ERASMUS UNIVERSITY ROTTERDAM ◆ ERASMUS SCHOOL OF ECONOMICS ◆ MASTER THESIS

MSc Economics & Business
Master Behavioural Economics

Sources of Uncertainty

How do Knowledge and Epistemic or Aleatory Uncertainty affect Ambiguity Attitudes?

ABSTRACT

The aim of this thesis is to understand how (1) knowledge and (2) epistemic uncertainty interact with ambiguity attitudes. Conducting a survey using the setting of the Dutch Football League Eredivisie provides insight in preferences between ambiguous and risky bets for 59 respondents. Using the source method to quantify the ambiguity index and likelihood sensitivity index for each respondent shows clear positive interaction between knowledge and ambiguity seeking attitudes and positive interaction between epistemic uncertainty and ambiguity seeking attitudes. Our sample provides no evidence for interaction between knowledge and likelihood sensitivity or epistemic uncertainty and likelihood sensitivity. However, this interaction has not been studied before using the source method and thus is the first of his kind.

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[1] I would like to thank Ilke Aydogan for his efforts and continuous guidance during the master thesis process.

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1. Introduction

Uncertainty is something that everybody encounters on a daily basis. Whether it will rain tomorrow or whether the Dow Jones index will go up in two days are both uncertain events. Or managerial decisions for example, managers decide whether to invest (uncertain) or payout dividend to their stakeholders. Moreover, most decisions contain certain amounts of uncertainty. However, uncertainty unfolds in different forms and with different levels of uncertainty. Whether it will rain in Amsterdam tomorrow is less uncertain for people living in Amsterdam than for people living in Sidney. In other words, the level of uncertainty depends on available information and the source of uncertainty.

Two concepts that are closely related with sources of uncertainty are risk and ambiguity. When the probabilities of uncertain events are objectively known it is called risk. In case of ambiguity the probabilities of uncertain events are not objectively known. Both events are thus uncertain, however, the ambiguous event contains additional uncertainty due to unknown probabilities. Therefore ambiguity is also referred to as uncertainty beyond risk. This additional uncertainty unfolds in three different attitudes towards ambiguity: ambiguity aversion, ambiguity neutrality and ambiguity seeking. Each attitude describes an attitude of an individual towards the additional uncertainty compared to a similar event with only risk as the uncertain source. A rational ambiguity neutral individual would thus be indifferent between an ambiguous and risky event with similar likelihoods. However, the common finding is that people are not rational and that different aspects affect their ambiguity attitude. Therefore ambiguity attitudes have been of great interest in literature. Furthermore, understanding ambiguity attitudes and what affects them can help people making better decisions for uncertain events.

Recently Abdeoulli et al. (2011) proposed another ambiguity attitude, namely ambiguity generated likelihood (in)sensitivity. This concept captures whether individuals differentiate sufficiently between different likelihoods of ambiguity. When people show more likelihood insensitivity then they discriminate insufficiently between different likelihoods, transforming subjective likelihoods towards 50-50. Hence, people show ambiguity seeking attitudes for low likelihoods and ambiguity aversion for high likelihoods. Resulting in overweighting unlikely events and underweighting events with high likelihoods. Our study focuses on all ambiguity attitudes and is able to measure ambiguity seeking and ambiguity aversion attitudes as well as ambiguity likelihood sensitivity quantitatively.

Another distinction within the studies of sources of uncertainty is epistemic and aleatory uncertainty. An epistemic source is one where it is in principle possible to know the answer or outcome when enough information is acquired. An aleatory source on the other hand is unknowable in any case. The effects of an event being epistemic or aleatory have been studied in different settings. For this thesis results of Chow & Sarin (2002) and Tannenbaum et al. (2016) are of particular interest to our research question. They study the interaction between epistemic and aleatory uncertainty on preferences and judgements about uncertain events relatively. Although, Chow & Sarin (2002) also study affects of epistemic and aleatory uncertainty on ambiguity attitudes, their conclusion remains purely qualitatively. Our study extents this direction by capturing these affects quantitatively and also looking into likelihood sensitivity. Both studies are elaborated in more detail in the literature review.

Until now above concepts and their interactions related to the sources of uncertainty have been studied separately. This thesis focuses on combining these concepts using a dataset collected from an online survey. Measuring ambiguity attitudes of different individuals quantitatively and study how these attitudes are affected by (1) knowledge and (2) epistemic or aleatory uncertainty. This thesis thus contributes to the sources of uncertainty literature by creating a bridge between ambiguity attitudes and epistemic versus aleatory uncertainty. The research question is: *How do Knowledge and Epistemic or Aleatory Uncertainty affect Ambiguity Attitudes?*

The remaining thesis proceeds as follows. First, prior literature of ambiguity research and epistemic versus aleatory events are discussed separately to provide an overview of the concepts and theories that are used. Followed by paragraph §2.3 where these theories converge into five hypotheses. Subsequently, the analysing methods are discussed followed by an explanation of the survey in chapter three. Chapter four provides an overview of our results and contains tables of the regressions. Chapter five and six respectively provide a conclusion and discussion.

2. Literature Review

§2.1 Aleatory versus Epistemic Events

When studying uncertainty using uncertain events, two different events are often distinguished: aleatory and epistemic events. Aleatory events are described as events that are unpredictable and random, like the outcome of a coin flip. Epistemic events are on the other hand in principle knowable, but are classified uncertain due to a lack of knowledge, information or skills. Most common example of an epistemic event is an answer to a Trivia question. Although most people are presumably not familiar with concepts of aleatory or epistemic events, several studies show that people naturally distinguish between aleatory and epistemic uncertainty (Ulkumen & Fox, 2011). A study from Robinson et al. (2006) shows that young children behave differently when they face aleatory versus epistemic events. In their first experiment children are told that a block still had to be placed behind one of two doors (aleatory). Subsequently the children are asked behind which door the block could be. Most children respond that the block could be behind both doors. When the children are told that the block already has been placed (epistemic), then they choose for a single door instead. Furthermore, studies from neuroscience also show that people have different activation patterns in their brain when they face rule-based uncertainties (assumed to be epistemic) and stochastic uncertainties (assumed to be aleatory) (Volz, Schubotz, & Von Cramon, 2005). Moreover, studies on language show that people use different words for describing the degree of epistemic and aleatory uncertainty (Ulkumen, Fox, & Malle, 2015). For example, people use the word "sure" when there is mainly aleatory uncertainty and the word "chance" when there is mainly epistemic uncertainty.

Since people distinguish between aleatory and epistemic events naturally, researchers have studied how aleatory and epistemic events influence probability judgements of such events. These studies are especially relevant for important decisions that are made on a daily basis by managers and risk analysts. A study from Kiureghian & Ditlevsen (2009) shows that a distinction in epistemic or aleatory uncertainty is necessary when modelling risk and reliability problems. They use a hypothetical model for which epistemic and aleatory uncertainty is determined by their modelling choices. Using this model they show how the reliability of the model is affected by distinguishing different types of uncertainty. They show that failing to do so may cause under- or overestimation of the probability of a failure according to the model. Depending on the magnitude of the model, under- or overestimation can have significant impact on the probability estimate, which can have catastrophic consequences. Furthermore, they argue that distinguishing between different types of uncertainty provides insight in what sources of uncertainty can be reduced. Another study from Hora (1996) also confirms that a distinction between aleatory and epistemic uncertainty is useful for experts in eliciting their probability estimates. From an example of hazardous waste management they show that models that are meant to predict uncertainty have a tendency to include aleatory uncertainty based on variables that represent epistemic uncertainty. They show that using concepts of aleatory or epistemic uncertainty wrongly may bias probability estimation models, resulting in decisions based on inaccurate predictions.

Another study that sheds light on probability judgements under epistemic or aleatory uncertainty is a study from Tannenbaum et al. (2016). In this study they are mainly interested in how epistemic or aleatory uncertainty affects probability judgements for uncertain events. To research this question they ask respondents to estimate probabilities for outcomes of NBA basketball matches. Every respondent also provides thoughts about three random NBA games being epistemic or aleatory events. The main finding of the study concludes that there is a general tendency among respondents to elicit more extreme judgements (closer to 0 and 1) when the event is seen as more epistemic and less extreme when the event is seen as more aleatory. They also argue that this judgement extremity can help to explain the stylized findings in literature on judgement accuracy and overconfidence. Tannenbaum et al. (2016) mention in their paper that having knowledge or experience in the task may interact with how the epistemic rating affects evidence sensitivity of judgements. They argue that having knowledge in the task should amplify the effect of "epistemicness" on evidence sensitivity and lacking knowledge should attenuate this effect. For this paper the evidence sensitivity measure of judgements is not of interest. However, it can also be argued that knowledge interacts with the effect of likelihood sensitivity or ambiguity, which is in line with our research interests. As uncertain events being classified as aleatory or epistemic influence judgements about probability, it can be hypothesized that it also affects ambiguity attitudes. This study continues in line with the study from

Tannenbaum et al. (2016) to extent the effect of aleatory or epistemic events to ambiguity attitudes.

Chow & Sarin (2002) also study how behaviour is affected by events as being epistemic or aleatory. They do this by conducting experiments using three different situations: (1) the knowable situation, (2) the unknown situation and (3) the unknowable situation. The knowable situation is a classic situation where there exists only risk. A bet in this situation has clear probabilities of winning, which are known to all. The unknown situation is a situation where the respondent does not know the probability of winning the bet, but does know that each probability on the interval 0-100% is equally likely. In this situation the experimenter does know the exact probability of winning the bet. And lastly, the unknowable situation is where the respondent and the experimenter are both unfamiliar with the probability of winning the bet, but do know that all possibilities are again equally divided on the interval 0-100%. Chow & Sarin (2002) show that the willingness to pay for bets in situation one till three respectively, while keeping a-neutral probabilities of winning constant, varies depending on the situation. Respondents are willing to pay more for a bet in situation one, where they have full knowledge than for the same bet in situation two or three. Respondents also pay more for a bet in situation three compared to the same bet in situation two. Implying that knowing for sure that everybody is unknowledgeable (aleatory) is valued above a situation where it is known that the experimenter knows the probability (epistemic). However, this result only holds under comparative conditions. When respondents provide their willingness to pay and probability estimates for one of the three situations, then no significant differences are observed between the three conditions. Chow & Sarin (2002) argue that this is line with the comparative ignorance hypothesis of Tversky (1995), which is discussed in paragraph §2.2.3.

