Job-related Decisions under Uncertainty: the Influence of Ambiguity Attitude on Self-employment and the Reservation Wage

Master's Thesis

Behavioural Economics

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Abstract

This study investigates the effects of ambiguity attitudes on job-related decisions in real life. Both the decision to become self-employed and to accept a job when looking for work involve ambiguity (i.e. the probabilities of success are unknown). The source method is used to measure ambiguity attitude in a large sample representative of the general American population. The results show that individuals who are ambiguity seeking or neutral are more likely to be self-employed than those who are ambiguity averse. The global ambiguity measures for ambiguity aversion and a-insensitivity, however, have no influence. Also, no effect is found for ambiguity aversion in the domain of gains or losses or for a-insensitivity when studying the reservation wage at which unemployed individuals would accept a job. Several suggestions are made to explain the results obtained in this study. Especially the use of different ambiguity aversion measures for different likelihood levels would improve the measurement of ambiguity attitude and the study of its effect on real-life decisions. Finally, the difference in beliefs about ambiguity may play a critical role in the decision-making process, interfering with the effect of ambiguity attitudes.

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1. Introduction

A fundamental aspect of decision-making is the element of uncertainty. Many decisions in real life are made under uncertainty since the future can never be fully predicted. When studying decision-making under uncertainty, it is crucial to distinguish risk from ambiguity. The two concepts differ from each other regarding the probabilities of the possible outcomes: risky choices involve known probabilities, but for ambiguous choices these probabilities are unknown. Most research has focused on risk, which has become a popular topic in many disciplines including economics, psychology, sociology, and neuroscience. Many situations and decisions, however, involve unknown probabilities. This has been known since Keynes (1921) and Knight (1921), but has only been incorporated in models since 1989 (Gilboa & Schmeidler, 1989; Schmeidler, 1989). Recently, a new method to study uncertainty has been developed by Abdellaoui et al. (2011). This source method makes it possible to analyse ambiguity empirically and investigate the effect of ambiguity attitudes on the decision-making process. Although the interest in ambiguity is growing, relatively little attention has been devoted to the relation between ambiguity attitudes and decisions in real life. The aim of this paper is to contribute to this topic. Specifically, this paper will look into the relation between ambiguity and job-related decisions regarding self-employment and unemployment using a large and representative sample of the general population in the US. The research question is formulated as follows:

Are ambiguity attitudes related to real-life job-related decisions concerning self-employment and unemployment?

The question why some individuals become self-employed instead of an employee with a fixed wage has received a serious amount of attention in the literature. In this paper the New Oxford American Dictionary definition of self-employment is used: "the state of working for oneself as a freelancer or the owner of a business rather than for an employer". The reason for the large amount of interest is the fact that self-employment broadens the choice for starting workers and the unemployed. Paid employment is not the only option and this influences the dynamics of the labour market. Moreover, self-employers have a substantial economic impact: they create new jobs for themselves and possibly for their personnel; they are considered essential for economic growth; and they increase competition and innovation in the market. Consequently, politicians are interested in measures to promote self-employment such as legislation, tax benefits, and the provision of loans to start-ups. The study on self-employment and its determinants helps to construct the optimal policies. It is also common knowledge that self-employment comes with more uncertainty than wage-employment (Cramer et al., 2002). The decision to start a company involves ambiguity, as the chances of success are unknown: entrepreneurs are often inexperienced and information on the odds of success is incomplete or non-existent. Furthermore, the amount of income is uncertain. Nonetheless, little attention has been given to the relation of ambiguity attitude to self-employment. This can be partly explained by the fact that ambiguity has only recently been implemented in models and theory. Even so, it is a relevant topic that this paper aims to investigate. With an extensive dataset of the general US population, this paper analyses the relation between ambiguity attitude and the likelihood to become self-employed. Another addition to the existing literature on this topic is the inclusion of ambiguity attitude in the domain of losses. Self-employment not only comes with a chance to become successful, it also comes with the chance to fail. Hence, potential losses play a major role in the decision to start working for oneself, paired with a large amount of ambiguity. This paper examines how this affects the choice to become self-employed.

Another economic variable that many researchers and the government are interested in is unemployment. The unemployment level is an important indicator of labour market- and economic performance. Unemployment affects individuals and their families both financially and non-financially: without work families lose wage income and purchasing power, but also their health and social lives are affected. The lower purchasing power of unemployed individuals negatively affects the economy and leads to more unemployment. Furthermore, those who are not working do not contribute to the national economy and might even receive benefits from the government. Policy makers thus aim at reducing unemployment and have to decide on regulations and the height of unemployment benefits. One model they often use to make these decisions is the search and matching model by Mortensen and Pissarides (1994). This model is valuable, but not always empirically correct (Shimer, 2005). This paper aims to contribute to this model by introducing the effect of ambiguity on unemployment. The wage distribution in the job market is often unknown and therefore uncertain. Hence, this paper investigates the effect of risk and ambiguity attitude on the decision whether to continue searching or accept a job offer if provided. Specifically, the effect of ambiguity attitude on the reservation wage (i.e. the minimum wage at which the unemployed individual stops searching and accepts the job offer) is analysed. Having knowledge about this relationship makes it possible to make better predictions and policies regarding unemployment, because the reservation wage, and consequently the job search period, contribute to the unemployment level and the use of unemployment benefits.

The paper proceeds with a discussion of the relevant literature and terms. First, ambiguity attitudes will be covered in sections 2.1 and 2.2, followed by self-employment and unemployment in sections 2.3 and 2.4: these sections will explain the concepts and the relation with ambiguity. Section 2.5 states the hypotheses, followed by a description of the data and the methods used to test the hypotheses in section 3. The next section (i.e. section 4) presents the main empirical results, followed by the discussion and limitations in section 5. The paper closes with a conclusion and suggestions for further research in section 6.

2. Literature review

2.1. Ambiguity attitudes

Both ambiguity and risk play an important role in the decision-making process when the outcomes are uncertain. Keynes (1921) and Knight (1921) were the first to establish the distinction between measurable and immeasurable uncertainty, which they called risk and uncertainty respectively. The latter has later been called Knightian uncertainty or ambiguity and involves unknown probabilities. This concerns chances of events to happen, such as the chance that the price of a stock will go up. The probability that such an event will take place is unknown, but everyone can establish his own subjective probability and give this probability a subjective weight. 40 years later, Daniel Ellsberg (1961) continued studying this distinction. He predicted that individuals prefer risk to ambiguity and are therefore ambiguity averse. This is known as the Ellsberg paradox[1] and has been analysed further by many

[1] In his famous experiment, Ellsberg presented subjects with two urns. One urn with exactly 50 black and 50 red balls, the other urn with 100 black and red balls in an unknown ratio. The subject could choose one urn from which one ball would be drawn. If this ball would be black, the subject would win $100. Most subjects preferred to bet on the first urn with known probabilities. However, if the red ball was the winning ball, the subjects still preferred the first urn with known probabilities. This presents a paradox and indicates a general preference of risk over ambiguity.

researchers. This paper studies ambiguity attitude and takes into account that it is a component of the general attitude towards uncertainty that comes on top of risk attitude.

Dimmock, et al. (2016b) and Abdellaoui et al. (2011) contributed to the study on ambiguity attitudes by showing that it has two components: ambiguity aversion and ambiguity generated likelihood insensitivity (a-insensitivity). The former describes the extent to which someone prefers risk over ambiguity or vice versa. The latter implies that individuals do not sufficiently distinguish between different levels of likelihood. Although the probability of an event is unknown, it is still possible to judge if it is very likely to take place or very unlikely. If an individual is a-insensitive, he tends to perceive events as if they have a fifty-fifty chance to occur. Consequently, if small likelihood events are translated towards fifty-fifty, people overweigh small likelihood events and are therefore ambiguity seeking. The opposite holds for high-likelihood events. However, these findings hold in the gain domain only. Baillon and Bleichrodt (2015) found that the opposite pattern occurs in the domain of losses, which is called the reflection effect. This indicates that a fourfold pattern for ambiguity attitudes exists (see Figure 1), depending on the likelihood (high or low) and domain (gains or losses). For example, in the case of the unlikely event of a new business to become an enormous success, individuals might act in an ambiguity seeking manner by starting their own company.

Figure 1: fourfold pattern of ambiguity aversion

	Gains	**Losses**
High likelihood	Ambiguity averse	Ambiguity seeking
Low likelihood	Ambiguity seeking	Ambiguity averse

2.2. Empirical evidence

Ambiguity attitudes have been studied extensively in the laboratory, mainly in the moderate likelihood gains domain (Trautmann & van de Kuilen, 2015). In this domain ambiguity aversion is most common, but in the domain of low likelihood gains or high likelihood losses, individuals are often ambiguity seeking. Some factors influence the effect of ambiguity on decision-making, although the results are mixed. Source preference and competence affect ambiguity attitudes, as was already hypothesized by Heath & Tversky (1991). They developed competence theory, which states that individuals are less ambiguity averse when they feel more competent or knowledgeable for the task. This implies a form of source preference where the person prefers the source for which he feels competent. For example, Tversky and Fox (1995) show that basketball fans prefer to bet on basketball events (ambiguous) rather than chance events (risk). Football fans, on the other hand, prefer to bet on the chance event. The pattern reverses when the ambiguous event is a football match instead of a basketball match. This effect of source preference and competence is strongest when the difference in competence levels for the different tasks is emphasized. Fox and Tversky (1995) show that if risky and ambiguous choice tasks are presented jointly, ambiguity aversion is strongest, because the ambiguous event can be compared to the risky event. This ambiguity aversion diminishes or even disappears when such comparison is absent. Fox and Tversky called this the comparative ignorance hypothesis.

Studies have shown that the level of ambiguity aversion is also influenced by other factors such as age, gender, education, and social factors, but the results are mixed. For example, Borghans et al. (2009) find that males react more strongly to increases in ambiguity in low ambiguity situations than females. Baillon et al. (2014) and Dimmock et al. (2016b), on the other hand, find no relation between gender and ambiguity attitudes. The latter two papers agree when it comes to income (i.e. no effect on ambiguity attitude), but when it comes to education only Baillon et al. (2014) find an effect: they show that better educated individuals deviate less from ambiguity neutrality, while Dimmock et al. (2016b) show little effect of education. Furthermore, ambiguity aversion is not stable over time. Duersch et al. (2013) discovered that after two months, consistency is lower than without a time lag. Furthermore, learning seems to affect ambiguity attitude as well (Baillon et al, 2015). Additionally, ambiguity attitude could change with age, although the findings are mixed. For example, Tymula et al. (2012) study ambiguity attitudes over the life span and conclude that adolescents are least ambiguity averse. On the contrary, Baillon et al. (2014) find an opposite effect with higher ambiguity aversion among younger subjects and Dimmock et al. (2016b) find no relation with age. No final conclusions can be drawn when it comes to demographic characteristics and their relations with ambiguity attitude. Although it is not the main purpose, this paper can provide new insights into the factors that influence ambiguity attitude in the American population.

