb/Score ^ 2) - 22.623 * gr://SC_2mMx8UwDCtvGaDb/Score + 61.086, 1)} percentile
High scorers on this scale crave excitement and stimulation. They like bright colors and noisy environments. Excitement-Seeking is akin to some aspects of sensation seeking. Low scorers feel little need for thrills and prefer a life that high scorers might find boring.

E6 Cheerfulness: $e{round (-0.066 * (gr://SC_9NzC6dfb34jsN3n/Score ^ 3) + 2.9515 * (gr://SC_9NzC6dfb34jsN3n/Score ^ 2) - 33.762 * gr://SC_9NzC6dfb34jsN3n/Score + 116.07, 1)} percentile
The last facet of Extraversion assesses the tendency to experience positive emotions such as joy, happiness, love, and excitement. High scorers on this scale laugh easily and often. They are cheerful and optimistic. Low scorers are not necessarily unhappy; they are merely less exuberant and high-spirited. Research (e.g. Costa& McCrae, 1980a) has shown that happiness and life satisfaction are related to both Neuroticism and Extraversion, and that Cheerfulness is the facet of Extraversion most relevant to the prediction of happiness.

Openness

Your raw score on Openness: $e{round (gr://SC_4YFzSoIZCPG4hGl/Score + gr://SC_9Xr4VB46MhYuQ8R/Score + gr://SC_0BcVDwe7oFchICF/Score + gr://SC_5169tjHeLJ2IElf/Score + gr://SC_d4f38X4WsaBI6sl/Score + gr://SC_9SSMqJFrb5shbM1/Score) }

Percentile Rank	>4	4 - 10	11 - 22	23 - 39	40 - 59	60 - 76	77 - 88	89 - 95	95<
Score	>63	64 - 68	69 - 72	73 - 80	81 - 85	86 - 93	94 - 99	100 - 105	105<

Openness has been described as the depth and complexity of an individual's mental life and experiences. It is also sometimes called intellect or imagination. Openness concerns an individual's willingness to try to new things, to be vulnerable, and the ability to think outside the box. An individual who is high in openness to experience is likely someone who has a love of learning, enjoys the arts, engages in a creative career or hobby, and likes meeting new people. An individual who is low in openness to experience probably prefers routine over variety, sticks to what they know, and prefers less abstract arts and entertainment.

Your Openness facet percentile scores:

O1 Imagination: $e{round (-0.0728 * (gr://SC_4YFzSoIZCPG4hGl/Score ^ 3) + 3.3777 * (gr://SC_4YFzSoIZCPG4hGl/Score ^ 2) - 41.646 * gr://SC_4YFzSoIZCPG4hGl/Score + 155.64, 1)} percentile
Individuals who are open to fantasy have a vivid imagination and an active fantasy life. They daydream not simply as an escape but as a way of creating for themselves an interesting inner world. They elaborate and develop their fantasies and believe that imagination contributes to a rich and creative life. Low scorers are more prosaic and prefer to keep their minds on the task at hand.

O2 Artistic Interest: $e{round (-0.0539 * (gr://SC_9Xr4VB46MhYuQ8R/Score ^ 3) + 2.3855 * (gr://SC_9Xr4VB46MhYuQ8R/Score ^ 2) - 25.6 * gr://SC_9Xr4VB46MhYuQ8R/Score + 81.776, 1)} percentile
High scorers on this scale have a deep appreciation for art and beauty. They are moved by poetry, absorbed in music, and intrigued by art. They need not have artistic talent, nor even necessarily what most people would consider good taste; but for many of them, their interest in the arts will lead them to develop a wider knowledge and appreciation than that of the average individual. Low scorers are relatively insensitive to and uninterested in art and beauty.