§2.2 Ambiguity Attitudes

Since the introduction of the Ellsberg Paradox in 1961, there has been growing interest for ambiguity research (Ellsberg, 1961). Although Ellsberg was not the first who wrote about uncertainty other than risk, Ellsberg is known for the concept of ambiguity[2]. In

[2] Knight was the first one that wrote about "uncertainty other than risk" in his paper dating as early as 1921 (Knight, 1921).

this study Ellsberg introduces a hypothetical experiment with two urns containing both red and black balls. Urn I contains 100 balls in total, but the composition between red and black is unknown. There could be 100 red balls, 100 black balls or any other composition between the two. Urn II also contains 100 red and black balls, but for this urn it is common knowledge that there are exactly 50 red and 50 black balls. The majority of the respondents prefers a bet on a red ball from urn II over urn I. And a bet on a black ball from urn II over the same bet for urn I. Ellsberg argues that this is contradicting with the axioms of Savage[3]. If you prefer a bet on the red ball from urn II over the same bet on the red ball from urn I this implies that there are less than 50 red balls in urn I, assuming rationality. However, this also results in the belief that there are more than 50 black balls in urn I, as the total number of balls is equal to 100. The same accounts for the bet on a black ball from urn I and II. The majority prefers a bet on the black ball from urn II than from urn I, implicitly creating the belief that there are less than 50 black balls in urn I and more than 50 red balls in urn I. Hence, this example leads to a violation of probability estimation as the choices of the respondents violate consistent decisions and rationality.

In the years to follow, the urns from the Ellsberg Paradox are often used to study ambiguity attitudes. Becker & Brownson (1964) are one of the first that used the Ellsberg-type setting to study ambiguity. They select respondents based on their ambiguity attitude. After selection they ask ambiguity averse respondents to choose between an ambiguous urn and an unambiguous urn. Respondents always choose the unambiguous one and are willing to pay an ambiguity premium (amount to avoid ambiguity) of 60% of the difference in the ranges of the two urns. In later studies the three color urns are introduced. MacCrimmon & Larsson (1979) lower the known probability of drawing a red ball to measure the ambiguity premium. When the probability on drawing a red ball becomes below 25% only six of their 19 subjects commit to the paradox. Resulting in an ambiguity premium between 0.05 and 0.10. Later on more studies used other settings than the urn example from Ellsberg to study ambiguity. Larson (1980) studied ambiguity attitudes using a deck of cards. Subjects choose between two decks of cards with different expected probabilities. The majority

[3] Savage (1954) developed the Subjective Expected Utility model in 1954. This model measures preferences between choices with a numerical utility. This model does not hold with the Ellsberg paradox.

of the subjects show preference for the less ambiguous deck in all pairs roughly independent of the expected value. Another study uses bets on natural events (Goldsmith & Sahlin, 1983). Furthermore it is observed that half of the subjects prefer bets on ambiguous events with losses and avoid ambiguity when the bet is rewarded with gains (Ulkumen & Fox, 2011).

§2.2.1 *Competence Hypothesis*

While the ambiguity research gained territory using other ambiguous events than the Ellsberg urn, Heath & Tversky (1991) asked the question whether ambiguity aversion is related with the domain of chance or with the domain of knowledge. They conducted experiments comparing the willingness to bet on clear chance events and their uncertain beliefs. They find that respondents prefer to bet on their beliefs instead of the clear chance event when they perceive themselves knowledgeable about the event. Subjects are asked to make choices between bets in three different settings of uncertainty; the presidential election 1988, football matches and a draw from an urn. Respondents are selected based on their knowledge in football and politics. Only the subjects that are knowledgeable in one topic and unknowledgeable in the other one are invited to participate. Respondents that are knowledgeable about politics prefer a bet on the election to an equiprobable chance event. When they are asked about the football bet then they prefer the chance event. The same results are found for the participants that have knowledge in football. They prefer the football bet to the chance bet, but the chance bet to the politics bet. Heath & Tversky (1991) converge this finding in the competence hypothesis. This hypothesis states that ambiguity depends on the level of knowledge in the ambiguous source. Heath & Tversky (1991) also provide reasoning behind the competence hypothesis. They belief, that besides the monetary pay-off, a psychological pay-off between satisfaction and possible embarrassment is present. This is a pay-off between taking credit and experiencing blame. A knowledgeable person can take credit for a correct prediction, as this individual is knowledgeable. On the other hand this person can better defend himself with arguments when a wrong prediction is provided and thus avoids blame. Unknowledgeable individuals cannot take credit when they provide correct predictions as this is clearly due to pure luck. When they provide an unjust prediction, they do however take full blame. As they are unknowledgeable they cannot justify their prediction. This argument was later partly confirmed by Taylor (Taylor, 1995).

§2.2.2 *Calibration*

While the competence hypothesis explains ambiguity seeking behaviour for people with expertise in certain tasks, it remains unanswered whether this ambiguity seeking behaviour is justified by better predictions. Studies with various settings examine whether experts are better predictors than so called lay people. Lichtenstein, Fischhoff & Philips (1977) show that in general the amount of true responses is less than the probability assigned to such propositions. This also accounts for experts. However, whether experts are better predictors also depends on the context. For example, Tyszka & Zielonka (2002) study the differences between expert probability estimation capabilities for financial analysts and weather forecasters. They show that however both groups are overconfident in their judgements, the financial analysts showed significantly higher overconfidence than the weather forecasters. Another study from McKenzie et al. (2008) concludes that overall overconfidence for lay people and experts is equal, but that it is constructed differently. Experts tend to provide smaller confidence intervals, which lowers the hit rate of their predictions, while being closer to the true value, which increases the hit rate. For lay people this is the other way around, resulting in equal levels of overconfidence. These studies thus suggest that experts are only better predictors in some cases. Most of these studies look into the fact whether the predictions of experts are closer to the real outcome (Camerer & Weber, 1992). However, for our study it is of interest whether expertise affects the probability estimation itself independently of the correctness of the judgements.

§2.2.3 *Comparative Ignorance Hypothesis*

Following from the competence hypothesis Fox & Tversky (1995) formulated a new question. The competence hypothesis states that ambiguity attitudes depend on a state of mind feeling competent or incompetent. The follow-up question is what sort of conditions are required to feeling competent or incompetent? Fox & Tversky argue that feeling incompetent requires contrasting an event where you have limited knowledge with an event where you have superior knowledge. Or in other words, comparing yourself with an expert on the topic. Moreover, Fox & Tversky argue that this comparison is the dominant source of ambiguity aversion. Proposing that ambiguity aversion does not exist when subjects are asked to evaluate ambiguous and chance bets in isolation. What follows are six experiments where they test their own proposition. In their experiments they ask respondents about their preferences between bets for Ellsberg urns, future events and knowledge. The general finding is supportive for their hypothesis.

§2.2.4 *Modelling Ambiguity*

Since Ellsberg provided evidence for violation of the Subjective Expected Utility model from Savage (1954), efforts have been made to capture ambiguity attitudes in a model. For many years the common conclusion has been that subjective probabilities cannot accommodate the Ellsberg paradox, until Chew & Sagi (2006) (2008) came with a new insight. First they refer to the sources of uncertainty from Tversky & Fox (1995) that an ambiguous urn and a chance urn from the Ellsberg paradox should be treated as two different sources of uncertainty. Thus uncertainty from the ambiguous urn depends on another source than uncertainty from the chance urn. Secondly, it is assumed that people may have different attitudes to probabilities from different sources. This means that someone can have different weightings for the probability of a red ball from an ambiguous urn than for a draw from the chance urn. For the Ellsberg paradox this would mean that people prefer the draw from the chance urn, because they underweight the probability from the ambiguous urn due to ambiguity.

Using the sources of uncertainty theorem from Tversky & Fox (1995), the SEU model could be used again for capturing ambiguity attitudes. Based on this theory Abdellaoui et al. (2011) proposed a new model to capture ambiguity attitudes called the source method. Ambiguity attitudes can be captured quantitatively in a traceable manner using this method. Moreover, this model provides exact quantitative predictions about future behaviour. The Source Method uses graphs to quantitatively capture ambiguity attitudes towards different likelihoods. Using these graphs it is not only possible to capture ambiguity aversion or ambiguity seeking behaviour for a certain probability, but also a concept called ambiguity likelihood sensitivity or likelihood sensitivity. This concept quantifies how strongly people distinguish between different levels of ambiguity. For this thesis ambiguity likelihood sensitivity is a measure of interest. Therefore, these concepts and how the source method is used are explained in more detail in paragraph §3.2.

§2.3 Hypotheses

Based on the debated literature from ambiguity and likelihood sensitivity research, five hypotheses are proposed. First of all, recall that the competence hypothesis states that being competent or having knowledge in a task results in more ambiguity seeking behaviour. Therefore, it is expected that respondents who perceive themselves knowledgeable in football show more ambiguity-seeking behaviour.

H1: Knowledge increases ambiguity-seeking behaviour.

Secondly, from the results of Chow & Sarin (2002) it is expected that epistemic uncertainty increases ambiguity averse behaviour. Their findings show that an unknowable situation is preferred to an unknowledgeable situation. Recall that this unknowable situation is more epistemic than the unknowledgeable situation. They find that the willingness to pay for the unknowable bet is higher than the unknowledgeable bet. Based on this finding it is expected in our research that the ambiguous bet becomes less desirable in comparison with the risky bet when the epistemic rating increases. Therefore, it is expected that respondents who perceive football as more epistemic show more ambiguity averse behaviour.

H2: Epistemic uncertainty increases ambiguity averse behaviour.

Thirdly, the finding from Tannenbaum et al. (2016) is that people have the tendency to elicit more extreme judgements when an event is seen as epistemic. More extreme judgements imply more judgements closer to 0 and 100 percent. Using the source method as a quantitative measure this finding unfolds as larger differences between different levels of ambiguity. Thus, it is expected to observe that respondents have increased ambiguity likelihood sensitivity when they experience epistemic uncertainty.

H3: Epistemic uncertainty increases ambiguity likelihood sensitivity.

Furthermore, Tannenbaum et al. (2016) emphasize that likelihood sensitivity is able to explain overconfidence. As discussed, there are several studies about overconfidence and calibration of estimates, but they are mainly focused on calibration of experts. However, for this thesis it is interesting how knowledge affects likelihood sensitivity in a setting of subjective estimates. Recall from the literature that overconfidence and miscalibration are observed for both experts and laypeople, also depending on the context. Although evidence is mixed, it is expected that knowledge in our setting induce more extreme judgements. Therefore it is expected that knowledge increases likelihood sensitivity. As far as known to us, this has never been studied before and thus this thesis is a pioneer in researching this interaction.

H4: Knowledge increases likelihood sensitivity.