When it comes to research on ambiguity attitudes outside the laboratory to test for the external validity of the concept, little evidence exists. Dimmock et al. (2013; 2016a) look into the relation between ambiguity attitudes and financial or economic decisions. The authors conclude among others that more ambiguity averse people are less likely to participate on the equity or stock market and are more likely to plan their retirement. Moreover, individuals who are more insensitive to ambiguity-likelihood have a higher probability of being insured. When it comes to other fields, Muthukirshnan et al. (2009) discover that ambiguity aversion is related to the preference for established brands; Sutter et al. (2013) illustrate that ambiguity attitude of children is a weak predictor of misbehaviour at school; and Engle-Warnick et al. (2007) find that ambiguity attitudes of farmers predict the use of new technology or crops. This shows that ambiguity attitudes and their different components are related to real-life decisions. Almost all of these studies, however, use ambiguity measures involving only gains while many real-life decisions involve losses as well. Therefore, this paper adds to the existing literature by also looking into the loss domain. Furthermore, this paper will expand the scope of ambiguity studies regarding real-life decisions to job-related ones. The next section will look into the research done on job-related real-life decisions.

2.3. Self-employment

Self-employed individuals are often seen as entrepreneurs who create jobs, not only for themselves but also for others. The positive impact of those self-employed individuals on the economy makes it interesting to look into the determinants of self-employment. Different determinants have been studied, such as access to capital, tax effects, and more recently, the attitude towards risk (Ekelund et al., 2005). Becoming self-employed or becoming an entrepreneur requires a decision that involves uncertainty in different domains. It is uncertain if the company will become successful, even if it will survive and it is also uncertain how many working hours it requires, how much satisfaction it will give, and how much salary it will provide. The studies on the uncertain aspect of becoming self-employed focus mainly on risk. Among others, Cramer et al. (2002) discover a negative relation between risk aversion and the choice of being self-employed. However, McMullen and Shepherd (2006) explain that entrepreneurs have to deal with ambiguity, not just risk. They have to make decisions under uncertainty; not knowing what is going to happen in the future and what the impact of their decisions may be. Therefore, it is important to investigate this new relation between ambiguity and self-employment. Shyti and Paraschiv (2014) suggest that there is a difference in ambiguity attitudes for entrepreneurs and non-entrepreneurs, but it remains an under-investigated topic. Especially since self-employment involves a substantial chance of failure, losses should play a large role in the relation between ambiguity attitude and self-employment. This, however, has not been studied before.

When studying self-employment, it is important to take into account that some individuals did not voluntarily choose to start their own business. Some self-employed workers may have been forced into a residual sector out of necessity to obtain or improve income or independence. These improvement-driven self-employed individuals often only work for themselves without creating any extra jobs. They become self-employed just to be able to provide themselves and their family. This is what Earle and Sakova (2000) call disguised unemployment and is not inherently related to ambiguity or risk attitudes in the same way as self-employment is. Whether they are ambiguity averse or not and whether starting a business involves uncertainty or not, they did not make the choice to become self-employed and were not inherently motivated to do so. Kelley et al. (2015) discovered that on average 22% to 31% of the entrepreneurs becomes self-employed out of necessity.

A second aspect to bear in mind is that many start-up owners do not necessarily believe that the situation is uncertain. Landier and Thesmar (2009) asked French entrepreneurs about their expectation for the future. 31% expected to start hiring within a year, 58% expected to develop their company in some way and only 6% expected difficulties. Similarly, Cooper et al. (1988) found that 80% of the owners rated the likelihood that their start-up would succeed at over 70% and 33% even estimated this likelihood to be no less than 100%. This is particularly interesting when looking at the actual surviving rates of new establishments in the US: after five years only half of the new businesses still exist (US Bureau of Labor Statistics, 2016). The fact that finding a new company is risky and ambiguous is not always interpreted as such by the founders (Koellinger et al., 2007).

2.4. Unemployment

When looking for a job, an unemployed worker faces uncertainty about the labour market conditions and the wage offer distribution. This uncertainty affects the length of the search period and the reservation wage of the unemployed. The Nobel Prize-winning search and matching model of Mortensen and Pissarides (1994) is used to analyse the unemployment equilibrium and the rate at which unemployed workers find a job. The model is useful in order to study the labour market, but also to determine the optimal policies regarding unemployment benefits and firing restrictions. The following section will explain what the search and matching model is and how and why it can take into account ambiguity.

The search and matching model is based on search theory, which studies the markets in which buyers and sellers do not directly interact with each other. This leads to search time, requires resources, and consequently leads to frictions. For example, when employees try to find an acceptable job with and acceptable wage, they often cannot immediately find it. They have to look for vacancies, go through application processes, network, take additional education, and look even further before they possibly find a job. The search models focus on the optimal stopping rule, which explains when it is optimal to stop searching and take action. The Mortensen-Pissarides search and matching model applies this search theory to the labour market to explain why unemployment and vacancies can exist simultaneously. Mortensen and Pissarides (1994) study how firms and workers decide to continue or stop searching, how and when jobs are created or destroyed and how this is influenced by aggregate shocks (e.g. productivity shocks due to technology changes). Furthermore, they demonstrate the effects of regulation and policies, such as unemployment benefits: higher unemployment benefits lead to longer searching periods and higher unemployment rates (The Royal Swedish Academy of Sciences, 2010).

What the model cannot explain, however, is why the cyclical behaviour of unemployment and vacancies is varying as much as it does. According to the model, the variance is explained by changes in labour productivity, but the volatility of labour productivity is much lower than for unemployment rates. Shimer (2005) was the first to dispute the quantitative accuracy and after, the problem was called the unemployment volatility puzzle. He shows that in response to a positive labour productivity shock (e.g. because of a technology chance) firms increase the number of vacancies. According to the model this results in a decrease of the duration of unemployment, which puts pressure on wages. The higher wages bring the unemployment and vacancy levels back to its initial value. Therefore, the model predicts that a change in labour productivity does not lead to a change in the number of vacancies and the duration of unemployment. In reality, on the other hand, these factors are highly correlated (Shimer, 2005). This discrepancy has been a puzzle for over a decade now.

Several suggestions have been made to improve the fit of the model. Some are more successful than others, but they never fully explain the puzzle. The most investigated improvement possibility is the inclusion of wage rigidity into the model. Shimer (2004) and Gertler et al. (2008) show that this would improve the model. If wages are constant, rather than determined by Nash bargaining, the model predicts more correct variances of unemployment and vacancy levels. Pissadires (2009), to the contrary, argues that wage stickiness alone cannot fully explain the unemployment volatility puzzle. He mentions asymmetric information and on-the-job search as other factors that could explain the volatility of unemployment. Furthermore, all models focus on the effect of labour productivity shocks on unemployment, while other factors have influence as well. A more recent line of reasoning incorporates risk into the model to improve its empirical validity. Kilic and Wachter (2015) create a model with time-varying risk that incorporates a varying probability of the occurrence of an economic disaster. The fear for such a disaster, which can be linked to risk-aversion, influences job creation incentives and thereby affects unemployment levels. Along these lines, Schaal (2015) studies the effect of idiosyncratic risk on unemployment in recession periods in particular. He discovers that including this risk into the model improves the models' fit. However, uncertainty cannot fully explain the unemployment levels during recession periods. This is where ambiguity could offer an explanation. Both Kilic And Wachter (2015) and Schaal (2015) do not look at the role of ambiguity. Moreover, the models concentrate on the effects on vacancies and job-creation, leaving the effect on the workers untouched. One possible solution to explain the puzzle of high volatility is the presence of uncertainty in the labour market and its effect on the searching periods of workers (Ying Tung & Chi Man, 2015).

Nishimura and Ozaki (2004) show that uncertainty plays an important role in the determination of a suitable stopping rule (i.e. the reservation wage at which it is optimal to take the job and stop searching) in theory. They define risk in their model as the variance of the wage offer distribution that is known to the unemployed workers. The measurement of ambiguity is based on the certainty about the correctness of this distribution, which is unknown. In their job search model, both risk and ambiguity affect the reservation wage, but in opposing directions; an increase in risk increases the reservation wage while an increase in ambiguity leads to a decrease in the reservation wage. The latter can be explained by the fact that individuals who are unsure about the wage offer distribution tend to believe that a higher wage is less likely to be realized. In the former case, when there is no ambiguity, but only risk, the individual knows the distribution. This implies that the unemployed workers know if there is a higher wage available, which will increase their reservation wage. They continue looking because they are confident that they can find a more appealing job offer with a higher wage. If the distribution is not known, on the other hand, the individual is not certain that there is a better offer available. This leads to a shorter searching period and a lower reservation wage. In addition, by accepting a job, the uncertainty about the future and the possible job offers is removed. The researchers assume that when the workers do not know the wage distribution they consider a set of distributions and make decisions based on the minimum. This is an important assumption that they do not test. Asano et al. (2015) do test the theory and support its findings with a laboratory experiment, which shows that reservation points drop when ambiguity increases.

If higher ambiguity levels as manipulated in the experiment by Asano et al. (2015) have the same effect as more pronounced ambiguity attitudes, these findings imply that for example higher ambiguity aversion leads to a higher reservation wage and a longer search period. For risk, a similar inference can be made: if higher risk levels have the same effect as higher risk aversion, it also implies that higher risk aversion leads to a lower reservation wage and a shorter search period. Integrating ambiguity attitudes into the search and matching model of Mortensen and Pissarides (1994) could improve its quantitative accuracy. Additionally, a better understanding of the reservation wage leads to a better prediction of early exit from unemployment insurance (Kruger & Mueller, 2011). Therefore, this thesis looks into the effects of ambiguity attitude and risk attitude on the reservation wage of unemployed individuals. More specifically, it tests if the Mortensen-Pissarides search and matching model also holds in the general American population.

2.5. Hypotheses

Self-employment involves a great deal of uncertainty and more ambiguity averse individuals dislike ambiguity. Therefore, the individuals who are willing to take that uncertainty and actually become self-employed are expected to be less ambiguity averse or even ambiguity seeking. Self-employment does not only involve ambiguity in the domain of gains, but also in the domain of losses. The measure of ambiguity aversion in the domain of losses measures a separate component of ambiguity aversion. The individuals who are more ambiguity averse in the domain of losses are expected to be less likely to become self-employed.