O3 Emotionality: $e{round (-0.0891 * (gr://SC_0BcVDwe7oFchICF/Score ^ 3) + 4.0904 * (gr://SC_0BcVDwe7oFchICF/Score ^ 2) - 51.26 * gr://SC_0BcVDwe7oFchICF/Score + 196.04, 1)} percentile

Openness to feelings implies receptivity to one's own inner feelings and emotions and the evaluation of emotion as an important part of life. High scorers experience deeper and more differentiated emotional states and feel both happiness and unhappiness more intensely then others. Low scorers have somewhat blunted affects and do not believe that feeling states are of much importance.

O4 Adventurousness: $e{round (-0.0748 * (gr://SC_5169tjHeLJ2IElf/Score ^ 3) + 2.8157 * (gr://SC_5169tjHeLJ2IElf/Score ^ 2) - 24.672 * gr://SC_5169tjHeLJ2IElf/Score + 63.965, 1)} percentile
Openness is seen behaviorally in the willingness to try different activities, go new places, or eat unusual foods. High scorers on this scale prefer novelty and variety to familiarity and routine. Over time, they may engage in a series of different hobbies. Low scorers find change difficult and prefer to stick with the tried-and-true.

O5 Intellect: $e{round (-0.0597 * (gr://SC_d4f38X4WsaBI6sl/Score ^ 3) + 2.6362 * (gr://SC_d4f38X4WsaBI6sl/Score ^ 2) - 28.935 * gr://SC_d4f38X4WsaBI6sl/Score + 94.916, 1)} percentile
Intellectual curiosity in an aspect of Openness that has long been recognized. This trait is seen not only in an active pursuit of intellectual interests for their own sake, but also in open-mindedness and a willingness to consider new, perhaps unconventional ideas. High scorers enjoy both philosophical arguments and brain-teasers. Intellect does not necessarily imply high intelligence, although it can contribute to the development of intellectual potential. Low scorers on the scale have limited curiosity and, even when highly intelligent, narrowly focus their resources on limited topics.

O6 Liberalism: $e{round (-0.0682 * (gr://SC_9SSMqJFrb5shbM1/Score ^ 3) + 2.3341 * (gr://SC_9SSMqJFrb5shbM1/Score ^ 2) - 16.304 * gr://SC_9SSMqJFrb5shbM1/Score + 33.332, 1)} percentile
Liberalism means the readiness to re-examine social, political, and religious values. Closed individuals tend to accept authority and honor tradition and as a consequence are generally conservative, regardless of political party affiliation. Liberalism may be considered the opposite of dogmatism.

Agreeableness

Your raw score on Agreeableness: $e{round (gr://SC_cASbMcPDa4PEUyp/Score + gr://SC_bDEbaGLTB8NKiJn/Score + gr://SC_eqDWlxnHegSAbOt/Score + gr://SC_8f7GDq7zdcafW5v/Score + gr://SC_8cRliFGeyX3MtP7/Score + gr://SC_9odLr5MDTyqjpKl/Score) }

Percentile Rank	>4	4 - 10	11 - 22	23 - 39	40 - 59	60 - 76	77 - 88	89 - 95	95<
Score	>64	65 - 71	72 - 77	78 - 83	84 - 91	92 - 96	97 - 102	103 - 108	108<

This factor concerns how well people get along with others. While extroversion concerns sources of energy and the pursuit of interactions with others, agreeableness concerns your orientation to others. It is a construct that rests on how you generally interact with others. People high in agreeableness tend to be well-liked, respected, and sensitive to the needs of others. They likely have few enemies, are sympathetic, and affectionate to their friends and loved ones, as well as sympathetic to the plights of strangers. People on the low end of the agreeableness spectrum are less likely to be trusted and liked by others. They tend to be callous, blunt, rude, ill-tempered, antagonistic, and sarcastic. Although not all people who are low in agreeableness are cruel or abrasive, they are not likely to leave others with a warm fuzzy feeling.
Your Agreeableness facet percentile scores:

A1 Trust: $e{round (-0.0581 * (gr://SC_cASbMcPDa4PEUyp/Score ^ 3) + 2.3189 * (gr://SC_cASbMcPDa4PEUyp/Score ^ 2) - 21.058 * gr://SC_cASbMcPDa4PEUyp/Score + 56.421, 1)} percentile
High scorers have a disposition to believe that others are honest and well-intentioned. Low scorers on this scale tend to be cynical and skeptical and assume that others may be dishonest or dangerous.