Additionally to the main hypotheses, one additional interest is analysed as well. As this paper measures knowledge and "epistemicness" and both are expected to affect ambiguity attitudes, one might suppose that knowledge affects the interaction between "epistemicness" and ambiguity attitudes. Therefore hypotheses H5a and H5b are included as an addition to above hypotheses. These additional hypotheses suggest that knowledge mediates the affect of "epistemicness" on ambiguity attitudes. Note that these additional hypotheses result from our hypotheses H1 till H4. However, this thesis is the first to study the interaction proposed in hypothesis H4 and thus predictions about likelihood sensitivity are less straightforward than for ambiguity aversion, which has been studied extensively. Therefore, hypotheses H4, H5a and H5b are more speculative (although well considered) compared to hypotheses H1 till H3. As this thesis is first in studying these interactions directly, it is less convenient to form clear predictions.

H5.a: Having knowledge in the task reduces the effect of epistemic uncertainty on ambiguity aversion and likelihood sensitivity.
H5.b: Lacking knowledge in the task increases the effect of epistemic uncertainty on ambiguity aversion and likelihood sensitivity.

3. Experimental Design

§3.1 Source Method and Matching Probabilities

Prior to explaining the survey that is used to collect the data, the source method and matching probability functions are discussed in more detail. Understanding these concepts allows the explanation of the survey to be more convenient. The quantitative indexes that are used to answer the hypotheses are based on the methods explained in this section. These methods are thus the theoretic foundation of this thesis.

A substantial part of the used method in this thesis originates from the source method. This method uses source functions from ambiguous and risky events in comparison to measure ambiguity attitudes quantitatively (Abdellaoui, Baillon, Placido, & Wakker, 2011). To quantify ambiguity attitudes of an individual two functions are created, one for an ambiguous source and one for a risky source. Because people provide different weights to the ambiguous source and the risky source, the slope and elevation of both functions are compared to measure ambiguity attitudes. Mathematically a prospect using the source method for an ambiguous source, is evaluated as follows: $w_s(P(E))u(x) + \left(1 - w_s(P(E))\right)u(y)$, where w_s is the source function (dependent on the source and individual), $P(E)$ is a subjective probability of occurrence of event E and $u(x)$ and $u(y)$ are the utility functions of an individual for outcomes x and y[4]. Normally it is assumed that $w_s(0) = 0$ and $w_s(1) = 1$, with w_s being continuous and strictly increasing (Fox, Rogers, & Tversky, 1996). Assuming that events with known probabilities, or risky events, underlie one uniform source of uncertainty, then the subscript of the weighting function can be dropped. The same equation for a risky event is therefore formulated as follows: $w(p)u(x) + (1 - w(p))u(y)$, with p being the objective probability and $w(p)$ the weighting function of the objective probability. Creating a source function for an individual for both a risky event and an ambiguous event allows a comparison of the weightings of different probabilities in order to measure the ambiguity attitude of this respondent. However, this method requires both the utility function and the weighting function of the respondent, which are not convenient to measure.

[4] See Abdellaoui et al. (2011) for an extensive overview of the source method.

Dimmock et al. (2015) elaborate on this theory by capturing ambiguity attitudes using matching probability functions, which are strongly related to source functions. The biggest advantage however, is that utility functions and weighting functions of individuals need not to be measured, because the matching probability function captures ambiguity attitudes in one function. Suppose a prospect $\alpha_E\beta$ yields outcome α when event E occurs and β otherwise. Assume that both α and β are non-negative and $\alpha \geq \beta$. Equal to the source method this prospect is evaluated by the following function $w_s\big(P(E)\big)U(\alpha) + \Big(1 - w_s\big(P(E)\big)\Big)\,U(\beta)$. Similar to the source method the subscript of the source function is dropped when the source contains known objective probabilities (risk). Moreover, $\alpha_E\beta$ can be written as $\alpha_p\beta$ with p being the objective probability of E. Up until this point above concept is equal to the source method. Dimmock et al. (2015) however, argue that measuring ambiguity attitudes can be more convenient by introducing matching probabilities. A matching probability can be measured using an ambiguous event and an ambiguity neutral risky event. Recall that an ambiguity neutral individual is indifferent between an ambiguous event and a risky event with equal likelihoods of occurrence. Therefore ambiguity neutral probabilities or a-neutral probabilities are equal to the subjective likelihood of the ambiguous event. However, individuals are rarely ambiguity neutral and show ambiguity aversion or ambiguity seeking attitudes towards different likelihoods. The matching probability is able to capture the ambiguity attitudes. This concept is defined as the known probability that induces indifference between an ambiguous and risky event with a-neutral probability for non-neutral individuals $P(E) = p$. It is formally defined by $\alpha_E\beta \sim \alpha_p\beta$ for some $\alpha \succ \beta$, which then holds for all $\alpha \succ \beta$. In the paper of Dimmock et al. (2015) it is argued that a matching probability function can be formulated by $m_s(p) = w^{-1}w_s$ and thus can be written as $w_s(p) = w(m_s(p))$. This function is able to capture differences in weightings of known and unknown probabilities and thus it captures the ambiguity attitude. Although it might appear difficult to measure the matching probability function, Dimmock et al. provide a convenient shortcut that avoids measuring utility and weighting function of risk and uncertainty. They provide the following proof using the equation from the source method: “assume for $\alpha \succ \beta$, that $\alpha_E\beta \sim \alpha_q\beta$, implying that q is the matching probability of event E and of a-neutral probability $P(E)$. Then”

$$w\left(m_s(P(E))\right)\left(U(\alpha)-U(\beta)\right)=w(q)(U(\alpha)-U(\beta))$$
$$w\left(m_s(P(E))\right)=w(q)$$
$$m_s(P(E))=q$$

According to this theorem the ambiguous prospect $\alpha_E\beta$ is equivalent to the risky prospect $\alpha_{m_s(E)}\beta$. This implies that the matching probability function allows us to immediately measure ambiguity attitudes without measuring utility and weighting functions.

Depending on the ambiguity attitude of the respondent, matching probability functions show different patterns. Figure 1 depicts possible functions, each describing specific ambiguity attitudes. The x-axis designates a-neutral probabilities p, which in our case are the judged probabilities of football outcomes[5]. The y-axis designates the matched probabilities. Figure 1a shows behaviour according to expected utility with a linear matching probability function. This line follows an ambiguity neutral attitude, because matching probabilities are equal to a-neutral probabilities. Figure 1b shows a convex source function that is in line with an ambiguity averse attitude. Here all a-neutral probabilities are matched with smaller objective probabilities. Figure 1c is an inversed S-shape matching probability function. This function has both a convex part as a concave part. The convex part near 1 explains the tendency to be ambiguity averse for favourable outcomes that have high probabilities. The concave part near 0 shows ambiguity seeking behaviour for favourable events that happen with small probability. This optimism is often referred to as the long shot effect. This typical curve explains why people gamble and insure themselves (Tversky & Kahneman, 1992). The inversed S-shape also reflects a lack of sensitivity to distinguish between different levels of likelihood (different probabilities). Consequently, all intermediate likelihoods are pushed towards the likelihood of 50-50. As discussed, this phenomenon is called ambiguity likelihood insensitivity. It suggests that when people make real decisions in probability estimates, they will not update their estimate enough when receiving new information. When likelihood insensitivity, ambiguity aversion and ambiguity seeking are combined, the line from 1d is observed. This function describes the common finding in literature.

[5] Note that these probabilities do not have to objective (Abdellaoui, Baillon, Placido, & Wakker, 2011).

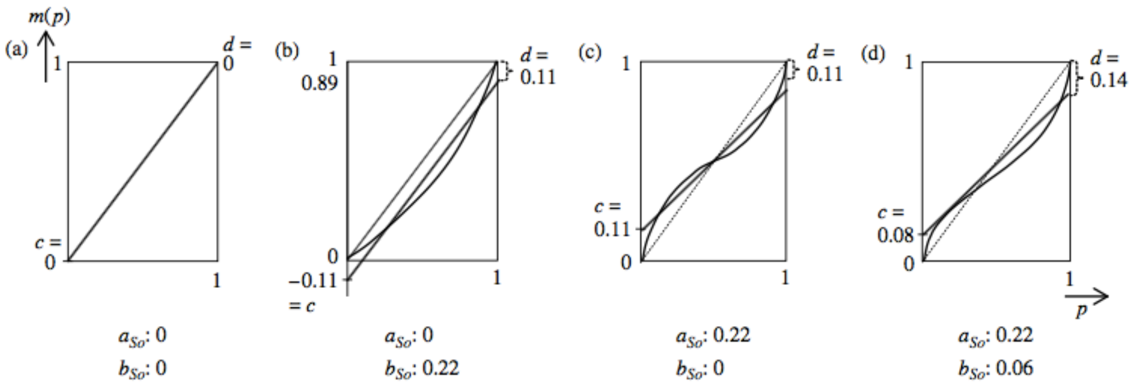

Figure 1: Quantitative Indexes Ambiguity Aversion b_{so} and Ambiguity Insensitivity a_{so} (Dimmock, Kouwenberg, & Wakker, 2015)

As discussed, matching probability functions are able to capture ambiguity attitudes into one function. However, for some applications it can come in handy when the ambiguity attitudes can be captured in one or two simple indexes. This is what Abdellaoui et al. (2011) proposed for their source functions. For matching probability functions the method is similar. From the matching probability function the best fitting (linear) line can be created. Using a linear line allows to use the slope and the intercept to define ambiguity attitudes relatively easily. Assume that the best fitting line on the interval (0,1) is described by $p \mapsto c + sp$. Where c is the intercept and s is the slope. Denote $d = 1 - c - s$ as the dual intercept. This is the distance from 1 on the regression line at $p = 1$. The slope of this line provides information about the likelihood (in)sensitivity of the respondent as it describes the difference in matched probability when the objective probability increases. Thus, the index of ambiguity insensitivity is defined as $a = c + d\ (= 1 - s)$ similar to Dimmock et al (2015). However, for this study it is expected that respondents show more sensitivity based on their rating of "epistemicness" and knowledge, thus a measure equal to s (slope of the best fitting line) is used as a measure of likelihood sensitivity. Positive values of the slope indicate more likelihood sensitivity and negative values indicate insensitivity. The intercept of this linear line is used for a measure of ambiguity aversion. A positive intercept (0,0) implies that the respondent is ambiguity seeking for low probabilities. The same accounts for the dual intercept (1,1). When the dual intercept is negative, this implies that this person is ambiguity averse for high probabilities. By combining these two intercepts, we find the ambiguity attitude over the whole distribution of probabilities. The index of ambiguity aversion is thus defined as $b = d - c\ (= 1 - s - 2c)$. Positive values of b indicate ambiguity aversion and negative values of b indicate ambiguity seeking attitudes.