When it comes to a-insensitivity, the theory explained in section 2.1 predicts that small chances of success lead to ambiguity seeking while high chances of success lead to ambiguity aversion. When it comes to monetary returns, the chances for success are moderate (i.e. around 50% of the start-ups survive the first three to five years). On the other hand, self-employment also involves many non-monetary returns such as job satisfaction and independence (Hamilton, 2000) and the probability of these returns is much higher (Benz & Frey, 2008). Additionally, those who start their own business are in general overconfident and overestimate the chances of success (Landier & Thesmar, 2009). Overall, individuals who start a company believe that the likelihood of becoming successful is high. A high probability of success leads to ambiguity aversion for individuals with high a-insensitivity. This leads to the following hypotheses:

H1a: Individuals with higher levels of ambiguity aversion are less likely to be self-employed
H1b: Individuals with higher levels of ambiguity aversion in the domain of losses are less likely to be self-employed
H1c: Individuals with higher levels of a-insensitivity are less likely to be self-employed

Ambiguity attitude also influences the searching time and reservation wage of unemployed workers. The prediction is that more ambiguity averse individuals will have a lower reservation wage. Next to ambiguity, the effect of risk attitude is also tested. The expectation is that the more risk averse an individual is, the higher the reservation wage. When looking for a job, it can be assumed that only gains are involved. The individual either remains unemployed or finds a job and receives a wage, so there is no chance of losing anything. Therefore, it is expected that the ambiguity measure for losses does not have an effect on the reservation wage. The effect of a-insensitivity depends on the likelihood of finding a job. According to a study done by Hobijn and Sahin (2009) the job-finding rate in the US was 56% in 2005. Due to the economic crisis and the increase in unemployment, the job-finding rate has decreased remarkably (Gregory et al., 2014). Therefore, it can be assumed that the job-finding rate in 2012, the time of the study on ambiguity attitudes used in this paper, is less than 50%. If an individual is a-insensitive, this probability will be overweighed. Therefore, for more a-insensitive individuals the reservation wage is expected to be higher. This leads to the following hypotheses:

H2a: Unemployed individuals with higher levels of ambiguity aversion have a lower reservation wage

H2b: Unemployed individuals with higher levels of risk aversion have a higher reservation Wage

H2c: Unemployed individuals with higher levels of a-insensitivity have a higher reservation wage

3. Methodology

3.1. Data

The data that are used in this study are from the RAND American Life Panel (ALP). The ALP consists of more than 6000 18+ members from the Unites States that regularly answer surveys over the Internet. The survey that measures ambiguity attitudes was conducted in 2012 and contains 3290 participants. The response rate for this survey is 70.75%. This dataset is suitable for this study because it is representative of the American population, and it makes use of real incentives. In total $23850 were paid out to 1590 ALP subjects. By letting RAND ALP, a credible organization, pay out the incentives any possible suspicions about trustworthiness were eliminated. The variables that measure the reservation wage and most of the control variables (section 3.5 explains how they are measured) are taken from another ALP survey conducted between 2010 and 2013. Because some ALP members that participated in the ambiguity survey did not participate in this survey, the number of observations is reduced.

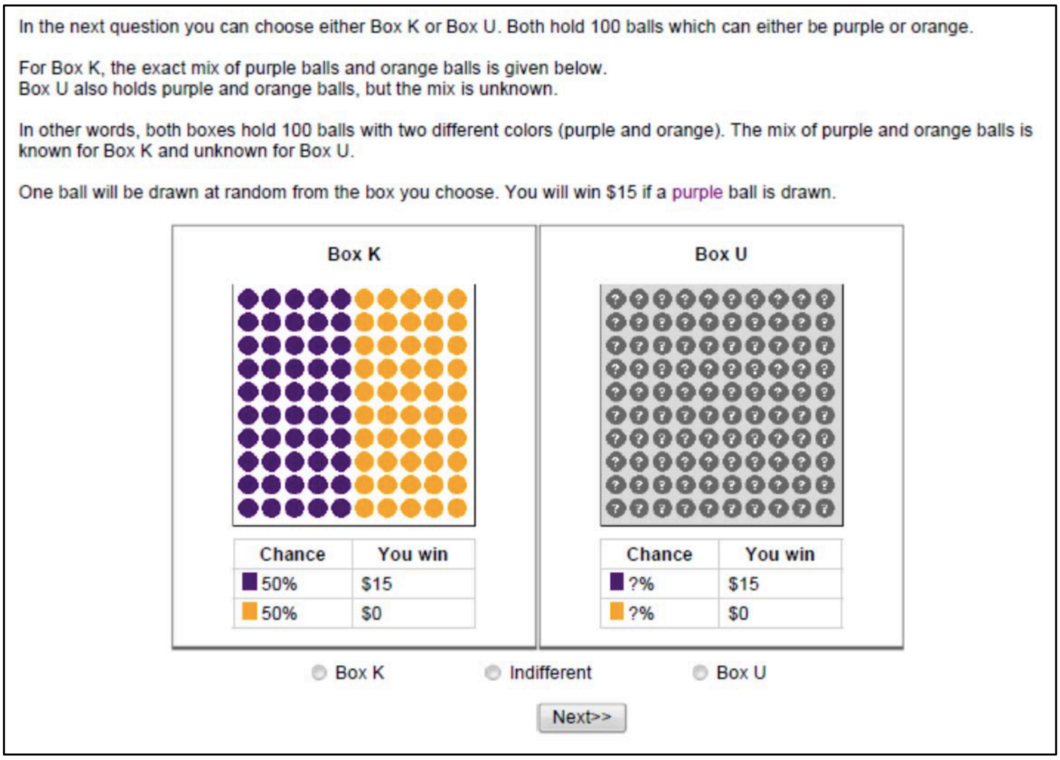
3.2. Measuring ambiguity attitudes

The method used to measure ambiguity attitudes is based on the source method (Abdellaoui et al., 2011) that Dimmock et al. (2013; 2016a) implemented in a questionnaire using matching probabilities. In this questionnaire, individuals have to choose between two boxes: an unambiguous box that contains 50 purple and 50 orange balls and an ambiguous box for which the distribution of colours is unknown (see Figure 2). In both cases, the individual wins \$15 when the randomly drawn ball is purple and nothing if the ball is orange[2]. If the subject is indifferent between the two boxes, he is considered to be ambiguity neutral, if the subject prefers the unambiguous box, he is ambiguity averse, and if the subject prefers the ambiguous box, he is ambiguity seeking. The subjects are presented a series of binary choices with varying colour distributions in the unambiguous box, depending on the previous answer, until they reach their indifference point. For example, if an individual is indifferent between an unambiguous box with 40 purple balls and an ambiguous box, the so-called matching-probability, m(0.5), is 40% (i.e. 0.4). In general, the matching probability is the objective probability at which the individual is indifferent between betting on the ambiguous and the risky box (Dimmock et al., 2016a). This is translated into an ambiguity measure:

$$AA_{0.5} = 0.5 - m(0.5).$$

Positive values represent ambiguity aversion, zero represents ambiguity neutrality and negative values ambiguity seeking.

Figure 2: Measuring ambiguity attitudes



[2] The subjects could not choose their own colour. Since the ALP RAND pays out subjects on a regular basis, it is known as a trustworthy organization. This should eliminate the possibility that subjects perceive not being able to choose a winning colour as being deceived. An additional, smaller survey confirmed that being able to choose the colour does not lead to significant differences in ambiguity attitudes.

A-insensitivity is measured by two additional series of binary choices, this time with boxes containing 100 balls with 10 different colours. For low-likelihood events the unambiguous box contains 10 purple balls and the individual can win $15 when a purple ball is drawn. The colour distribution in the ambiguous box is unknown. Hence, the ambiguity-neutral probability is 10% and for this series of questions the matching probability m(0.1) is obtained. For example, a matching probability of 0.15 implies that the individual is indifferent between betting on the risky box with a 15% probability of winning or the ambiguous box. This is translated into the following ambiguity measure:

$$AA_{0.1} = 0.1 - m(0.1).$$

To measure the matching probability m(0.9) a similar series of questions is used in which the individual can win $15 if the drawn ball is not purple but another colour. This is a high-likelihood event for which the ambiguity-neutral probability is 90%. Again, the indifference point is obtained. For example, if m(0.9) is 0.85, the individual is indifferent between betting on the risky box with 85% of winning and betting on the ambiguous box. This gives the following measure of ambiguity aversion:

$$AA_{0.9} = 0.9 - m(0.9).$$

Again, positive values indicate ambiguity aversion and negative values ambiguity seeking. In addition, a positive value of $AA_{0.9}$ in combination with a negative value of $AA_{0.1}$ indicates a-insensitivity.

The previously mentioned indexes are event-specific indexes (Dimmock et al., 2016b). To find the global ambiguity attitude indexes, the three matching probabilities are used: I find the best fitting line for the three points with neutral probabilities on the x-axis and matching probabilities on the y-axis. This gives a constant c and a slope s for each subject. The index of ambiguity aversion is defined as:

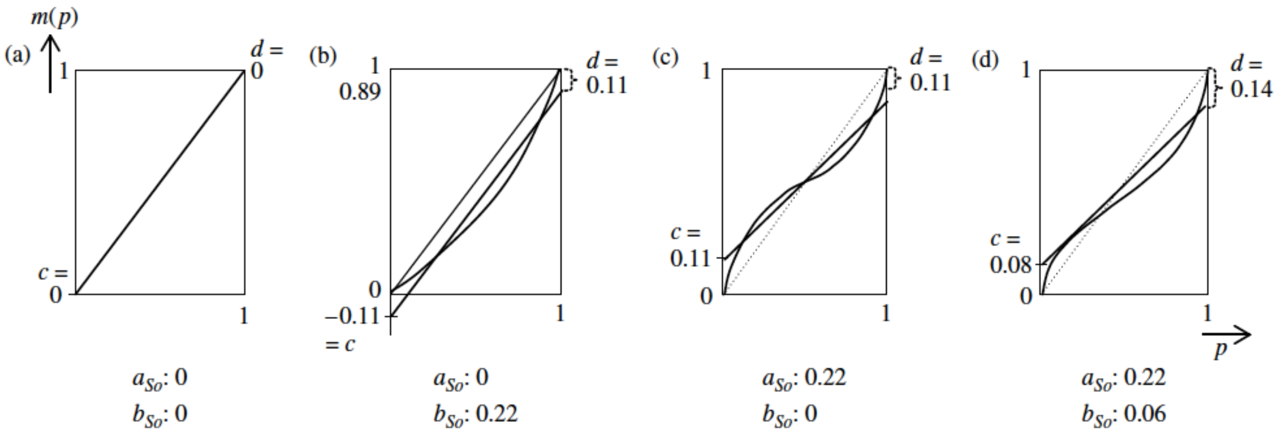
$$b_{so} = 1 - s - 2c.$$

The index of a-insensitivity is defined as:

$$a_{so} = 1 - s.$$

The ambiguity aversion index represents the average height of the line, as can be seen in figure 3. The first line in *figure a* represents ambiguity neutrality, so the matching probabilities are equal to the neutral probabilities. If the best fitted line lies below this neutral line, b_{so} is positive and the subject is ambiguity averse. This is represented in *figure b*. The a-insensitivity index represents the steepness of the slope. If the slope is less than one, the flatness reflects a lack of discrimination of the different probability levels. This is represented in *figure c*. The last figure shows a combination of ambiguity aversion and a-insensitivity.

Figure 3: Ambiguity indexes. Reprinted from Dimmock et al., 2016b.