A2 Morality: $e{round (-0.0848 * (gr://SC_bDEbaGLTB8NKiJn/Score ^ 3) + 4.0817 * (gr://SC_bDEbaGLTB8NKiJn/Score ^ 2) - 54.403 * gr://SC_bDEbaGLTB8NKiJn/Score + 222.09, 1)} percentile
High scores on this scale are frank, sincere, and ingenuous. Low scorers on this scale are more willing to manipulate others through flattery, craftiness, or deception. Note: A low scorer on this scale is more likely to stretch the truth or to be guarded in expressing his or her true feelings, but this should not be interpreted to mean that he or she is a dishonest or a manipulative person. In particular, this scale should not be regarded as a lie scale.

A3 Altruism: $e{round (-0.1293 * (gr://SC_eqDWlxnHegSAbOt/Score ^ 3) + 6.3651 * (gr://SC_eqDWlxnHegSAbOt/Score ^ 2) - 91.66 * gr://SC_eqDWlxnHegSAbOt/Score + 411.36, 1)} percentile
High scorers on the Altruism scale have an active concern for others' welfare as shown in generosity, consideration of others, and a willingness to assist others in need of help. Low scorers on this scale are somewhat more self-centered and are reluctant to get involved in the problems of others.

A4 Cooperation: $e{round (-0.0481 * (gr://SC_8f7GDq7zdcafW5v/Score ^ 3) + 2.0401 * (gr://SC_8f7GDq7zdcafW5v/Score ^ 2) - 19.664 * gr://SC_8f7GDq7zdcafW5v/Score + 55.91, 1)} percentile
This facet of Agreeableness concerns characteristic reactions to interpersonal conflict. The high scorer tends to defer to others, to inhibit aggression, and to forgive and forget. Compliant people are meek and mild. The lowscorer is aggressive, prefers to compete rather than cooperate, and has no reluctance to express anger when necessary.

A5 Modesty: $e{round (-0.0589 * (gr://SC_8cRliFGeyX3MtP7/Score ^ 3) + 2.2203 * (gr://SC_8cRliFGeyX3MtP7/Score ^ 2) - 18.03 * gr://SC_8cRliFGeyX3MtP7/Score + 42.985, 1)} percentile
High scorers on this scale are humble and self-effacing although they are not necessarily lacking in self-confidence or self-esteem. Low scorers believe they are superior people and

may be considered conceited or arrogant by others. A pathological lack of modesty is part of the clinical conception of narcissism.

A6 Sympathy: $e{round (-0.0845 * (gr://SC_9odLr5MDTyqjpKl/Score ^ 3) + 3.8146 * (gr://SC_9odLr5MDTyqjpKl/Score ^ 2) - 46.313 * gr://SC_9odLr5MDTyqjpKl/Score + 170.9, 1)} percentile
This facet scale measures attitudes of sympathy and concern for others. High scorers are moved by others' needs and emphasize the human side of social policies. Low scorers are more hard headed and less moved by appeals to pity. They would consider themselves realists who make rational decisions based on cold logic.