§3.2 Survey

In order to test the hypotheses and quantify the ambiguity attitudes a 10-minute survey is conducted. The survey uses the setting of upcoming football matches in the Dutch professional league Eredivisie. Sports are often used for research in economics. Despite many differences, sports also share aspects with economic theory. Hence, sports and especially sports that require team effort, are perpetual in economic literature. For example a study of Scully (1994) uses coaching in baseball, football and other sports to study managerial efficiency. Other studies use sports betting to study a variety of decision-making theories (Nilsson & Andersson, 2010; Cain, Law & Peel, 2000; Andersson et al., 2009). Using the Eredivisie league allows observing ambiguity attitudes while knowledge and epistemic rating may differ between different respondents. Each respondent is asked to report their subjective probabilities for all three possible outcomes (team A win, draw, team B win) and two combined outcomes (team A wins or draw, team B wins or draw) of two matches selected from the Eredivisie. These estimates are used as the a-neutral probabilities for each respondent and thus the starting point for the analysis.

The survey starts by randomly assigning the participating respondents to one of two groups. Groups one and two only differ in the matches that are asked for. Participants from group one are asked to estimate probabilities for the match FC Utrecht-AZ and FC Groningen-Heracles and respondents in group two estimate probabilities for the match Roda JC-Willem II and FC Twente-Vitesse. These four matches are selected based on the position of each team and take place on the same date (8^{th} May 2016). The match FC Utrecht-AZ from group one and Roda JC-Willem II from group two are two matches where both teams are direct competitors for the same position in the league. At the time the survey was handed out AZ and FC Utrecht were at the 4^{th} and 6^{th} position in the league respectively. Roda JC and Willem II were at the 14^{th} and 15^{th} place respectively. The other match in both groups is a line up between two teams with a clearer favourite based on their positions. Groningen was 11^{th} and Heracles 6^{th}. In group two Twente was on the 13^{th} position and Vitesse 7^{th}. It is expected that these two matches with different character provide us with a better distribution of probabilities, which is required to estimate the ambiguity indexes later on. Respondents are also acknowledged about the position of each team to assure that each respondent is able to estimate probabilities to a certain extent.

Respondents provide a total of five probability estimates for each match in order to measure their ambiguity attitudes more precise later on. First it is asked to estimate the probabilities that team A wins, that team B wins and that the match ends in a draw. In our experimental design, it is ensured that these probabilities add up to 100%. Next, respondents estimate combined probabilities that team A wins or the match ends in a draw and team B wins or the match ends in a draw. Note that these probabilities should be a sum of the first three probability estimates if respondents are consistent. Matches with teams that are very popular in the Eredivisie are deliberately avoided to make certain that respondents provide their true probability estimates. Asking a respondent to estimate the probability that their favourite team will win would possibly allure them to provide higher estimates. As it is assumed that such respondent desires both that his favourite team will win as well as the money he can make filling out the survey. This might interfere with uncertainty attitudes, thus only matches with teams that do not belong to the favourites (Ajax, PSV, Feyenoord) are used. The survey also controls for this afterwards by asking the respondent for which Eredivisie team he or she primarily roots.

For the second part of the survey respondents choose between two bets. The first bet (bet A) is on one of the possible outcomes of the football match, for which they just estimated a probability. The second bet (bet B) is a bet on a random draw from an urn containing a total of 100 white and black balls with a known distribution between white and black. Respondents win the bet when they draw a white ball from the urn[6]. The amount of white balls in the urn depends on the probability judgement from the first part of the survey. For example, when a respondent estimates the probability that Utrecht will win at 70%, then the urn will contain 70 white balls and 30 black balls.

[6] Note that respondents do not have the option to choose which colour wins the bet. Dimmock et al. (2015) show in their trial experiment that a prefixed colour does not lead to a bias in the results. Hence, it is assumed that using white as the prefixed winning colour does not affect the results.

Therefore, independently of what the estimates of the respondents are, the urn will contain a distribution of white and black that is on an ambiguity neutral level. The amount of white balls in the urn for which the respondent is indifferent between bet A and B expresses the matching probability. In order to elicit the indifference point bet B is made more or less attractive based on the preference from the ambiguity neutral choice. For example, when a respondent prefers bet A over bet B, then bet B is made more attractive by increasing the probability of drawing a white ball by 5%. On the other hand, when a respondent has a preference for bet B, then option B is made less attractive by decreasing the probability of drawing a white ball with 5%. This process continues until the respondent selects indifferent or when the respondent received the maximum of six interventions. If a respondent still prefers option A or B after six interventions, then the average of the remaining options is taken[7]. After the respondent has made choices for all his probability estimates and has selected indifference for all bets, he continues to the second match to do it again. However, when a respondent switches preference between bet A and B due to interventions, then the respondent also proceeds to the next part of the survey. In this case the mean between interventions, where the respondent switched preference, is taken as the matching probability. Respondents choose between bets directly after elicitation of probability estimates for a given match. This is done to assure that the probability estimates are freshly in memory and not confused with estimates for the second match. Figure 2 contains questions from the survey, the first one is the estimation of probabilities for three possible outcomes of the match and the second one shows the first question to choose between the first outcome estimation and the corresponding a-neutral bet B. Although, respondents also depict estimates for combined outcomes and select their preferences for all estimates, these two questions provide an overview of the type of questions used in survey. See Appendix A for the full survey.

[7] The same method is used in Dimmock, Kouwenberg, & Wakker, 2015

Football Match 1.1

For the following question we ask you to estimate the probability for different outcomes of an upcoming Eredivisie match on 8th May. For example: if you answer 30, this means that you think that this outcome will happen 30 times out of 100.

Sunday 8th of May Roda jc (currently 14th) plays against Willem II (currently 15th). What is the probability of the following outcomes?
Note: Your answers should add up to 100.

Only numbers may be entered in these fields.
The sum must equal 100.

Roda jc Wins	34
Willem II Wins	28
Draw	38
Remaining:	0
Total:	100

Bets 1

For the following questions we ask you to consider a choice between two bets. Please consider carefully which bet you prefer. Bet A is a bet based on the real outcome of the football match and Bet B is a draw from an urn containing 100 balls with a known distribution between white and black. **If you think that both bets are equally attractive, then select "indifferent".**

Bet A

Bet B

OR

Win 10 euros when Roda jc wins and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 34 white balls and 66 black balls.

Choose one of the following answers

- ◯ I prefer bet A
- ◯ I prefer bet B
- ◯ I am indifferent

Figure 2: Probability estimation question and one a-neutral preference question

From the survey each respondent provides estimates for two matches. This implies that for each respondent two matching probability functions are created. For each source function the best fitting line is estimated using the least square method to calculate the index of ambiguity aversion and likelihood sensitivity. Therefore each respondent has two indexes for ambiguity version and two indexes for likelihood sensitivity. The mean is taken to create one variable for ambiguity sensitivity and one for ambiguity aversion for each respondent.

For the third part of the survey the same method as in Fox et al. (2015) is used to rate the football match as epistemic or aleatory. This is a 10-item epistemic-aleatory scale. Respondents rate their agreement with statements that both measure epistemic and aleatory uncertainty on a 1-7 Likert Scale (Likert, 1932). For this study the rating for "epistemicness" is particularly interesting thus the aleatory ratings are reverse-coded similarly as in Tannenbaum et al. (2016) to create epistemic indexes. The mean of these indexes are used to create one single index for "epistemicness". There is however one difference between this paper and Tannenbaum et al. (2016) related to epistemic rating. Tannenbaum et al. randomly select three games for each respondent and ask them rate each statement explicitly for each of these three games. By doing this randomly for each respondent it is assumed that each game is accounted for in the epistemic rating. Before the survey of this paper was set out, a trial version was conducted to test whether all questions are clear. At that time the epistemic rating question was included for each match separately. From the trial version (5 students in economics) however, it is observed that respondents do not differ in the epistemic rating for different games. Hence, it is assumed that the epistemic rating is equal for all matches.

Lastly, perceived knowledge is a measure of interest for the analysis. Respondents are asked to rate their knowledge in football in general and specifically for the Eredivisie League on a Likert scale from 1-7. Additionally, respondents are asked to rate how often they watch NOS Studio sport and Eredivisie Live and if they attend Eredivisie matches in the stadium. NOS studio sport broadcasts match highlights for each Eredivisie match during weekends. Eredivisie Live is an additional television channel that requires a monthly subscription. This channel broadcasts most matches live. Overall these questions should provide enough information about the knowledge of the respondents.

The survey concludes with some demographics and control questions. Most common are age and education.

Once concern about our survey is the use of external sources in addition to personal knowledge. Importantly relying on sources like Google, Wikipedia or odds from betting agencies, may affect the probability estimates and confidence in those estimates. This influences the ambiguity attitudes and the perceived knowledge of the respondent. Hence, the survey includes a simple yes or no question whether the respondent used sources other than their own knowledge[8]. Respondents that used other sources are therefore excluded from the sample. As mentioned before, the survey also controls for the team the respondent roots for. Respondent are excluded from the sample when they root for one of the teams they are asked to estimate probabilities for. These respondents may have interest in both the money they can earn from participating as well as in their favourite team winning, which causes a bias in the results. For a full overview of an example survey, see appendix A.

In conducting experiments and surveys there have been extensive debates about the validity of the results using hypothetical choice. There are studies where the hypothetical group leads to similar results as a non-hypothetical group, but more often hypothetical choices are not valid due to a lack of incentives. Until now there is no universal rule for using hypothetical choices in surveys. Studies from Camerer & Hogarth and Herwig & Ortmann provide surveys on this topic (Camerer & Hogarth, 1999; Hertwig & Ortmann, 2001). Whether a study can be conducted using hypothetical choice depends mainly on the topic and effort that is required to participate in the experiment. In our survey respondents are not directly rewarded for the choices they make, in that way their choices are hypothetical. However, three respondents are randomly selected afterwards to play one of their choices for real money. By informing respondents on beforehand about this random selection, it is assumed that respondents are incentivized sufficiently to make decisions if it were for real money. A more extensive debate on this can be found in the discussion part (chapter 6).

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[8] Alternatively it is possible to inform respondents before they start the survey that it is not allowed to use external sources. However, this reminds them that external sources can be useful to estimate probabilities. Therefore this method is not preferred, as it can induce respondents to use external sources and lie about using them afterwards.

§3.3 Regression Models

As mentioned earlier, two indexes of likelihood sensitivity and ambiguity aversion are observed from the survey for each respondent. Hence, the dataset contains two observations (two matches) per individual. For analysis purposes two options are most common: ordinated least square method and panel data analysis. In order to analyse panel data, two regression models are often used; fixed effects model and random effects model. Hedges & Vevea (1998) emphasize that a choice between these two models should depend on the goal of the analysis (despite different assumptions between the two models). They argue that the fixed effects model should be used when results of the study are not meant to generalize to other populations. The random effects model on the other hand does allow for unconditional inferences. However, the fixed effects model exploits the within variation for each individual where the random effects uses the between variation. Hence, the fixed effects model is not suitable for this analysis. As discussed earlier, it is assumed that epistemic rating is equal for both matches, resulting in zero within variation. Also knowledge does not change for the two matches, and thus also for knowledge there is no within variation. The model that remains for panel data analysis is the random effects model. One assumption of using this method is that all unobserved variables are uncorrelated with all observed variables. Although this assumption might be hard to adopt, the random effects model is often still preferable to use. For this analysis the effectiveness of the random effects model is compared to an ordinary least squares model to see which method is better for our case. This can be done using a simple Breusch & Pagan Langrangian multiplier test (Breusch & Pagan, 1980).