The advantage of using this method is that it measures ambiguity attitudes relative to risk attitudes. Therefore, all other aspects of the decision-making process cancel out, including probability weighting and risk attitude. Another advantage is that the interpretation of the indexes a_{so} and b_{so} is straightforward. What should be taken into account is that the best-fitting line should be truncated at 0 and 1, because the probability interval is constrained at the range (0,1). This, however, is not possible within the standard Stata software, so the indexes in this thesis will be slightly biased. Finally, the elicitation method is subject to measurement error. To check for this error, two control questions are included in the survey. The first control question is generated by taking the matching probability m(0.5) of each subject and increasing this by 10 percentage points. The subject is asked to choose between the known and unknown box. If the subject chooses the ambiguous box, this response is considered inconsistent. In the second control question the matching probability m(0.5) is decreased by 10 percentage points. Here, inconsistency occurs if the subject prefers the unambiguous box.

The global ambiguity indexes only measure ambiguity attitude in the domain of gains. Since many decisions also involve possible losses, these measures are therefore not complete. The ALP dataset also contains a measure for ambiguity involving losses. In this series of questions the subjects have to choose between a risky (i.e. unambiguous) box that contains 50 purple balls and 50 orange balls and an ambiguous box with an unknown distribution. If the purple ball is drawn, the subject looses \$15, if the orange ball is drawn nothing is lost nor won. Again, a series of binary questions is asked until the indifference point is reached and the matching probability $m(-0.5)$ can be inferred. For example, if the matching probability is 0.6 the subject is indifferent between betting on the risky box with a 60% chance to loose \$15 or the ambiguous box. The questions in the loss domain are hypothetical, so the subjects cannot actually lose money. Since the questionnaire only contains one series of ambiguity questions in the domain of losses, it is not possible to construct the global ambiguity indexes. The only measure available in the domain of losses is:

$$AA_{-0.5} = m(-0.5) - 0.5.$$

Values higher than zero indicate ambiguity aversion, zero represents ambiguity neutrality and negative values ambiguity seeking. Since only one instead of three ambiguity observations are available in the domain of losses a-insensitivity cannot be measured directly in this domain. However, as A-insensitivity is a cognitive aspect it is likely that a-insensitivity in the domain of losses is the same as in the domain of gains. This claim is confirmed by studies on event weighting for gains and losses (Abdellouai et al., 2005; Baillon & Bleichrodt, 2015).

3.3. Measuring self-employment, unemployment, and reservation wage

The first dependent variable is *Self-employment*. This variable is a dummy variable that equals 1 if the individual is self-employed and 0 if the individual is not self-employed. In this sample, 12.6% of the subjects are self-employed, as is also shown in table 3. The data do not control for the fact that some individuals are forced to become self-employed because they are unemployed and need to earn money. Unfortunately, the dataset does not contain information regarding the reason to become self-employed. As an alternative control, the individuals who were unemployed in the year before they reported to be self-employed (i.e. 2011) are identified. The individuals who were unemployed before becoming self-employed are likely to become self-employed just to earn some income. Therefore, all analyses are done again excluding the individuals that were unemployed before becoming self-employed in the year of the survey. It should be taken into account, however, that this only corrects for forced self-employment due to unemployment. Furthermore, only for those who became self-employed in the most recent year that the survey was distributed, previous unemployment could be retrieved. An additional robustness test only includes the self-employed who also report their current job status as “working now”. This ensures that the analysis is done with the individuals who work for themselves and consider doing so as a job and excludes everyone for whom the self-reported job status is missing.

The second dependent variable regards unemployment. This is measured in two different ways. It can be measured how many individuals are unemployed. *Unemployed* is a dummy variable equal to 1 if the subject is unemployed and looking for work and equal to 0 otherwise. Overall, 10.8% of the sample is unemployed and looking for work at the moment of participating. The variable that is used in the analyses measures the hourly *Reservation wage* for which the individual would accept a job. The adjusted reservation wage is measured as the hourly reservation wage divided by the hourly income earned a year before the survey was conducted[3]. This assures that the reported reservation wage is adjusted for the previous income that the subject earned, but reduces the sample size due to missing data on the previous income variable. It has to be taken into account that using the wage earned the preceding year is not a perfect control measure as some individuals have been unemployed for multiple years. The reservation wage earned in the last period the individuals was working would have been a better control variable, but unfortunately this is not available in the current dataset. Furthermore, the reservation wage is self-reported, which could lead to biased or misreported wages. Kruger and Mueller (2011), however, show that self-reported reservation wages predict whether a job is actually accepted of not. Therefore, it is a valuable measure that indicates the job search period of unemployed workers. The average adjusted reservation wage is 1.6, which means that the hourly reservation wage is around 1.6 times the income of last year. The median of one, on the other hand, shows that the median individual reports a reservation wage equal to their previous salary.

[3] The hourly income plus one is used to make sure none of the data points is divided by zero or divided by a value less than one. Dividing by zero is impossible and would lead to more missing data and dividing by values less than zero would lead to extremely large values. To correct for the outliers due to this adjustment, the adjusted reservation wage is constrained to have a maximum value of two if the hourly wage is zero.

3.4. Other variables

The control variables included in the regressions are age, gender, education level, ethnicity, marital status, household size, family income, wealth, trust, financial literacy, question order and risk aversion. These variables are correlated to the probability of being self-employed (or the reservation wage), ambiguity attitude, or both (Dimmock et al., 2013; 2016a, Rees & Shah, 1986, Le, 1999). Table 1 summarizes all variables.

Table 1: Variable descriptions

Variable name	**Definition**
Self-employed	Indicator if subject is self-employed
Unemployed	Indicator if subject is unemployed
Reservation wage	Minimum hourly wage at which subject would accept a job
Adjusted reservation wage	Reservation wage/(hourly wage last year + 1)
Age	Age in year
Male	Indicator if subject is male
< high school	Indicator if subject has less than a high school degree
High school	Indicator if subject has a high school degree
College	Indicator if subject has a college degree
Bachelor +	Indicator if subject has a bachelor degree or higher
White	Indicator if subject is white/Caucasian
Hispanic	Indicator if subject is Hispanic
African American	Indicator if subject is African American
Other ethnicity	Indicator if subject is of another ethnicity than white, Hispanic or African American
Married	Indicator if subject is married
Household members	Number of living household members
Family income	Total income for all household members older than 15, including from jobs, business, farm, rental, pension benefits, dividends, interest, social security, and other income
Wealth	Sum of financial and non-financial assets: checking account, savings, pension savings, businesses/farms, stocks, bonds, houses, real estate and transportation devices (in 100,000 dollars)
Trust	On a scale from 0 to 5, how much others can be trusted (0 indicating "most people can be trusted" and 5 indicating "you can't be too careful"
Financial literacy	Number of financial questions answered correctly, ranging from 0 to 3
Risk first	Indicator if subject answered risk questions before the ambiguity questions
Risk aversion	Estimated coefficient of risk aversion based on CRRA where a value of 0 indicates risk neutrality, values lower than 0 indicate risk seeking and values higher than 0 indicate risk aversion.

Both the likelihood of becoming self-employed and the reservation wage are influenced by many factors. Bates (1995) found before that wealth and education are important determinants of self-employment, as well as age, ethnicity and gender. When it comes to the reservation wage, those who have more experience and/or a higher education level expect a higher salary and therefore have a higher reservation wage. Furthermore, those with a higher wealth or with a higher family income may be less eager to find a job, while those with many dependent children to take care of would feel more pressure to find a job. Finally, the amount of benefits the unemployed individual receives also influences the need to find a new job and thus the reservation wage. The adjusted reservation wage is already corrected for salary earned last year. Furthermore, the analyses will include all control variables such as family income, wealth, education and number of household members.

Age is a continuous variable indicating the age in years, which ranges from 18 to 70 with an average of 47. *Male* is an indicator variable equal to one if the respondent is male and equal to zero if female. More than half of the sample subjects is female (i.e. 60%). Education is a categorical variable with higher numbers indicating higher education levels. Since the categories are not linearly increasing, the variable is coded into four dummy variables: *< high school* is equal to one if the individual has less than a high school degree, *High school* is equal to one if the individual has a high school degree, *College* is equal to one if the individual has a college degree, and *Bachelor +* is equal to one if the individual has a bachelor degree or higher. *< high school* is the reference category in the analyses and is thus not included in the regressions. Similarly, ethnicity is coded into four dummy variables: *White, Hispanic, African American,* and *Other*. The reference category for ethnicity is *Other*. *Married* is an indicator variable equal to one if the subject is married and equal to zero otherwise. *Household members* is a numerical variable indicating the number of living household members, which is on average slightly over one. The variable *Family income* measures the total income for all household members together, including all types of income such as wage and dividends. Additionally, *Wealth* is included and measures the sum of financial (e.g. savings) and non-financial assets (e.g. house).

In addition, Cumurovic and Hyll (2016) found that financial literacy positively affects the likelihood of being self-employed. Moreover, financial literacy is included in the analysis to ensure that it is not measuring the same as ambiguity attitude. To measure financial literacy, three questions were included in the questionnaire. Appendix A shows the exact wording of the questions and the variable *Financial literacy* measures the number of questions that the subject answered correctly. Table 2 shows that on average this is equal to 2.2 questions.

The measure for ambiguity attitude is measured relative to risk attitude, but risk aversion is included as control variable anyway. This variable is included to ensure that ambiguity attitude is distinct from risk attitude and to check for the difference in effect of ambiguity and risk attitude. Risk attitude is measured with a series of binary choices between a certain and a risky option. The elicited indifference point is used to estimate the coefficient of relative risk aversion. Appendix B shows the elicitation procedure to find the measure of risk aversion. A value of zero indicates risk neutrality, values below zero indicate risk seeking and values above zero indicate risk aversion.

Another control variable is *trust*, measured by one question as shown in Appendix A and table 1. A high value of this variable indicates that the individual has a low trust level. Trust could be related to ambiguity aversion, as those who have low trust in others could think that ambiguous events are never in their favour. The average trust is 3.17 and the median is 3.

Finally, the question order of the risk and ambiguity questions was randomized to control for order effects. *Risk first* is an indicator equal to 1 if the risk questions were asked first and equal to zero if the ambiguity questions were asked first. It is important to check for these questions, because of the comparative ignorance effect explained in section 2.2. First answering risk questions could influence the way the ambiguity questions are perceived, because they can be compared to the risk questions.

4. Results

This section shows the results of the analyses that test the hypotheses and the relation between ambiguity attitude and job-related decisions regarding self-employment and unemployment. In all regression analyses four different models are estimated. The first and third model use the ambiguity indexes b_{so} and a_{so} as ambiguity measures in the domain of gains, while the second and fourth model use $AA_{0.1}$, $AA_{0.5}$ and $AA_{0.9}$. Moreover, the first two models use the complete dataset and last two only use the subset with individuals who answered both of the check questions correctly. Consequently, this sample is smaller, but still consists of more than 800 subjects that are all consistent in their ambiguity preference. Before testing the hypotheses, some descriptive statistics are discussed.

4.1. Descriptive statistics

Table 2 shows the summary statistics of all dependent and control variables. The mean value of risk aversion is .34, which indicates that on average the population is risk averse. A two-sided t-test indicates that this value is larger than zero ($t = 46.30$, $p < .001$).