Appendix D – Frequency Tables

Table D1. Frequency Table Risk attitudes

Reservation Price	Frequency	Percent	Valid Percent	Cumulative Percent
.00	5	2.1	2.1	2.1
1.00	9	3.8	3.8	5.9
3.00	1	.4	.4	6.3
4.00	1	.4	.4	6.8
10.00	3	1.3	1.3	8.0
35.00	1	.4	.4	8.4
40.00	2	.8	.8	9.3
50.00	12	5.1	5.1	14.3
75.00	1	.4	.4	14.8
90.00	2	.8	.8	15.6
99.00	1	.4	.4	16.0
100.00	91	38.4	38.4	54.4
101.00	13	5.5	5.5	59.9
102.00	1	.4	.4	60.3
105.00	1	.4	.4	60.8
109.00	1	.4	.4	61.2
110.00	3	1.3	1.3	62.4
112.00	1	.4	.4	62.9
115.00	2	.8	.8	63.7
120.00	6	2.5	2.5	66.2
124.00	1	.4	.4	66.7
125.00	2	.8	.8	67.5
130.00	2	.8	.8	68.4
133.00	1	.4	.4	68.8
150.00	18	7.6	7.6	76.4
155.00	1	.4	.4	76.8
160.00	1	.4	.4	77.2
175.00	2	.8	.8	78.1
185.00	1	.4	.4	78.5
190.00	2	.8	.8	79.3
198.00	1	.4	.4	79.7
199.00	3	1.3	1.3	81.0
200.00	45	19.0	19.0	100.0
Total	237	100.0	100.0	

Note. The two largest portions of price setting are at the 1 euro and 2 euro mark, combined, over 57% of the participants stated one of these two reservation prices.

Table D2. Frequency Table Ambiguity Attitudes

Ambiguity Premium	Frequency	Percent	Valid Percent	Cumulative Percent
-200.00	2	.8	.8	.8
-199.00	1	.4	.4	1.3
-188.00	1	.4	.4	1.7
-150.00	1	.4	.4	2.1
-100.00	1	.4	.4	2.5
-100.00	16	6.8	6.8	9.3
-99.00	5	2.1	2.1	11.4
-98.00	1	.4	.4	11.8
-90.00	6	2.5	2.5	14.3
-80.00	6	2.5	2.5	16.9
-79.00	2	.8	.8	17.7
-75.00	2	.8	.8	18.6
-70.00	2	.8	.8	19.4
-60.00	1	.4	.4	19.8
-50.00	29	12.2	12.2	32.1
-49.00	2	.8	.8	32.9
-45.00	1	.4	.4	33.3
-40.00	3	1.3	1.3	34.6
-40.00	1	.4	.4	35.0
-39.00	1	.4	.4	35.4
-32.00	1	.4	.4	35.9
-30.00	3	1.3	1.3	37.1
-30.00	1	.4	.4	37.6
-28.00	1	.4	.4	38.0
-25.00	7	3.0	3.0	40.9
-21.00	1	.4	.4	41.4
-20.00	8	3.4	3.4	44.7
-20.00	1	.4	.4	45.1
-10.00	1	.4	.4	45.6
-10.00	1	.4	.4	46.0
-9.00	1	.4	.4	46.4
-3.00	1	.4	.4	46.8
-1.00	4	1.7	1.7	48.5
.00	99	41.8	41.8	90.3
1.00	1	.4	.4	90.7
5.00	1	.4	.4	91.1
10.00	1	.4	.4	91.6
25.00	3	1.3	1.3	92.8
49.00	1	.4	.4	93.2
55.00	1	.4	.4	93.7
75.00	1	.4	.4	94.1

Ambiguity Premium	Frequency	Percent	Valid Percent	Cumulative Percent
99.00	4	1.7	1.7	95.8
100.00	6	2.5	2.5	98.3
190.00	1	.4	.4	98.7
197.00	1	.4	.4	99.2
199.00	1	.4	.4	99.6
200.00	1	.4	.4	100.0
Total	237	100.0	100.0	

Note. Over 41% of the participants stated the same reservation price for gamble 1 and gamble 2.