4. Results

§4.1 Overview of Variables

Before the actual results are discussed, the different variables are debated in more detail for better understanding of the regressions. Nine different variables are obtained from the survey. Ambiguity aversion and likelihood sensitivity are the dependent variables for our regressions. As mentioned, measures for gender, education, different matches and groups are also obtained from the survey. The variables of gender, education, different matches and groups are all included in the regressions as dummy variables. For education there are in total six dummies: primary school, HAVO, VWO, MBO, HBO, WO. These include all common education levels in the Netherlands except for VMBO, for which there are no observations in the data set. In the regressions these different levels of education are organized in rising order starting from lowest level of education primary school (EDUC1) till second highest level of education HBO (EDUC5). The highest level of education is left out in order to overcome perfect multicollinearity (Mansfield & Helms, 1982). Hence, variables EDUC1-EDUC5 are compared to the group of respondents with WO education. The other dummy variables are included as follows: gender (GENDER), different matches (MATCH) and group (GROUP). Furthermore, a variable MATCHGROUP is included. This variable is an interaction dummy variable between MATCH and GROUP. Recall that each group includes two different matches, where the dummy MATCH controls for different matches within the first group, GROUP for different groups for the first match, while the first match in the first group provides the baseline for comparison. Adding MATCHGROUP allows controlling for the second match within the second group, therefore the dummy MATCHGROUP3 is added to the regressions. MATCHGROUP3 is the interaction of the dummies for group two and match two. Additionally to the continuous variable for age (AGE), the variable age squared (AGE2) is included in the data. It is a common finding that age squared can be a useful addition to better predict the effect of age on dependent variables. Furthermore, the variable for perceived knowledge (KNOW_MEAN) consists of the mean for perceived knowledge about football in general and knowledge in the Eredivisie League specific. As you may recall the survey includes also a question that asks about the frequency that a respondents watches “NOS studio sport” or attends Eredivisie matches in the stadium. These answers are not used in the regression as variables. The variable mean knowledge provides sufficient proof for the hypotheses and is theoretically better specified for measuring knowledge. However, the answers do serve the purpose to check for consistency of the respondent's perceived knowledge. Finally, the variables for ambiguity aversion (AMBIGUITY_AVERSION) and likelihood sensitivity (LIKELIHOOD_SENSITIVITY) are used as dependent variables in the analysis.

§4.2 Data Consistency

In total 59 respondents completed the survey[9]. Each participant provided estimates for two matches, depending for which group they were selected. Totalling 118 unique observations. Prior to the analysis, the data is monitored for consistency and other possible errors. From the raw data set six unique observations are dropped, because of inconsistency. Inconsistency in this dataset manifests in a violation of the principle of dominance. According to this principle an option that is better than all other options in one state, and at least as good for all other states, should be preferred (Tversky & Kahneman, 1986). For example, assume that a respondent provided the following three subjective probability estimates: 30% that Utrecht will win, 20% draw, 50% that AZ wins. Following from the next questions it is observed that this respondent has the following three matched probabilities: 40% for Utrecht, 45% draw, 60% AZ wins. This respondent violates the dominance principle because 45% is higher than 40%, while the a-neutral probability is lower (20%<30%). Thus, in other words, it requires more white balls in the urn for a lower subjective probability of 20% than for a higher subjective probability of 30% to reach the indifference for this respondent. And therefore, it implies that the matching probability function is decreasing, which is not allowed as it violates the dominance principle. Next to that, 17 observations are dropped, because of too little variation in the subjective probability estimates. It occurs when respondents estimate the probability for both teams to win equally likely. A few respondents even estimate the chance on a win for team A or B at 50%, leaving 0% chance for a draw. Although the accuracy of this estimate is questionable, it results in only one unique a-neutral probability. Using only one unique observation to estimate the best fitting line between a-neutral and matched probabilities is not accurate. Resulting in inaccurate ambiguity aversion and likelihood sensitivity estimates later on. For this reason observations with less than three unique a-neutral probabilities per match are dropped

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[9] In total the survey has been started 117 times, of which 59 individuals completed it. See discussion part for an overview of completion rate of the survey.

from the sample. Lastly, one observation was dropped from the sample because this respondent might have more interest in the outcome of the match than in the possibility to win money. This respondent roots primarily for FC Twente and was assigned to group two where this respondent estimated the probability for the match FC Twente – Vitesse.

Excluding these observations from the dataset does affect the balance of the panel. Some respondents are only inconsistent in one of the two matches that they estimated, or they have enough variation in their a-neutral probabilities for the first match, but not enough for the second match. Dropping one out of two observations from a respondent results in an unbalanced panel. An unbalanced panel causes an extra error term when using panel data regressions (Baltagi, 2008). However, an unbalanced panel is often preferred over an "artificial" balanced panel. In our sample the unbalanced panel can be balanced by dropping respondents that have only one consistent observation (one match). Although this results in a balanced panel, it also results in a loss of efficiency. On the other hand, the unbalanced panel only harms the results when the additional error due to unbalance is not random. To prevent biases in the results all regressions are conducted over both the unbalanced panel and the artificial balanced panel. Throughout this thesis only the regressions of the unbalanced panel are presented, as the balanced panel leads to inefficiency while the results are not affected[10].

§4.3 Data Summary

The dataset is left with 94 unique observations divided by 51 unique respondents after excluding inconsistencies. In total 43 respondents with two observations (two matches) and 8 with one observation (one match). The observations are almost equally divided across the two groups. In total there are 46 observations in group one and 48 observations for group two. Mean age of the sample is 34 years with 12 years being the youngest respondent and 73 years the oldest. Men are more present in this sample than woman. In total this sample includes 39 observations from female respondents and 55 observations from males. Moreover, about half of the respondents of each gender type are assigned to group one and two respectively. Furthermore, mean knowledge in football and the mean knowledge in the Eredivisie league specifically show almost no

[10] There is one exception in the analysis, where the unbalanced panel causes a spurious result for education level. This is discussed later on.

difference for each respondent. This implies that respondents perceive their knowledge in football in general equal to their knowledge about the Eredivisie league. Therefore one mean for knowledge is used; these means are 4,0 and 3,7 on a 7-point Likert scale for groups one and two respectively. Also, the mean epistemic rating is slightly higher for group one than for group two with 3,7 and 3,5 respectively. The table below provides the mean estimates and corresponding matching probability estimates of the respondents per match. From this table the ambiguity aversion attitudes can be roughly estimated by looking for the trend. The data suggests that on average respondents are more ambiguity seeking for low probabilities (i.e. mean matching probability is less than the mean judged probability) and ambiguity averse for higher probabilities (i.e. mean matching probability is greater than the mean judged probability). This pattern is a common finding in research within decision making under ambiguity (Einhorn & Hogarth, 1986). However, this finding is not as clearly pronounced by our data than in some other studies as differences between judged probabilities and matching probabilities differ only by 0.01-0.05. The mean of the sample implicates that respondents are on average slightly ambiguity seeking with mean ambiguity aversion index of -0.0048 for group one and -0.0054 for group two. Respondents from group one also show a slightly higher index for likelihood sensitivity (0.98) than respondents in group two (0.96).

Match	Win A		Win B		Draw		Win A/Draw		Win B/Draw	
	P	MP	P	MP	P	MP	P	MP	P	MP
Utrecht – AZ	0,46	0,47	0,37	0,41	0,17	0,20	0,60	0,59	0,45	0,45
Groningen - Heracles	0,34	0,33	0,47	0,49	0,19	0,20	0,48	0,44	0,60	0,58
Roda – Willem II	0,38	0,42	0,35	0,38	0,27	0,29	0,61	0,57	0,50	0,47
Twente - Vitesse	0,38	0,38	0,43	0,45	0,19	0,24	0,51	0,50	0,55	0,54

Table 1: Mean Estimated Probabilities & Matched Probabilities

§4.4 Quantitative Results

Key to analysing results is to control for possible differences between groups and individuals. In this dataset there are two observations per individual divided over two groups. Therefore, possible differences between group one and two should be considered to prevent biases in the results. A possibility to test for differences between two groups is the simple t-test. It tests if the difference between two means is significantly different from zero (Cressie & Whitford, 1986). Nonetheless, to perform this test few conditions have to be met in order to gain trustworthy results. Hence, these conditions should be tested first. From a F-test for normality it is concluded that ambiguity aversion and likelihood sensitivity are not normally distributed. Moreover, likelihood sensitivity also violates the condition of equal variance between group one and two. An alternate test for differences between groups is the non-parametric Mann-Whitney two-sample test (Mann & Whitney, 1947). This test does not require normal distribution or equal variances. Hence, it suits the data set. For this analysis it is of interest how different variables affect ambiguity aversion and likelihood sensitivity. Therefore the Mann-Whitney test is performed on both variables based on group one or two respectively. From the output it is observed that both means of ambiguity aversion and likelihood sensitivity do not differ. Hence, when analysing results, groups are combined into one regression.

As an additional analysis, it is hypothesized that knowledge mediates the effect of epistemic rating on ambiguity attitudes. Testing for correlation between knowledge and mean epistemic rating provides insight in how these two might interact and if collinearity can be a problem. The Spearman correlation has a coefficient of 0.0590 indicating a weak positive correlation, though this result is insignificant (Spearman, 1904)[11]. Nonetheless, different regression models are tested to see if knowledge affects the coefficient of epistemic rating in the regression analysis.

§4.4.1 Ambiguity Aversion Index

As discussed earlier, a random effects panel regression is used to test the hypotheses. The results from the first regression are shown in table 2. The regression includes all discussed variables. P values are shown below each coefficient between brackets with *, ** and *** indicating significance at levels 0.1, 0.05 and 0.01 respectively.

[11] The Spearman correlation is used instead of Pearson's Correlation, because Pearson's Correlation requires the variables to be normally distributed. The Shapiro-Wilk test shows that both variables are not normally distributed on 10% significant level.