Table 2: Summary statistics

Variable	Mean	SD	Min.	Median	Max.	N
Self-employed	0.13	0.33	0	0	1	2181
Unemployed	0.11	0.31	0	0	1	3279
Reservation wage	42.64	220.56	0	15	2600	330
Adjusted reservation wage	1.57	2.13	0	1.05	22.66	156
Age	47.34	13.55	18	50	70	3290
Male	0.40	0.49	0	0	1	3289
< high school	0.05	0.22	0	0	1	3290
High school	0.43	0.50	0	0	1	3290
College	0.13	0.34	0	0	1	3290
Bachelor +	0.39	0.49	0	0	1	3290
White	0.69	0.47	0	1	1	3290
Hispanic	0.16	0.37	0	0	1	3290
African American	0.11	0.31	0	0	1	3290
Other ethnicity	0.04	0.21	0	0	1	3290
Married	0.60	0.49	0	1	1	3290
Household members	1.21	1.53	0	1	10	3288
Family income	59,942	46,514	2,500	45,000	200,000	3277
Wealth	4.29	24.75	−0.50	0.94	800	3251
Trust	3.17	1.38	0	3	5	3256
Financial literacy	2.22	0.92	0	2	3	3284
Risk first (order)	0.51	0.50	0	1	1	3288
Risk aversion	0.34	0.43	−0.55	0.40	1	3265

Table 3 summarizes all the descriptive statistics of the ambiguity variables in the ALP dataset. Panel A shows the proportion of people that is ambiguity averse, neutral and seeking as revealed by the first question for all four probability levels (0.1, 0.5, 0.9 and −0.5). When making a choice between a risky box with 50% chance to win $15 and an ambiguous box with unknown probabilities, 52% prefers the risky one and is therefore classified as ambiguity averse. A chi-square test shows that ambiguity aversion is indeed the dominating attitude in this sample ($\chi^2 = 808.7$, $p < .001$). For the high probability box (gains 90%), also a majority of 56% is ambiguity averse, which is also the dominating attitude ($\chi^2 = 825.1$, $p < .001$). For the low probability (gains 10%) and loss domain (losses 50%), on the other hand, the majority is ambiguity seeking with $\chi^2 = 826.6$, $p < .001$ and $\chi^2 = 33.72$, $p < .001$.

Table 3: Ambiguity attitude statistics

Panel A - Ambiguity attitude: proportion of sample per question (in %)

	Gains 10%	Gains 50%	Gains 90%	Losses 50%
Ambiguity averse	19.2	52.1	56.0	32.3
Ambiguity neutral	24.0	11.9	16.0	29.8
Ambiguity seeking	56.8	36.0	28.0	37.9

Panel B – Ambiguity measures

	Mean	SD	Min	Median	Max
$AA_{0.1}$	−0.124	0.20	−0.75	−0.025	0.085
$AA_{0.5}$	0.022	0.21	−0.415	0.03	0.425
$AA_{0.9}$	0.182	0.26	−0.090	0.075	0.845
$AA_{-0.5}$	−0.015	0.20	−0.440	0.000	0.470

Panel C - Check questions: proportion of sample (in %)

	Correct	Indifferent	Wrong
Check 1	52.5	18.1	29.4
Check 2	74.1	11.7	14.2

Panel D – Ambiguity index measures

	Mean	SD	Min	Median	Max
b_{so}	0.05	0.33	−.84	0.03	.90
a_{so}	0.39	0.38	−1.03	0.34	2.11

Panel B shows the ambiguity measures based on the matching probabilities that were retrieved after the complete sequence of questions. For example, it can be seen that $AA_{0.5}$ = 0.02 and $AA_{0.9}$ = 0.18, which shows that on average the population is ambiguity averse (i.e. the values are larger than zero). T-tests show that both means are different from zero with $t = 6.13$, $p < .001$ and $t = 40.65$, $p < .001$. For $AA_{0.1}$ and $AA_{-0.5}$ the population is on average ambiguity seeking, since those measures are negative: $AA_{0.1} = -0.12$ ($t = -35.06$, $p < .001$) and $AA_{-0.5} = -0.015$ ($t = -4.41$, $p < .001$). All measures have a wide spread, indicating strong heterogeneity in ambiguity aversion levels among the population. This is in line with previous findings (Stahl, 2014; Trautmann & van de Kuilen, 2015), which disconfirm the notion that in general everyone is ambiguity averse. To check if ambiguity aversion is different in the gain and loss domain, a t-test is used to assess if $AA_{0.5} = AA_{-0.5}$. This test indicates that the means are different, $t = -8.48$, $p < .001$, so ambiguity aversion differs for gains and losses. Furthermore, to test the reflection effect a t-test is done to check if $AA_{0.5} = -AA_{-0.5}$. This null-hypothesis cannot be rejected, $t = 1.06$, $p = .29$, so the reflection effect for ambiguity aversion does indeed occur in the general American population.

Panel C shows that 29% of the subjects chooses an inconsistent answer for the first check question. For the second check question this drops to 14%. This inconsistency rate is similar to error rates found by Harless and Camerer (1994). A chi-square test indicates that subjects did not randomly answer the check questions, $\chi^2 = 602.3$, $p < .001$ and $\chi^2 = 2459.9$, $p < .001$ for the first and second check question. To make sure that these inconsistencies do not influence the results, the analyses will be done both with and without the inconsistent subjects.

Lastly, panel D contains the final ambiguity indexes for ambiguity aversion (b_{so}) and a-insensitivity (a_{so}). On average, the ambiguity aversion measure is 0.05, which indicates that on average, the subjects are slightly ambiguity averse. A two-sided t-test shows that this mean is larger than zero ($t = 8.95$, $p < .001$). The average for the a-insensitivity measure is 0.39, which indicates that on average the subjects are a-insensitive. Also this mean is larger than zero ($t = 58.84$, $p < .001$).

Table 4 shows the correlations between the different ambiguity measures. It shows that both indexes a_{so} and b_{so} are positively correlated, although very weakly[4]. The positive relation can be explained by the fact that both indexes measure a form of irrationality and the weak form indicates that both indexes measure separate components. Furthermore, the b_{so} index is positively and strongly[4] correlated with $AA_{0.5}$ (i.e. a correlation of 0.77), which can be explained by the fact that they both measure ambiguity aversion. The a-insensitivity index a_{so}, on the other hand, is not significantly correlated with $AA_{0.5}$. This supports the notion that a-insensitivity is an additional, cognitive aspect of ambiguity attitude different from ambiguity aversion. Finally, the positive correlation between $AA_{0.5}$ and $AA_{-0.5}$ is not in line with the reflection effect discussed in section 2.1. On the aggregate level, as shown in table 3 (panel B), the reflection effect occurs, but table 4 shows that on the individual level this is not the case.

Table 4: Correlations between ambiguity attitude measures

Correlations (correlations between brackets are not significant)						
	$AA_{0.1}$	$AA_{0.5}$	$AA_{0.9}$	$AA_{-0.5}$	b_{so}	a_{so}
$AA_{0.1}$	-					
$AA_{0.5}$	0.40	-				
$AA_{0.9}$	0.19	0.31	-			
$AA_{-0.5}$	0.25	0.25	0.18	-		
b_{so}	0.68	0.77	0.73	0.30	-	
a_{so}	−0.51	(0.01)	0.74	(−0.01)	0.17	-

[4] According to the interpretation of correlation coefficients by Evans (1996), 0.17 is a very weak correlation and 0.77 is strong correlation.

4.2. Relation of control variables to ambiguity measures

To test how the control variables are related to ambiguity attitude, table 5 shows the regressions with the different ambiguity measures as dependent variables and the control variables as independent variables. Due to heteroskedasticity, the model is estimated with robust standards errors.

Table 5: Regression for demographic variables

Variable	$\mathbf{b_{so}}$	$\mathbf{a_{so}}$	$\mathbf{AA_{0.1}}$	$\mathbf{AA_{0.5}}$	$\mathbf{AA_{0.9}}$	$\mathbf{AA_{-0.5}}$
Age	−.001*	.000	−.001**	−.001***	−.001***	−.001
Male	.055*	.045*	.012	.030*	.044*	.007
< high school	-	-	-	-	-	-
High school	−.008	−.033	−.009	.021	−.035	−.034*
College	−.001	−.037	−.005	.022	−.031	−.056***
Bachelor +	.057***	−.002	.016	.043**	.015	−.048**
White	−.033	.095*	−.058*	−.010	.017	−.040**
Hispanic	.007	.063***	−.025	.007	.024	−.018
African American	.011	.033	−.010	.011	.016	−.012
Other ethnicity	-	-	-	-	-	-
Married	−.002	.004	−.005	−.000	−.000	.023***
Household members	.003	−.006	.003	.002	−.000	−.003
Family income	.001**	.000	.000	.001**	.000	−.000
Wealth	.000	.000	−.000	−.000	−.000	−.000
Trust	.006	−.007	.006**	.006**	−.000	.005**
Financial literacy	.002	.016***	−.006	−.002	.008	−.001
Risk first (order)	.105*	.040*	.026*	.073*	.061*	.007
Risk aversion	.116*	.008	.046*	.082*	.049*	.039***
R^2	.068	.020	.030	.065	.037	.021
N	3192	3192	3124	3190	3161	3177

significant at 10%, **significant at 5%, * significant at 1%*

The regression shows that age and gender have an effect on ambiguity aversion. Older individuals are less ambiguity averse, but age does not have an effect on a-insensitivity. This result is in line with Baillon et al. (2014). When it comes to gender, males are more ambiguity averse and more a-insensitive. This is interesting, because in general women seem to be more risk averse (Croson & Gneezy, 2009). This indicates that the gender differences in risk aversion do not translate to gender differences in ambiguity attitude. Furthermore, those with the highest education level are more ambiguity averse compared to those with the lowest education level. The dummy variables for education are jointly significant ($p < .001$) in the regression on the ambiguity aversion index b_{so} and also for $AA_{0.1}$ ($p = .02$), $AA_{0.5}$ ($p = .02$), $AA_{0.9}$ ($p < .001$) and $AA_{-0.5}$ ($p = .03$). This effect is in line with Dimmock et al. (2016b) who also found that the education variables are jointly significant for b_{so}. Ethnicity only affects the a-insensitivity index, $AA_{0.1}$ and $AA_{-0.5}$. The dummy variables together, however, are also jointly significant for the regression on b_{so} ($p = .03$). Family income affects the level of ambiguity aversion positively, but wealth has no effect. Individuals with a higher financial literacy are more a-insensitive and those with lower levels of trust (note that higher values indicate lower trust) have higher levels of $AA_{0.1}$ and $AA_{0.5}$.

The two variables that seem to have the most consistent influence on the ambiguity measures are question order and risk aversion. If the risk question was asked first, ambiguity aversion and a-insensitivity is higher. This confirms the comparative ignorance hypothesis discussed previously. Hence, it is important to control for question order in the analyses. Finally, risk aversion is positively related to ambiguity aversion, but unrelated to a-insensitivity. This is in line with many studies that also found a positive correlation, although many other studies did not discover any correlation (Trautman & Kuilen, 2015).