Appendix E – Robustness Check

Table E1. Robustness check

Variable	Risk	Ambiguity
Constant	0.443	0.042
	[0.242]	[0.336]
Neuroticism	0.000	-0.003
	[0.001]	[0.002]
Extraversion	-0.002	0.001
	[0.001]	[0.002]
Openness	0.002	0.001
	[0.002]	[0.002]
Agreeableness	-0.003	**0.004****
	[0.001]	[0.002]
Conscientiousness	**0.003****	-0.002
	[0.001]	[0.002]
Adjusted R Square	0.016	0.029
F-test	1.781	**2.393****

Note. Running the Big Five trait model regressions using Sutter et al (2013) risk and ambiguity indexes produced the same significant Big Five trait variables as when Borghans et al's (2009) parameter definitions were employed: Conscientiousness positively relates to risk aversion and Agreeableness positively relates to ambiguity aversion.
** p < 5%; *** p < 1%

Table E2. Robustness check

Variable	Risk	Ambiguity
Constant	0.668	0.134
	[0.318]	[0.462]
<u>Neuroticism</u>		
N1 Anxiety	-0.004	-0.001
	[0.009]	[0.013]
N2 Anger	-0.007	0.006
	[0.006]	[0.008]
N3 Depression	0.010	-0.005
	[0.008]	[0.012]
N4 Self-Consciousness	**-0.022*****	0.009
	[0.008]	[0.012]
N5 Immoderation	0.003	-0.010
	[0.007]	[0.010]
N6 Vulnerability	0.017**	-0.009
	[0.008]	[0.012]
<u>Extraversion</u>		
E1 Friendliness	-0.016**	0.006
	[0.008]	[0.011]

Variable	Risk	Ambiguity
E2 Gregariousness	-0.002	0.016
	[0.007]	[0.011]
E3 Assertiveness	-0.015**	-0.005
	[0.008]	[0.011]
E4 Activity Level	-0.008	0.009
	[0.008]	[0.012]
E5 Excitement-Seeking	0.003	-0.015
	[0.008]	[0.011]
E6 Cheerfulness	0.011	-0.03
	[0.008]	[0.012]
Openness		
O1 Imagination	-0.012	-0.017
	[0.007]	[0.010]
O2 Artistic Interests	0.003	-0.01
	[0.006]	[0.009]
O3 Emotionality	0.004	0.009
	[0.007]	[0.011]
O4 Adventurousness	-0.002	0.017
	[0.008]	[0.011]
O5 Intellect	0.015	0.014
	[0.008]	[0.011]
O6 Liberalism	-0.002	0.002
	[0.007]	[0.010]
Agreeableness		
A1 Trust	0.005	0.002
	[0.006]	[0.009]
A2 Morality	-0.004	-0.005
	[0.008]	[0.011]
A3 Altruism	0.009	0.000
	[0.009]	[0.014]
A4 Cooperation	-0.013	0.009
	[0.008]	[0.012]
A5 Modesty	-0.017**	0.000
	[0.007]	[0.010]
A6 Sympathy	-0.007	0.006
	[0.009]	[0.013]
Conscientiousness		
C1 Self-Efficacy	-0.006	0.0.08
	[0.009]	[0.014]
C2 Orderliness	0.003	-0.008
	[0.005]	[0.007]
C3 Dutifulness	0.018**	0.002
	[0.009]	[0.013]
C4 Achievement-Striving	-0.000	-0.002
	[0.007]	[0.011]

Variable	Risk	Ambiguity
C5 Self-Discipline	0.001	-0.025
	[0.010]	[0.014]
C6 Cautiousness	0.012**	0.000
	[0.005]	[0.008]
Adjusted R Square	0.081	0.005
F-test	**1.696****	1.037

Note. Running the Big Five facet model regressions using Sutter et al's (2013) risk and ambiguity indexes produced the same significant Big Five facet variable as when Borghans et al (2009) parameter definitions were employed: N4 Self-Consciousness positively relates to risk seeking.
** p < 5%; *** p < 1%