Ambiguity Aversion	Coef.	Std. Err.	[95% Conf. Interval]	
EPI_MEAN	-.0277449 (0.107)	.0172177	-.061491	.0060012
KNOW_MEAN	-.0206173 (0.002)***	.0065141	-.0333846	-.0078499
2.MATCH	.0251745 (0.119)	.0161387	-.0064567	.0568058
EDUC1	-.0336831 (0.586)	.0618492	-.1549052	.087539
EDUC2	-.0120211 (0.822)	.0535615	-.1169996	.0929574
EDUC3	-.0167465 (0.696)	.0428993	-.1008276	.0673346
EDUC4	-.0053753 (0.892)	.0396008	-.0829913	.0722408
EDUC5	-.0130195 (0.666)	.0301826	-.0721763	.0461374
AGE	-.0023406 (0.618)	.0046918	-.0115365	.0068552
AGE2	.0000201 (0.723)	.0000568	-.0000912	.0001314
1.GENDER	.0000295 (0.999)	.022655	-.0443734	.0444325
2.GROUP	.010713 (0.651)	.023659	-.0356578	.0570837
1.MATCHGROUP3	-.0301146 (0.170)	.0219385	-.0731132	.0128839
CONSTANT	.2200859 (0.066)*	.1230516	-.0210908	.4612626

F-test prob 0.0959*

Table 2: Ambiguity Aversion Index Panel RE

From the regression it is observed that there are only significant results for the variable of knowledge and the constant. However, the variable for epistemic rating is close to significance. The F-test of the regression describes the significance of the model in general. An insignificant result of this test indicates that the regression is not well specified, due to missing variables or irrelevant variables. Although, this model is significant at 10% level, many variables are not significant. Therefore, the variables that are not individually significant are tested on joint significance. AGE, AGE2 and all dummies for education are not jointly significant. The dummies for different matches and groups are also not significant and excluded from the model. From earlier studies it is known that gender can affect ambiguity attitudes depending on the context (Schubert, Brown, Gysler, & Brachinger, 1999; Schubert, Brown, Gysler, & Brachinger, 2000). Experimental data from Hershey & Schoemaker (1980) also suggest that women are more risk-averse towards gambles, but that does not hold in our ambiguity setting. Hence, gender is excluded from the regression. A regression with ambiguity aversion as dependent variable and epistemic rating and knowledge as independent variables is what remains after excluding other variables. This model (table 3) is well specified (prob>chi2 = 0.0002) with both variables as well as the constant being significant at the 0.01 or 0.1 level.

Ambiguity Aversion	Coef.	Std. Error	95% Conf. Interval	
EPI_MEAN	-0.028872 (0.054)*	0.0149961	-0.0582638	0.0005197
KNOW_MEAN	-0.0169072 (0.000)***	0.0046456	-0.0260123	-0.0078021
CONSTANT	0.1635539 (0.005)***	0.0577013	0.0504615	0.2766463

F-test prob 0.0002***

Table 3: Ambiguity Aversion Index Panel RE

Both variables have negative coefficients, implying that they affect the ambiguity aversion index negatively. When a respondent increases his/her mean epistemic rating with one, it decreases the ambiguity aversion index with 0.028872. Also, an increase of the respondent's mean knowledge decreases the ambiguity aversion index with 0.0169072. However, these impacts may appear to be very small, note that interval of probabilities varies between 0 and 1 with mean ambiguity aversion index -0.0048. Therefore, both variables do have impact on the ambiguity aversion index of the respondent. Furthermore, it is verified whether the random effects model is better specified than the ordinary least square method (OLS) using the Breusch & Pagan Langrangian multiplier test. With 10% significance level the null hypothesis of OLS being the better estimator is rejected. Hence, the random effects panel regression is the most efficient estimator.

As mentioned before, an additional interest of this paper is if knowledge mediates the effect of epistemic rating on ambiguity aversion. Although, there is no significant correlation between epistemic rating and knowledge, it remains useful to regress both independent variables separately to see if it affects the coefficients. Using the same random effects model excluding only knowledge as independent variable results in lower significant level for mean epistemic rating, without having impact on the coefficient of mean epistemic rating[12]. The same accounts for only excluding knowledge as dependent variable. Both variables are unaffected, while the F-test shows no significance. Excluding one of the variables thus only results in a worse model. This supports the finding of the Pearson correlation. It suggests that knowledge does not mediate the effect of epistemic rating on the ambiguity aversion index in our sample.

§4.4.2. Likelihood Sensitivity Index

For likelihood sensitivity the same variables are used as for the regression of ambiguity aversion. Again the random effects model is used with likelihood sensitivity as dependent variable.

Likelihood Sensitivity	Coef.	Std. Err.	[95% Conf. Interval]	
EPI_MEAN	-.0076453 (0.554)	.0129255	-.0329787	.0176882
KNOW_MEAN	-.0064201 (0.191)	.0049086	-.0160409	.0032006
2.MATCH	.0054166 (0.701)	.0141052	-.0222292	.0330623
EDUC1	.0163319 (0.725)	.0464704	-.0747484	.1074122
EDUC2	.0326723 (0.423)	.0407548	-.0472057	.1125504
EDUC3	-.0075677 (0.813)	.0320636	-.0704112	.0552758
EDUC4	.0511796 (0.089)*	.0300594	-.0077358	.1100949
EDUC5	-.026332 (0.244)	.0226137	-.070654	.01799
AGE	-.0035745	.0035647	-.0105612	.0034123

[12]Output of these models can be found in appendix B table 6

	(0.316)			
AGE2	.0000329 (0.446)	.0000432	-.0000517	.0001175
1.GENDER	-.0245276 (0.150)	.0170391	-.0579237	.0088685
2.GROUP	-.026311 (0.153)	.0184233	-.0624201	.009798
1.MATCHGROUP3	.0166337 (0.388)	.0192607	-.0211166	.054384
CONSTANT	1.116141 (0.000)***	.0927855	.9342843	1.297997

F-test prob 0.0986*

Table 4: Ambiguity Likelihood Sensitivity Panel RE

From this model no significant results are observed for our variables of interest. Only the dummy for educational level MBO is significant at 10% significance level. Theoretically the significance of dummy EDUC4 is not logical. The coefficient of 0.0511796 is interpreted as a respondent that has MBO education has 0.0511796 higher likelihood sensitivity index compared to a respondent with WO education. If this would be true, then a trend in educational level is expected. This is not the case, the coefficients of education dummies have both positive and negative turnover when the educational level increases. Moreover, in our sample there are only four individuals with MBO education. Hence, it is most likely that this significant result captures another effect than education level. When looking closer at this group of four individuals with MBO education, it is observed that there are six observations from four students in our sample. This implies that for MBO education the sample is strongly unbalanced. Recreating the same regression for an artificial balanced panel leads to insignificance for the MBO education dummy. Although the unbalanced panel is most efficient for our main analysis, it causes a spurious result for this small education group where half of the respondents have only one observation. Hence, this significance is caused by an error term and is thus ignored in the analysis.

Dropping variables from the regression, as in the model for ambiguity aversion, does not result in a better model. By doing so the F-statistic increases and the model becomes insignificant. Alternatively, the variables EPI_MEAN and KNOW_MEAN can be transformed into dummies. Although it reduces efficiency and requires extra assumptions, it may help to compare respondents that perceive football as epistemic with respondents that perceive it as aleatory and respondents with high knowledge in football with respondents with low knowledge. The variable EPI_MEAN is transformed in the variable EPI_YN, which is a dummy variable that takes value 1 when a respondent has a mean epistemic rating larger than 3.5 and takes value 0 when the respondent's mean epistemic rating is equal or below 3.5. The same rule is used to split KNOW_MEAN into KNOW_YN. This model is presented in the table below. From this model it is observed that both dummies are not significant. Furthermore, the model becomes worse specified, due to the loss of efficiency. Therefore, this model does not help to answer our hypotheses for likelihood sensitivity.

Likelihood Sensitivity	Coef.	Std. Err.	[95% Conf. Interval]	
EPI_YN	-.0043949 (0.791)	.0165761	-.0368835	.0280938
KNOW_YN	-.0144993 (0.395)	.0170366	-.0478905	.0188918
2.MATCH	.0044721 (0.750)	.0140319	-.02303	.0319742
EDUC1	.0272533 (0.558)	.0464797	-.0638453	.1183519
EDUC2	.0267945 (0.513)	.0409127	-.0533929	.106982
EDUC3	-.0078181 (0.814)	.0332021	-.0728931	.0572569
EDUC4	.0516139 (0.093)*	.0307404	-.0086362	.111864
EDUC5	-.0263869 (0.250)	.0229372	-.0713431	.0185692
AGE	-.0024569 (0.484)	.003507	-.0093305	.0044168
AGE2	.0000214 (0.619)	.000043	-.0000629	.0001056
1.GENDER	-.0184355 (0.254)	.0161685	-.0501251	.0132541
2.GROUP	-.0235182 (0.202)	.0184201	-.0596209	.0125844
1.MATCHGROUP3	.0175781 (0.359)	.019164	-.0199826	.0551388
CONSTANT	1.048474 (0.000)***	.0661802	.918763	1.178185

F-test prob. 0.1511

Table 5: Likelihood Sensitivity Panel RE with dummies for epistemic rating and knowledge

It is not possible to analyse whether knowledge mediates the effect of epistemic rating on likelihood sensitivity as no significant effect is observed from the models.

§4.4.3 *Summary of Results*

Recall the first hypothesis of this paper: *H1: Knowledge increases ambiguity-seeking behaviour.* According to the competence hypothesis knowledge in a specific task or assignment increases ambiguity-seeking behaviour. In this paper knowledge in football and the Dutch league is measured by using a Likert scale. From regressing the ambiguity index that is created from the survey data using the source method and matching probabilities, it is clear that knowledge affects the ambiguity aversion negatively. Perceiving your knowledge as a respondent one point higher on the Likert scale results in 0.0169072 lower index of ambiguity aversion. As ambiguity aversion is the opposite of ambiguity seeking a negative index means ambiguity-seeking behaviour. This result is significant on a 5% significance level and in line with the competence hypothesis and expectation. And thus the first hypothesis is confirmed. There is clear evidence that knowledge increase ambiguity seeking behaviour.

Secondly, it was hypothesized that higher "epistemicness" results in more ambiguous averse behaviour. From the random effects model it is observed that this is not the case. In contrary, the opposite seems to be true in our sample. The coefficient from epistemic rating takes value -0.028872 (10% significance level). Describing that when the mean epistemic rating is perceived one point higher on the Likert scale this results in 0.028872 lower index for ambiguity aversion. In the discussion part it is discussed why this result is the opposite of our expectation.

The third hypothesis looks into the relation of epistemic uncertainty and ambiguity sensitivity. Recall hypothesis three: *H3: Epistemic uncertainty increases likelihood sensitivity.* For this hypothesis there is too little evidence from the regression models to confirm it. From the random effects model no significant relation for epistemic rating is observed. Adding an extra assumption by creating a dummy variable for epistemic rating leads not to significance either. Therefore this hypothesis remains inconclusive.