Looking at the measure for ambiguity attitude in the domain of losses, the results are slightly different. Education, ethnicity, marital status, trust and risk aversion all affect this measure, while age, gender and question order do not have any effect. This is interesting, because it indicates that ambiguity in the domain of losses has different determinants than in the domain of gains.

In general, the R^2 of the models lies between 2% and 6.8%. These low values indicate that only a small part of the variance of the ambiguity measures is explained by the demographic variables. Hence, the measures are not proxies for these control variables and measure a separate component.

4.3. Self-employment

A chi-square test of independence can give a first indication if ambiguity attitude is related to self-employment. The advantage of a chi-square test is that it requires fewer assumptions than a parametric test such as regression, and it is less sensitive to outliers. Furthermore, it is useful in case of categorical variables. Self-employment is such a variable that consists of two categories; self-employed or not. The categorical ambiguity variable is derived from the answer to the first ambiguity question and consists of three categories; ambiguity averse if the individual chooses the risky box, neutral if the individual is indifferent or seeking if the individual chooses the ambiguous box. Table 1 shows the summary statistics of this variable and table 6 shows the tabulation of the two variables and the results of the chi-square test. The expected frequencies are reported in brackets.

Table 6: Tabulation of ambiguity attitude and self-employment

Self-employed	Ambiguity attitude				
	Averse	Neutral	Seeking	Chi-square	p
Yes	151 (146.8)	41 (29.3)	83 (98.9)	8.44	.02
No	1013 (1017.2)	191 (202.7)	701 (685.1)		

Note: the tabulation shows the observed frequencies, and in brackets the expected frequencies

The chi-square test reveals that there is a relation between ambiguity attitude and self-employment, $\chi^2(2) = 8.44$, n = 2180, p = .02. Individuals who are ambiguity averse or neutral are more likely to be self-employed than those who are ambiguity seeking. This result is not in line with the hypothesis that higher ambiguity aversion is associated with lower likelihood of being self-employed. Appendix C shows the same test for the subsample of individuals who reported that they work, either for wage or for themselves. The conclusions from this test are the same. Similarly, the other robustness check is done for which all individuals who were unemployed in the preceding year are excluded. The results of this test are also the same. To take a closer look at the relation between ambiguity attitudes and self-employment while using the obtained ambiguity indexes and controlling for other variables, another statistical test is needed. Therefore, a regression is done next, including the ambiguity indexes and many demographic and other variables that were mentioned before as independent variables. Appendix D shows the means of the ambiguity measures by self-employment. The Mann-Whitney U test, also shown in appendix D, reveals that they do not differ for those who are self-employed and not self-employed.

Table 7 shows the results of the probit model with self-employment as dependent variable. Appendix E shows the marginal effects of the variables. Based on McFadden's R^2 and the AIC goodness of fit measures, this unrestricted model is preferred over the restricted model with only the ambiguity measures as independent variables. For model I, MacFadden's R^2 is 0.055 and AIC is 0.736 for the unrestricted model. These values are better than the values for the restricted model, which are 0.001 and 0.762 respectively. The same conclusion can be drawn for the other three models. A link test for model specification reveals that the dependent variable is correctly specified (p = .65).

Table 7: Regression results for self-employment

Variable	I	II	III	IV
b_{so}	.143		.112	
a_{so}	−. 120		.049	
$AA_{0.1}$		.111		−.318
$AA_{0.5}$		.288		.752***
$AA_{0.9}$		−.155		−.025
$AA_{-0.5}$	.034	.000	−.079	−.140
Age	.018*	.018*	.011**	.012**
Male	.177**	.164**	.122	.100
< high school				
High school	−.288	−.303	.468	.494
College	−.502**	−.510**	.058	.090
Bachelor +	−.203	−.240	.461	.470
White	−.030	−.056	−.221	−.268
Hispanic	−.174	−.166	−.460	−.459
African American	−.152	−.169	−.667***	−.707***
Other ethnicity				
Married	.241*	.225*	.213***	.190
Household members	.044	.042	.015	.003
Family income	−.006*	−.006**	−.013*	−.014*
Wealth	.004*	.003*	.024*	.023*
Trust	−.043	−.043	−.061	−.066
Financial literacy	.060	.070	.096	.134
Risk first (order)	.038	.024	.190***	.175
Risk aversion	.035	.046	.076	.062
Pseudo R^2	.055	.053	.098	.103
N	2133	2061	870	842

significant at 10%, **significant at 5%, * significant at 1%*

Notes: The table shows probit regressions with self-employment as dependent variable. Model I and III use the indexes b_{so} and a_{so} as measure for ambiguity attitude while model II and IV use $AA_{0.1}$, $AA_{0.5}$ and $AA_{0.9}$ as measures. Model I and II uses the full sample, model III and IV only uses the subsample with respondents who answered both check questions correctly.

The results show that, except for $AA_{0.5}$ in model IV, none of the ambiguity attitude measures has an effect on the probability of being self-employed in any of the models. Only in the model with the subsample of consistent individuals, those who score higher on $AA_{0.5}$ and are thus more ambiguity averse are more likely to be self-employed. This effect is significant at the 10% level (p = .08). This is, however, contradicting the hypothesis that more ambiguity averse individuals are less likely to be self-employed. Accordingly, none of the hypotheses regarding self-employment can be confirmed. In addition, the sign of the other coefficients of the ambiguity aversion measures are not even in the predicted direction. The ambiguity aversion index b_{so} has a positive, though insignificant, effect on the likelihood of becoming self-employed in both model I and III. The a-insensitivity measure a_{so} even has two different signs in both models. Next to ambiguity, also risk aversion does not influence the likelihood to work for yourself.

The factors that do have an effect on the probability of being self-employed are age, gender, education, marital status, income, and wealth. The older the individual is, the higher the chance that he is self-employed. This probability also increases with wealth and is higher if the individual is married and/or male. The probability decreases, on the other hand, with family income. Finally, the education dummies are jointly significant at the 5% level in model I ($p = .047$) and at the 10% level in model II ($p = .07$). In both models, individuals with college education are less likely to be self-employed than those who did not finish high school. The ethnicity dummy for African American is only significant in model III and IV, but the ethnicity dummies are not jointly significant ($p = .20$ for both models).

4.4. Unemployment

To study the effect of ambiguity attitude on reservation wage, only unemployed individuals are included in the analysis. A first analysis is done to check if ambiguity attitude is different for unemployed workers and others. Two t-tests show that the ambiguity aversion index and a-insensitivity index are not significantly different for the two groups: $t = -0.53$, $p = .59$ and $t = 1.04$, $p = .30$. The following analyses are done with only the sample of unemployed individuals who reported a reservation wage.

Table 8: Adjusted reservation wage by ambiguity attitude

	Median	SD	N
Ambiguity averse	1.43	1.48	85
Ambiguity neutral	12.25	4.99	19
Ambiguity seeking	1.53	1.11	52

At first sight, the median of this adjusted reservation wage looks different for ambiguity averse, neutral or seeking individuals. Table 8 shows that the three groups are equal in neither size nor variance ($p < .001$), so the assumptions for ANOVA are not met. Therefore, a Kruskal-Wallis test is performed. This is a non-parametric test that requires fewer assumptions and is less sensitive to outliers. The test shows that the adjusted reservation wage is not significantly different for the three groups, $\chi^2(2) = 2.77$, $p = .25$. Furthermore, a t-test reveals that the adjusted reservation wage is not significantly different for risk seeking and risk averse individuals ($t = 0.62$, $p = .53$). To analyse the effect of ambiguity attitude in more detail, a regression is done next.

Table 9 shows the results of the OLS regression with the logarithm of adjusted reservation wage plus one as dependent variable. The logarithm rather than the level value of adjusted reservation wage is used because the distribution is skewed. Due to heteroskedasticity, the model is estimated with robust standards errors. The unrestricted model is preferred over the restricted model, because the R^2 of .366 is higher than the R^2 of the restricted model of .003 in model I (similar results in the other three models). A link test reveals that the model is well specified ($p = .28$).

Table 9: Regression results for reservation wage

Variable	I	II	III	IV
b_{so}	−.050		.257	
a_{so}	.064		.117	
$AA_{0.1}$		−.052		.042
$AA_{0.5}$		−.099		.131
$AA_{0.9}$		.103		.323
$AA_{-0.5}$	.140	.098	. 411	.418
Age	.011*	.011*	.014**	.014**
Male	.240*	.237*	.400**	.401**
< high school				
High school	.029	.033	.027	.031
College	−.063	−.048	.005	.008
Bachelor +	.135	.131	.192	.197
White	−.092	−.106	−.352	−.356
Hispanic	−.142	−.157	−.065	.066
African American	.007	−.008	−.382	−.394
Other ethnicity				
Married	−.061	−.056	.211	.211
Household members	.000	−.000	−.032	−.032
Family income	−.010*	−.010*	−.012*	−.012*
Wealth	−.000	−.000	−.001	−.001
Trust	.002	.000	.036	.036
Financial literacy	.026	.027	.017	.019
Risk first (order)	−.057	−.064	−.021	−.021
Risk aversion	.100	.090	−.047	−.047
R^2	.366	.363	.486	.486
N	151	149	57	57

significant at 10%, **significant at 5%, * significant at 1%*

Notes: The table shows OLS regressions with the logarithm of adjusted reservation wage as dependent variable. Model I and III use the indexes b_{so} and a_{so} as measure for ambiguity attitude while model II and IV use $AA_{0.1}$, $AA_{0.5}$ and $AA_{0.9}$ as measures. Model I and II uses the full sample, model III and IV only uses the subsample with respondents who answered both check questions correctly.

When it comes to the reservation wage at which to accept a job when looking for one, none of the ambiguity measures has an effect. The sign of the coefficient for ambiguity aversion is positive, indicating that a higher level of ambiguity aversion leads to a higher reservation wage, although not significantly. This is in the opposite direction as hypothesized. Similarly, the coefficient for the a-insensitivity index is negative, which is also in the opposite direction as hypothesized. In the domain of losses ambiguity attitude also has no effect on the reservation wage. Finally, risk aversion does not affect the reservation wage either, although the sign is in the hypothesized direction.

One variable that does have an effect on reservation wage is age. Older unemployed workers have a higher reservation wage. Those with a higher family income and/or wealth also require a higher wage. Looking at the variables *married* and *college,* these coefficients are only significant in the full sample, but not in the sample with only the consistent individuals. The respondents who are married have a lower reservation wage than those who are not married. Those who have taken college education also have a lower reservation wage than those who took less than high school. Both the education dummies and the ethnicity dummies are not jointly significant (for model I, $p = .33$ and $p = .50$).

5. Discussion and limitations

The purpose of this study was to examine the relation between ambiguity attitude and job-related real-life decisions regarding self-employment and unemployment. Different components of ambiguity attitudes were studied in different domains: ambiguity aversion and a-insensitivity, for gains and losses. The regression analyses show that in general no significant relation exists between ambiguity attitude and the probability of being self-employed or the reservation wage. Hence, none of the hypotheses explained in section 2.5 can be confirmed. Nevertheless, some results are interesting and worth further investigation.

5.1. Self-employment

Some of the results regarding self-employment are different from what was expected. Hypothesis 1a states that individuals who are more ambiguity averse are less likely to be self-employed. The results indicate, on the other hand, that ambiguity averse and ambiguity neutral individuals are more likely to be self-employed than ambiguity seeking ones. In the regression, the coefficient for the ambiguity aversion index b_{so} is indeed positive although insignificant. One explanation for this finding is related to the belief about the amount of ambiguity related to starting your own business. As explained in section 2.3, studies have shown that owners of start-ups are overconfident: they overestimate the likelihood of success for their own company. This overconfidence is possibly related to beliefs: the self-employed may be so overconfident and overly optimistic in believing that working for themselves will be successful that they do not even consider self-employment to be ambiguous. More specifically, not only are they overconfident in becoming successful, but also in the probabilities that they themselves estimated being correct. Therefore, the situation appears unambiguous to them.

Along these lines, ambiguity attitude itself does not play a role in the decision to become self-employed, but the extent to which the individual believes the event to be ambiguous does. Especially ambiguity averse people want to assign probabilities to the chances of entrepreneurial success, basically to avoid ambiguous situations. Consequently, they are the ones that most believe that becoming self-employed is unambiguous and are most willing to act whether the situation actually is ambiguous or not. This explains why those that are ambiguity averse are more likely to be self-employed, as revealed by the chi-square test. To determine if overconfidence among self-employed individuals influences the belief in ambiguity and thereby explains the fact that the ambiguity averse are most likely to start their own business, more research is required. Some studies have looked into the effect ambiguity has on overconfidence and discovered a relation (Brenner et al, 2011; Ng, 2015; Shyti, 2013). For example, if the situation is more ambiguous, overconfidence decreases. These studies, however, only look at the causal relation of ambiguity influencing overconfidence and not at a possible reversed relation.

Future research that looks into the link between ambiguity attitude and overconfidence could also investigate the role of competence. As section 2.2 explains, people prefer sources for which they feel relatively competent. For example, the results presented in section 4.2 also confirm the comparative ignorance hypothesis: ambiguity aversion is higher when the risk questions are asked before the ambiguity questions, because in that case the ambiguous choice can be compared to the risky choice. Being able to compare the two types of boxes with each other makes the urn with unknown probabilities look especially ambiguous.

Similarly, self-employed individuals who started a business before may feel relatively competent in estimating the probabilities of success. The dataset used in this study does not include data on previous entrepreneurship by the respondents, but future studies could investigate this topic.

Another explanation for the surprising finding that ambiguity averse individuals are more likely to be self-employed entails the measurement of self-employment. As mentioned before, not all entrepreneurs are voluntarily self-employed, but some are forced into that situation. I tried to control for this with two robustness checks: one excluding all that were unemployed in the preceding year and one excluding all that did not call themselves employed. Both tests resulted in the same findings as the main test, which indicates that the distinction between voluntary and involuntary self-employment is not relevant in the study on ambiguity attitudes. Nevertheless, the robustness checks are imperfectly controlling for the type of self-employment. The dataset does not include a question about the reason for self-employment, which would make a better control question. Further research could look into this distinction and the effect of ambiguity aversion on the likelihood of working for oneself in both categories. Possibly, the ambiguity averse people want to avoid the ambiguous situation of unemployment more than others. Although self-employment is ambiguous as well, they may prefer this type of ambiguity to the type related to self-employment, for example because they feel they have more control. This would be an interesting topic of research.

Looking at the separate ambiguity measures, one result stands out: in the model with only consistent individuals (e.g. model IV) the direct measure for ambiguity in the moderate likelihood and gain domain has an effect on the probability of being self-employed. The marginal effect of .15 indicates that a one unit increase in ambiguity aversion leads to a 15% increase in the likelihood of being self-employed. Since the value of the $AA_{.50}$ measure ranges from −.415 to .425, this indicates that the most ambiguity averse individuals are around 15% more likely to work for themselves than the most ambiguity seeking individuals. This is an economically significant result, but it is also in contrast with the fact that the ambiguity aversion index b_{so} is not significant. It suggests that only the ambiguity attitude in the domain of moderate likelihood gains is relevant in the determination of self-employment. Indeed, in the short run only half of the businesses survive: a moderate likelihood for gains. Self-employed individuals probably believe that other uncertainties around self-employment, such as future income and job satisfaction, are also moderately likely. Seemingly, the ambiguity attitude in the domain of low and high likelihood is not applicable in the situation of start-ups. This suggests that when studying real-life decisions under uncertainty, it is important to consider which aspects of ambiguity attitude are applicable and which are not. For example, some decisions only involve high likelihoods and could therefore only be related to ambiguity attitude in the high likelihood domain leaving all other measures irrelevant. In this study, only moderate likelihood gains seem to be important when deciding to start working for oneself. This also explains why hypothesis 1c, that individuals with higher levels of a-insensitivity are less likely to be self-employed, is not accepted.

Remarkably, the ambiguity measure in the domain of losses is not significant in this study. This means that hypothesis 1b, stating that individuals with higher levels of ambiguity aversion in the domain of losses are less likely to be self-employed, cannot be confirmed. Apparently, the decision to become self-employed does not involve the consideration of losses. If losses are considered or not, depends on the reference point that the individual uses. If the reference point is the situation in which the person already made an investment, success of a start-up leads to gains and failure leads to no change from the reference point. Moreover, if the reference point is working for someone else or being unemployed, self-employment can lead to more independence or earnings rather than dependence on an employer or no income or unemployment benefits at its best. Again, only gains compared to the reference point are relevant in this case, explaining the fact that ambiguity attitude in the domain of losses does not significantly affect self-employment.

In addition to the ambiguity measures, some other determinants of self-employment were investigated. The analysis indicates that the likelihood to be self-employed increases with age and men are more likely to work for themselves than women. Furthermore, married individuals are more likely to be self-employed. Looking at education, those with college education are less likely compared to those with less than a high school degree to be self-employed. Finally, a higher wealth, but lower family income increases the chance of working for oneself. These results are similar to previous findings (Bates, 1995; Nikolova & Bargar, 2010; Kelley et al., 2015).

5.2. Unemployment and reservation wage

Hypothesis 2a and 2b state that unemployed individuals with higher levels of ambiguity aversion have a lower reservation wage while those with higher levels of risk aversion have a higher reservation wage. Both hypotheses cannot be confirmed in this study, since both coefficients are positive, but insignificant. The sign for the effect of ambiguity attitude is actually in the opposite direction as hypothesized. This suggests that the theory by Nishimura and Ozaki (2004) does not hold in the general American population: ambiguity and risk attitude do not seem to influence the reservation wage of unemployed workers. Looking at a-insensitivity, the results show that it does not have any influence on the reservation wage, so hypothesis 2c is not accepted either. These results could be explained by some limitations. First, the reservation wage is adjusted for income earned in the preceding year. This information is not available for everyone, for example because not everyone had a job in the preceding year. The last earned wage would have been a better control variable. Secondly, the amount of years someone has been unemployed influences the reservation wage: throughout these years the person can gather more information about the wage distribution and chances to find a job. Additionally, the necessity to find a job might increase over the years. The data to control for these aspects is not available in the current dataset, so future research can look into this further.

Another explanation is related to the link between ambiguity and ambiguity attitude. The theory by Nishimura and Ozaki (2004) that is tested in this thesis looks at the effect of increases in ambiguity and risk on the reservation wage. This study, on the other hand, looks at the effect of the attitude towards ambiguity instead of ambiguity itself. The assumption that this leads to similar results and affects the reservation wage in the same direction could be incorrect. Moreover, in real life the level of ambiguity in the job market is difficult to observe and is subject to interpretation differences among the workers. Similarly to the way beliefs about ambiguity around self-employment is different for everyone and possibly influenced by overconfidence, unemployed workers could differ in their belief about the probabilities of finding a job. Accordingly, ambiguity attitude itself does not explain variation in reservation wages, but the belief about ambiguity does. In the theory and the laboratory experiment done by Asano et al. (2015) the level of ambiguity is known to everyone. In this study this is not the case, since it investigates real-life decisions. If not everyone considers finding a job to be risky or ambiguous, the attitudes towards it also do not influence the reservation wage.

A last explanation for the results is that the assumption of the theory that unemployed workers maximize the minimum when facing ambiguity is incorrect. If workers do not consider the minimum distribution when the actual one is unknown, but react in a similar manner as to risk, it explains why the coefficient is positive. More ambiguity, just like more risk, leads to a higher reservation wage, because the worker hopes for a better wage and continues searching.

Finally, I predicted that the ambiguity measure in the domain of losses does not explain additional variation of the reservation wage, which cannot be rejected. This was expected, but in the face of the insignificance of the other results it seems like ambiguity attitude does not influence the reservation wage in any direction. The other variables included in the regression indicate that age has a positive effect on the reservation wage. This can be explained by the fact that older individuals have more working experience and therefore expect a higher wage. Furthermore, the unemployed workers who are married report a lower reservation wage. Also those with a higher family income and/or higher wealth have a lower reservation wage. This is logical as these individuals are less dependent on the wage they receive from work.

5.3. Ambiguity attitudes in the general population

This study also looked at prevailing ambiguity attitudes in the general American population. The number of people who are ambiguity averse, neutral or seeking confirms that not everyone is ambiguity averse and that the population is heterogeneous when it comes to ambiguity attitude. Moreover, the dominating attitude differs per domain and likelihood just like previous studies predict (Abdellouai et al., 2011; Baillon & Bleichrodt, 2015): for moderate and high likelihoods in the gain domain ambiguity aversion is dominating, while for small likelihoods in the gain domain and moderate likelihoods in the loss domain ambiguity seeking is dominating. The global ambiguity indexes that were calculated and used in this study are also comparable to results found by Dimmock et al. (2016b) in the Dutch population. The a-insensitivity indexes a_{so} are very similar (i.e. 0.39 and 0.41 respectively), but the ambiguity aversion index b_{so} is lower in the current study than in the study done by Dimmock et al. (2016b): 0.05 and 0.12. This could be due to the limitation in this study that no interval restrictions could be imposed on the regression coefficients when calculating the indexes. This leads to biased indexes and therefore slightly different results. Alternatively, it could be explained by differences between the American and Dutch population. Cozzi and

Giordani (2011) suggested before that attitudes towards ambiguity differ across cultures and countries. Rieger and Wang (2012) show that the proportion of ambiguity averse individuals is different in many country and from the countries they study (i.e. 27 countries, but excluding the Netherlands) the proportion is lowest in the USA.

Lastly, this paper provided some additional insights into the determinants of ambiguity attitudes. The regression in section 4.2 shows that the ambiguity indexes are no proxies for other demographic variables. It also shows that ambiguity aversion decreases with age, is higher for males, and increases with family income and risk aversion. A-insensitivity is higher for men and increasing with financial literacy. This is remarkable, because a-insensitivity is a cognitive component of ambiguity attitude. These results suggest that financial literacy and a-insensitivity measure two distinct aspects of cognition.