Fourthly, it was hypothesized that knowledge has positive effects on likelihood sensitivity. Despite the mixed evidence in previous literature, we hypothesized this positive interaction. Unfortunately, this hypothesis remains inconclusive. From two different regressions, one with knowledge as continuous variable and one where knowledge is a dummy, no results were observed. However, this thesis is the first to study this proposition and therefore it remains interesting for further analysis.

Finally, two additional hypotheses were included that test if knowledge mediates the effect of "epistemicness" on ambiguity attitudes. From the analysis it is concluded that there is no correlation between the two variables. Also, when creating two different regressions where knowledge and "epistemicness" are separated, the coefficients are not affected compared to the model where both variables are included. Therefore it can be concluded that knowledge does not mediate the effect of "epistemicness" on ambiguity attitudes. This research is unable to answer this hypothesis for likelihood sensitivity however. No significant results are found for hypotheses three and four and thus further analysis is not possible.

5. Conclusion

This thesis focused on two interactions in particular: (1) knowledge and (2) epistemic and aleatory uncertainty with ambiguity attitudes. In total 59 respondents participated in our survey, estimating probabilities for two upcoming Eredivisie matches. Subsequently respondents' matching probabilities were measured using their estimations as a-neutral probabilities and making the risky bet more or less attractive based on their preferences between risky and ambiguous bets. From the matching probability function we were able to measure ambiguity attitudes using the best fitting line. Two different indexes were used in our regressions to measure ambiguity attitudes quantitatively: ambiguity aversion and ambiguity likelihood sensitivity. First the index for ambiguity aversion was analysed. From the results it is observed that more knowledge and higher epistemic rating both result in increased ambiguity seeking behaviour. The interaction with knowledge is in line with the competence hypothesis and thus adds to its literature. However, the interaction with epistemic rating is contradicting our expectation, which is discussed in chapter 6. Secondly, ambiguity likelihood sensitivity was analysed using the same independent variables. However, different regressions and additional assumptions did not result in significance. Therefore, interaction with likelihood sensitivity remains inconclusive. Hence, the answer to our research question is two folded. Recall the research question: "*How do Knowledge and Epistemic or Aleatory Uncertainty affect Ambiguity Attitudes?*" Firstly, knowledge and epistemic uncertainty increase ambiguity-seeking behaviour. Secondly, there is insufficient evidence in our sample that knowledge and epistemic uncertainty affect likelihood sensitivity.

6. Discussion & Limitations

In this section, we elaborate on some of the findings from this research. First results that differ from expectation are discussed. Then more general comments on our research will be provided. Finally, some recommendations are provided for possible future research.

§6.1 Discussion of Results

The second hypothesis states that higher epistemic rating result in more ambiguous behaviour. However, from the regression the opposite is observed. When respondents in our sample increase their epistemic rating this results in more ambiguity seeking behaviour. This result is contradicting with the results of Chow & Sarin (2002). One substantial difference between their study and our study is that they use three situations where different levels "epistemicness" are perfectly manipulated, but the ambiguity likelihood is maintained constant. For each situation a similar event (bag of poker chips, bag of M&M's) is used for which they vary the amount of information for respondents, while the a-neutral probability is maintained at 50%. It can be argued that one a-neutral probability is insufficient to draw conclusions about interactions with ambiguity. Recall the general finding from figure 1d, this shows that people handle different ambiguity attitudes towards different likelihoods. Therefore, our ambiguity index is estimated using at least three different likelihoods, implying that our indexes provide a global measure of ambiguity aversion. This absence of relatively high and low likelihoods in Chow & Sarin's paper may explain different findings. Furthermore, in our study the ambiguous event is compared with subjective a-neutral probabilities instead of objective probabilities. This might help the respondents to feel less ambiguous about the football event as they individually estimated a probability for each outcome. These probabilities might be an anchor for respondents when choosing between two bets, interpreting the football bet less ambiguous than it should be handled, resulting in less ambiguity averse behaviour. Lastly, in their study they ask respondents to state their willingness to pay for a hypothetical bet in each situation, where in our study respondents provide preferences directly, while there is a chance to be selected to play the bet for real money. This difference may interfere with ambiguity attitudes as in our study respondents are able to gain money, while in their study respondents only provide hypothetical willingness to pay. Purely hypothetical choices are not sufficient for ambiguity research (Dimmock, Kouwenberg, & Wakker, 2015), which is discussed below.

§6.2 Limitations

As mentioned, our survey uses a concept of random selection to reward three respondents assuming it incentivizes respondents in a way if it were real choices. Choosing the best method in incentivizing respondents depends on several factors. For instance, available resources, the effort it requires from respondents to participate and of course the research question. The most important question is whether ambiguity can be measured using hypothetical choices. Previous literature provides us with an overview in ambiguity research. Dimmock et al. (2015) is a useful comparison as it also uses bets between an ambiguous choice and risky choice in their study. Dimmock et al. (2015) questioned whether hypothetical choice is sufficient for ambiguity measurement. For that reason they split their sample into two groups. One group participates in the survey purely making hypothetical choices. The other group makes the same choices but this time for real money. When analysing the results, they did find differences between the two groups. They conclude that the hypothetical group rarely reached significance for the ambiguous parameters. Only the highly educated people reached significance in some cases. The group that made choices based on real money did reach significance for ambiguity attitudes for all levels of education. Apparently measuring ambiguity is too complex to measure using purely hypothetical choices. Therefore, respondents should be incentivized by monetary rewards. However, paying each and every respondent is not feasible for this study, we used an alternative. Dimmock et al. (web appendix) conducted a trial version of their experiment before their main research (2015). In this trial they randomly selected three respondents that were paid based on their choices. This incentive is sufficient for reaching significant results. Hence, this study randomly selects three participants to play one of their choices for real money. With each choice between bets participants can win ten euro. By doing so it is assumed that participants are motivated sufficiently to think carefully about the decisions they make in the survey. However, paying every respondent would be the best method and therefore it remains a limitation to our study.

Finally, concerns about the response rate should be mentioned. In total 117 individuals started the survey, from which only 59 completed the survey. Whether this low response rate biases the results depends on the reason for not completing. Three possible reasons are discussed: intention, expectation and difficulty. It is assumed that the majority of incomplete surveys are due to people who never had the intention to finish the survey, but started it purely out of curiosity. Starting the survey informs people about the topic, while staying anonymous whenever the survey is left. This is observed from incomplete surveys that do not include any answers at all, implying that these people quit the survey directly after or even before reading instructions. Furthermore, it is assumed that for some people the expectation of the survey did not match with the actual survey. When asking people to fill out a survey, it evokes certain thoughts about surveys in general. The most common surveys are for example customer satisfaction surveys that are very short and simple and can easily be done without any effort. From the first question from our survey it immediately becomes clear that it requires more effort than customer satisfaction surveys. Thus it observed that some people quit the survey after filling out the first or first two questions. Lastly, two individuals shared thoughts about the difficulty of the survey. They found it hard to estimate probabilities. One respondent started the survey several times to try again, which results in additional incomplete responses. Apparently, estimating probabilities is something that requires quite some effort. This last reason biases the results when respondents complete the survey with insufficient understanding of the questions. Due to the relatively low completion rate it is assumed that individuals with sufficient capabilities to participate have self selected them to participate. However, this may result in a higher educated sample than the general population. Therefore our results should be interpreted carefully when validating to the general population.

§6.3 Recommendations

From this thesis it is observed that the hypotheses for likelihood sensitivity remain inconclusive in our sample. Therefore a similar hypothesis for other or larger samples may be interesting to study in future research. Moreover, the interaction between knowledge and likelihood sensitivity is first of its kind as far as known to us. Hence, this interaction provides numerous possibilities for further research. Furthermore, the source method and matching probabilities can easily be used in different settings to measure ambiguity attitudes quantitatively. Therefore, it is very interesting to apply this method to different settings (other than our Eredivisie setting) to study interactions of likelihood sensitivity and ambiguity attitudes. Finally, it is interesting to further extent this thesis by using purely epistemic and aleatory events instead of the perceived level of "epistemicness". This may provide interactions similar to our thesis, but then with pure epistemic or aleatory uncertainty.

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Appendix A

An example survey with simulated answers is added below. It includes all questions from group two that a respondent receives when providing similar estimates and preferences. However, the layout differs from the actual survey in order to shorten the appendix. Recall that the survey is responsive and thus the amount of white and black balls depends on the respondent's previous answers. Hence, the online survey includes almost 300 hidden questions to adapt to all possible estimates and preferences from respondents. The survey is programmed in way that the correct questions are asked based on the estimates and preferences of each respondent. Adding all possible questions would be too extensive as an appendix and meaningless for reporting purposes. The survey shown below is thus an example created from simulated estimates and preferences for a respondent assigned to group two.

Predicting Football Matches

This is a research study on how people think about upcoming football matches in the Dutch League Eredivisie.

You will provide estimates about possible outcomes for upcoming Eredivisie matches. Afterwards we will ask you some additional questions. There are no right or wrong answers. Filling out the survey will not take more than 10 minutes.

From the respondents we randomly select three participants that will play one of their choices from this survey at random. So please consider your choices carefully as you can win 10 euro's. If you want to make a chance to be selected, then please leave your e-mail at the end of the survey.

Football Match 1.1
For the following question we ask you to estimate the probability for different outcomes of an upcoming Eredivisie match on 8th May. For example: if you answer 30, this means that you think that this outcome will happen 30 times out of 100.

Sunday 8th of May Roda JC (currently 14th) plays against Willem II (currently 15th). What is the probability of the following outcomes?
Note: Your answers should add up to 100.

Only numbers may be entered in these fields.
The sum must equal 100.

Roda JC wins	40
Willem II wins	30
Draw	30

Football Match 1.2
For the following question we ask you again to estimate probabilities. But this time we ask you to provide probabilities for combined outcomes. For example, the probability of the match ending in a draw or a win.

Sunday 8th of May Roda JC (currently 14th) plays against Willem II (currently 15th). What is the probability of the following outcomes?

Only numbers may be entered in these fields.
Each answer must be at most 100

Roda JC Wins or it will be a draw	70
Willem II Wins or it will be a draw	60

Bets 1

For the following questions we ask you to consider a choice between two bets. Please consider carefully which bet you prefer. Bet A is a bet based on the real outcome of the football match and Bet B is a draw from an urn containing 100 balls with a known distribution between white and black. If you think that both bets are equally attractive, then select "indifferent".

Bet A **Bet B**

OR

Win 10 euros when Roda JC wins and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 40 white balls and 60 black balls.

- ○ I prefer option A
- ○ I prefer option B
- ⦿ I am indifferent

Bet A **Bet B**

OR

Win 10 euros when Willem II wins and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 30 white balls and 70 black balls.

- ⦿ I prefer option A
- ○ I prefer option B
- ○ I am indifferent

Bet A **Bet B**

- OR -

Win 10 euros when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 30 white balls and 70 black balls.

◉ I prefer option A
○ I prefer option B
○ I am indifferent

Bet A **Bet B**

- OR -

Win 10 euros when Willem II wins or when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 60 white balls and 40 black balls.

○ I prefer option A
◉ I prefer option B
○ I am indifferent

Bet A **Bet B**

- OR -

Win 10 euros when Roda JC wins or when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 70 white balls and 30 black balls.

○ I prefer option A
◉ I prefer option B
○ I am indifferent

Bet A **Bet B**

- OR -

Win 10 euros when Willem II wins and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 35 white balls and 65 black balls.

◉ I prefer option A
○ I prefer option B
○ I am indifferent

Bet A

Win 10 euros when the match ends in a draw and 0 otherwise

OR

Bet B

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 35 white balls and 65 black balls.

- ○ I prefer option A
- ○ I prefer option B
- ⦿ I am indifferent

Bet A

Win 10 euros when Willem II wins or when the match ends in a draw and 0 otherwise

OR

Bet B

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 55 white balls and 45 black balls.

- ○ I prefer option A
- ⦿ I prefer option B
- ○ I am indifferent

Bet A

Win 10 euros when Roda JC wins or when the match ends in a draw and 0 otherwise

OR

Bet B

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 65 white balls and 35 black balls.

- ○ I prefer option A
- ⦿ I prefer option B
- ○ I am indifferent

Bet A

Win 10 euros when Willem II wins and 0 otherwise

OR

Bet B

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 40 white balls and 60 black balls.

- ○ I prefer option A
- ○ I prefer option B
- ⦿ I am indifferent

Bet A | **Bet B**

OR

Win 10 euros when Roda JC wins or when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 60 white balls and 40 black balls.

○ I prefer option A
○ I prefer option B
⦿ I am indifferent

Bet A | **Bet B**

OR

Win 10 euros when Willem II wins or when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 50 white balls and 50 black balls.

○ I prefer option A
○ I prefer option B
⦿ I am indifferent

Football Match 2.1

For the following question we ask you again to estimate the probability for different outcomes of another Eredivisie match on 8th May. For example: if you answer 30, this means that you think that this outcome will happen 30 times out of 100.

Sunday 8th of May FC Twente (currently 13th) plays against Vitesse (currently 7th). What is the probability of the following outcomes? *Note: Your answers should add up to 100.*

FC Twente wins	25
Vitesse wins	60
Draw	15

Football Match 2.2

For the following question we ask you again to estimate probabilities. But this time we ask you to provide probabilities for combined outcomes. For example, the probability of the match ending in a draw or a win.

Sunday 8th of May FC Twente (currently 13th) plays against Vitesse (currently 7th). What is the probability of the following outcomes?

Only numbers may be entered in these fields.
Each answer must be at most 100

FC Twente wins or it will be a draw	40
Vitesse wins or it will be a draw	75

Bets 2

For the following questions we ask you to consider a choice between two bets. Please consider carefully which bet you prefer. Bet A is a bet based on the real outcome of the football match and Bet B is a draw from an urn containing 100 balls with a known distribution between white and black. If you think that both bets are equally attractive, then select "indifferent".

Bet A

Win 10 euros when FC Twente wins and 0 otherwise

OR

Bet B

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 25 white balls and 75 black balls.

- ◉ I prefer option A
- ○ I prefer option B
- ○ I am indifferent

Bet A

Win 10 euros when the match ends in a draw and 0 otherwise

OR

Bet B

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 15 white balls and 85 black balls.

- ◉ I prefer option A
- ○ I prefer option B
- ○ I am indifferent

Bet A

Win 10 euros when Vitesse wins and 0 otherwise

OR

Bet B

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 60 white balls and 40 black balls.

- ○ I prefer option A
- ◉ I prefer option B
- ○ I am indifferent

Bet A

Win 10 euros when FC Twente wins or when the match ends in a draw and 0 otherwise

OR

Bet B

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 40 white balls and 60 black balls.

- ○ I prefer option A
- ○ I prefer option B
- ◉ I am indifferent

Bet A

Bet B

OR

Win 10 euros when Vitesse wins or when the match ends in a draw and 0 otherwise

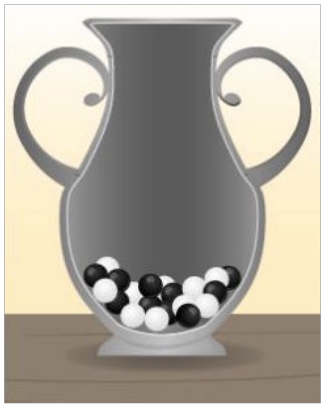
Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 75 white balls and 25 black balls.

- ○ I prefer option A
- ◉ I prefer option B
- ○ I am indifferent

Bet A

Bet B

OR



Win 10 euros when Vitesse wins and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 55 white balls and 45 black balls.

- ○ I prefer option A
- ○ I prefer option B
- ◉ I am indifferent

Bet A

Bet B

OR

Win 10 euros when FC Twente wins and 0 otherwise

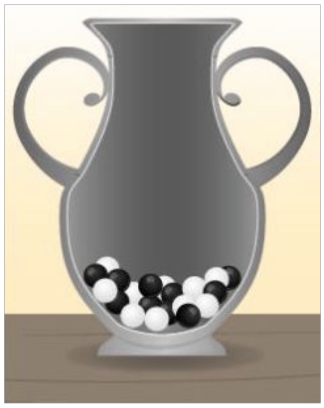
Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 30 white balls and 70 black balls.

- ◉ I prefer option A
- ○ I prefer option B
- ○ I am indifferent

Bet A

Bet B

OR



Win 10 euros when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 20 white balls and 80 black balls.

- ◉ I prefer option A
- ○ I prefer option B
- ○ I am indifferent

Bet A OR **Bet B**

Win 10 euros when Vitesse wins or when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 70 white balls and 30 black balls.

- ○ I prefer option A
- ◉ I prefer option B
- ○ I am indifferent

Bet A OR **Bet B**

Win 10 euros when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 25 white balls and 75 black balls.

- ◉ I prefer option A
- ○ I prefer option B
- ○ I am indifferent

Bet A OR **Bet B**

Win 10 euros when FC Twente wins and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 35 white balls and 65 black balls.

- ○ I prefer option A
- ○ I prefer option B
- ◉ I am indifferent

Bet A OR **Bet B**

Win 10 euros when Vitesse wins or when the match ends in a draw and 0 otherwise

Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 65 white balls and 35 black balls.

- ○ I prefer option A
- ○ I prefer option B
- ◉ I am indifferent

Bet A **Bet B**

OR

Bet A	Bet B
Win 10 euros when the match ends in a draw and 0 otherwise	Win 10 euros (and nothing otherwise) when you draw a white ball from the urn containing 30 white balls and 70 black balls.

○ I prefer option A
○ I prefer option B
⦿ I am indifferent

Prediction of Football Matches

Earlier you provided probabilities for different outcomes of two football matches. Please rate the following statements from scale 1-7 (1=Not at all, 7=Very much)
Determining which team will win...

	1	2	3	4	5	6	7
... is in principle knowable in advance	○	⦿	○	○	○	○	○
... is something that has an element of randomness	○	○	○	○	○	⦿	○
... is something that has been determined in advance	○	⦿	○	○	○	○	○
... feels unpredictable	○	○	⦿	○	○	○	○
... is knowable in advance, given enough information	○	○	○	⦿	○	○	○
... feels like it is determined by chance factors	○	○	⦿	○	○	○	○
... feels like it could play out in different ways on similar occasions	○	○	○	○	⦿	○	○
... is something that well-informed people would agree on	○	○	○	○	○	⦿	○
... is something that could be better predicted by consulting an expert	○	○	○	○	⦿	○	○
... is something that becomes more predictable with additional knowledge or skills	○	○	○	○	⦿	○	○

Other Questions

On a scale from 1-7, what is your knowledge about the Eredivisie? (1 = very unknowledgeable, 7 = very knowledgeable)

1	2	3	4	5	6	7
○	○	○	○	○	⦿	○

On a scale from 1-7, what is your knowledge about football in general? (1 = very unknowledgeable, 7 = very knowledgeable)

1	2	3	4	5	6	7
○	○	○	○	○	⦿	○

Comment on the following statements if they apply to you

	Never	Sometimes	Regularly	Often	Always
I watch NOS Studio Sport on Sunday evening	○	○	○	⦿	○
I watch Eredivisie Live during weekends	○	⦿	○	○	○
I attend Eredivisie games in the stadium	○	⦿	○	○	○

Which Eredivisie team do you primarily root for? Choose one of the following answers

Please choose...

What is your highest level of education? Choose one of the following answers

○ Primary school ○ VMBO ○ HAVO

○ VWO ○ MBO ○ HBO ⦿ WO

What is your gender?

- ○ Female
- ⦿ Male

Did you use any external sources during this survey? For example: Google, Odds from betting websites, Wikipedia**.**

- ○ Yes
- ⦿ No

Please leave your Email if you want to make a chance to play one of your bets for 10 euro's.

Your email will only be used to contact you when you win 10 euro's. Afterwards your contact details will be deleted.

example@gmail.com

Thank you for your participation!
You will be notified by an email after 8th of May if you are selected to play one of your choices for real money.

Appendix B

Ambiguity Aversion	Knowledge only		Epistemic only	
	Coef.	Std. Err.	Coef.	Std. Err
EPI_MEAN			-.0288243 (0.140)	.01952
KNOW_MEAN	-.0208549 (0.002)***	.0066379		
2.MATCH	.025279 (0.118)	.0161781	.0209344 (0.191)	.0160135
EDUC1	-.0380564 (0.546)	.0629976	.031872 (0.630)	.0661116
EDUC2	-.0261906 (0.626)	.0538157	-.0203358 (0.735)	.0601112
EDUC3	-.0123542 (0.777)	.0436723	-.0325718 (0.502)	.048463
EDUC4	-.0180794 (0.647)	.0394984	.009854 (0.824)	.0442899
EDUC5	-.0203237 (0.504)	.030432	-.0102973 (0.764)	.0342602
AGE	-.0011687 (0.804)	.0047197	.0007138 (0.890)	.0051609
AGE2	5.81e-06 (0.919)	.0000571	-6.52e-06 (0.918)	.0000631
1.GENDER	.0012339 (0.957)	.0230834	.0357827 (0.110)	.0223775
GROUP	.0165423 (0.486)	.0237485	.0191401 (0.461)	.0259844
1.MATCHGROUP3	-.0302191 (0.169)	.0219828	-.0258745 (0.234)	.0217217
CONSTANT	.1000285 (0.315)	.0996539	.0560179 (0.657)	.1260374
F-test prob. 0.1569			F-test prob. 0.7681	

Table 6 Ambiguity Aversion Panel RE Knowledge and Epistemic Rating Seperated