Looking at the direct measures of ambiguity attitude, $AA_{0.5}$ has very similar determinants as b_{so}, which is logical because they both measure ambiguity aversion and are highly correlated. The ambiguity measure in the domain of losses, on the other hand, has very different related factors. Education, being married and financial literacy are related to $AA_{-0.5}$, while age, gender, and family income are not. This shows that the two indexes truly measure different aspects of ambiguity attitude.

6. Conclusion

The decision to become self-employed or to accept a job when unemployed involves not only risk, but also ambiguity. The extent to which people can deal with ambiguity is very diverse and depends both on the person (i.e. his ambiguity attitude) and the situation (i.e. likelihood and domain). This thesis looked into the effect that ambiguity attitude has on the likelihood to be self-employed and the reservation wage at which to accept a job offer, but did not find many significant relations. The most important finding is that ambiguity averse individuals are more likely to be self-employed. The global ambiguity indexes that were used in this study, however, were not related to either of the decisions. These results suggest that future research on ambiguity attitudes should look into the different measures for ambiguity attitude and which measure should be used in which situation. For every decision a likelihood level can be established that requires a separate measure. Furthermore, individuals may have different beliefs about the level of ambiguity in case of ambiguous events. Further research can investigate how ambiguity measures can be improved to take into account this disparity. For example, the use of natural sources rather than the Ellsberg paradox could be a first step in that direction. Especially when considering the role of ambiguity in the decision to start working for yourself, beliefs regarding ambiguity and the role of confidence requires more research. When it comes to unemployment, this paper indicates that the inclusion of ambiguity attitude into the job search and matching model does not provide empirical improvement. Nevertheless, enhancements in the measurement of ambiguity attitude may lead to possible improvements. Overall, this paper provides insights that supplement studies on both ambiguity measures itself and the relation of ambiguity attitude to real-life decisions. Furthermore, it opens up some directions for research on the relevant topic of ambiguity and decision-making. Hopefully, future studies can answer the questions raised in this paper and build upon its findings.

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Appendices

The following appendices include additional material including survey questions, a detailed description of the measure of risk aversion, and additional statistical tests.

Appendix A: Financial literacy and trust questions

This appendix includes the exact wording of the financial literacy and trust questions that were used in the survey.

Financial literacy questions

Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

(1) More than $102

(2) Exactly $102

(3) Less than $102

(4) Don't know

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than, exactly the same as, or less than today with the money in this account?

(1) More than today

(2) Exactly the same as today

(3) Less than today

(4) Don't know

Please tell us whether this statement is true or false. Buying a [single company stock/stock mutual fund] usually provides a safer return than a [stock mutual fund/ single company stock]

(1) True

(2) False

(3) Don't know

Trust question

"Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please indicate on a score of 0 to 5."

The answers consist of a Likert scale ranging from 0 to 5, with 0 indicating strong agreement and 5 indicating strong disagreement.

Appendix B: Risk aversion measure

This appendix includes a detailed description if the method used to obtain the risk aversion methods. To measure risk aversion, the subjects are asked to choose between a certain amount of \$10 or a risky gamble with a 10% chance to win \$82 and a 90% chance to win \$3. Figure 4 shows the question that was asked. If the subject chooses the certain amount (box A), the subject gets a new question in which the high amount to be won in the risky box is higher. If the subject chooses the risky gamble (box B), the subject gets a new question in which the high amount to be won in the risky box is lower. If the subject chooses indifferent, no further questions are asked. This is done until the indifference point is elicited or after 4 rounds. This indifference point gives the following indifference point for every subject, with a different amount for X for every subject:

$10 \sim (0.1{:}X, 0.9{:}3)$

The same procedure is repeated for a different choice between a certain amount of \$50 and a risky gamble with 75% chance to win \$85 and a 25% chance to win \$5. This gives a second indifference point for every subject, with a different Y for everyone:

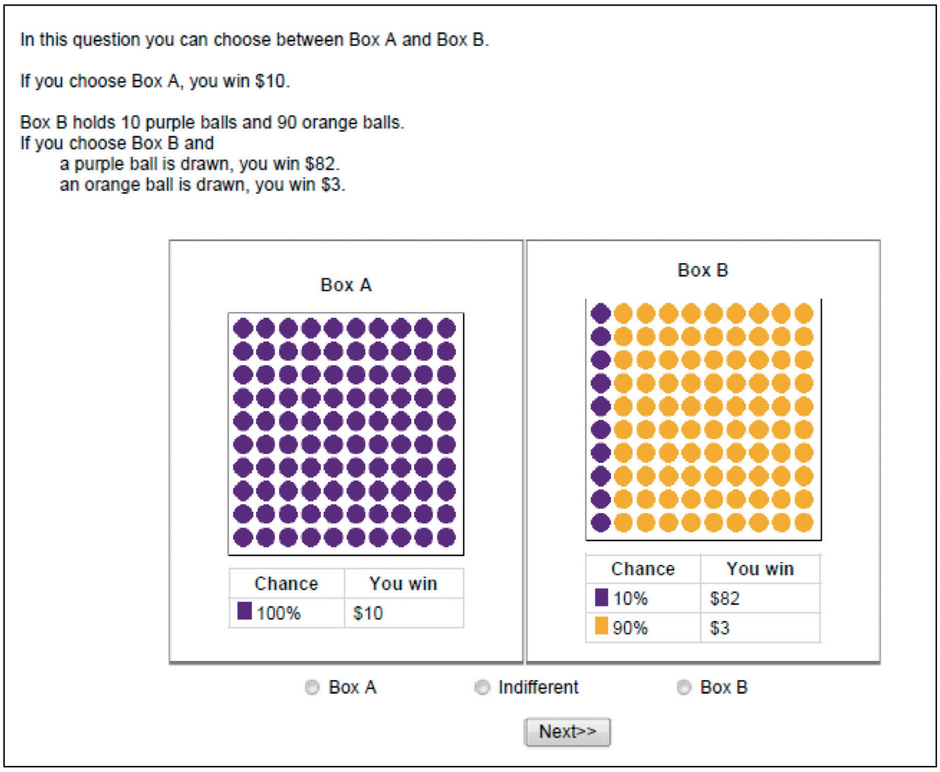
$50 \sim (0.75{:}Y, 0.25{:}5)$

Assuming constant relative risk aversion (CRRA), the risk aversion coefficient can be calculated for both elicited indifference points. With only two data points per individual, only the utility function can be estimated, not the probability weighting function. Therefore, expected utility is assumed, although this might lead to biased results. The formula for CRRA is the power function C^{θ}. Using this formula, the coefficient for CRRA (θ) is estimated for both indifference points. The risk aversion measure is created the following way:

$r = 1 - \theta$

The final risk aversion measure is constructed by taking the average of the two measures.

Figure 4: risk aversion question



Appendix C: Chi-square test for subsample of employed individuals

This appendix includes the chi-square test for the subsample of individuals who report to be employed in the survey. Table 10 shows the results of this test: those who are ambiguity averse or neutral are more likely to be self-employed.

Table 10: tabulation of ambiguity attitude and self-employment for only employed individuals

Self-employed	Ambiguity attitude				
	Averse	Neutral	Seeking	Chi-square	p
Yes	110	28	58	6.12	.047
	(106.1)	(19.9)	(70)		
No	913	164	617		
	(916.9)	(172.1)	(605)		

Note: the tabulation shows the observed frequencies, and in brackets the expected frequencies

Appendix D: Mann-Whitney U test for ambiguity measures and self-employment

This appendix shows the ambiguity measures for the individuals who are self-employed and those who are not self-employed. The means are presented in table 11.

Table 11: means of ambiguity measures by self-employment

Self-employed	b_{so}	a_{so}	$AA_{0.1}$	$AA_{0.5}$	$AA_{0.9}$	$AA_{-0.5}$
Yes	.075	.39	−.12	.04	.19	.01
No	.050	.40	−.13	.02	.19	.02

A Mann-Whitney U test indicates that the ambiguity aversion index b_{so} is not different for the self-employed and not self-employed, z=.051, p = .59. Similarly, the other ambiguity measures a_{so} (p = .99), $AA_{0.1}$ (p = .70), $AA_{0.5}$ (p = .18), $AA_{0.9}$ (p = .60) and $AA_{-0.5}$ (p = .71) are not significantly different for the self-employed and not self-employed.

Appendix E: Marginal effects of probit regression with self-employment as dependent variable

This appendix shows the average marginal effects of the probit regression with self-employment as dependent variable. The results are presented in table 12.

Table 12: Average marginal effects

Variable	**I**	**II**	**III**	**IV**
b_{so}	.028		.022	
a_{so}	−.024		.010	
$AA_{0.1}$		.022		−.063
$AA_{0.5}$		.057		.150***
$AA_{0.9}$		−.031		−.005
$AA_{-0.5}$	.007	.000	−.016	−.028
Age	.004*	.004*	.002**	.002**
Male	.035**	.033**	.024	.020
< high school				
High school	−.057	−.060	.092	.099
College	−.099**	−.101**	.011	.018
Bachelor +	−.040	−.048	.091	.093
White	−.006	−.011	−.043	−.053
Hispanic	−.034	−.033	−.091	−.091
African American	−.030	−.033	−.131***	−.141***
Other ethnicity				
Married	.047*	.045*	.042***	.038
Household members	.009	.008	.003	.001

Family income	−.001*	−.001**	−.003*	−.003*
Wealth	.001*	.001*	.005*	.005*
Trust	−.008	−.008	−.012	−.013
Financial literacy	.012	.014	.019	.027
Risk first (order)	.007	.005	.037***	.035
Risk aversion	.007	.009	.015	.012

significant at 10%, **significant at 5%, * significant at 1%*

Notes: The table shows average marginal effects of the probit regressions with self-employment as dependent variable. Model I and III use the indexes b_{so} and a_{so} as measure for ambiguity attitude while model II and IV use $AA_{0.1}$, $AA_{0.5}$ and $AA_{0.9}$ as measures. Model I and II uses the full sample, model III and IV only uses the subsample with respondents who answered both check questions correctly.

Appendix F: Ambiguity attitude for consistent individuals only

This appendix included the ambiguity attitude measures and results for the subsample of individuals who answered both check questions correctly. Table 12 shows the means and results for this subsample.

Table 12: Ambiguity attitude statistics for consistent individuals

Panel A - Ambiguity attitude: proportion of sample per question (in %)

	Gains 10%	Gains 50%	Gains 90%	Losses 50%
Ambiguity averse	15.3	61.9	64.4	33.9
Ambiguity neutral	15.7	6.1	8.1	21.4
Ambiguity seeking	69.0	32.0	27.5	44.7

Panel B – Ambiguity measures

	Mean	SD	Min	Median	Max
$AA_{0.1}$	−0.15	0.20	−0.75	−0.075	0.085
$AA_{0.5}$	0.03	0.16	−0.415	0.03	0.425
$AA_{0.9}$	0.19	0.24	−0.09	0.13	0.845
$AA_{-0.5}$	−0.03	0.17	−0.44	0	0.47

Panel C – Ambiguity index measures

	Mean	SD	Min	Median	Max
b_{so}	0.05	0.29	−0.84	−0.04	0.90
a_{so}	0.44	0.36	−1.025	0.43	1.99