



Ambiguity and risk measures in the lab and students' real-life borrowing behavior



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ABSTRACT

This study analyzes the external validity of experimentally elicited ambiguity aversion, likelihood insensitivity and risk aversion on real-life decision-making in the field of student loans. Our main finding is that ambiguity aversion, likelihood insensitivity and risk aversion are not related to the decision to take out a student loan nor to the amount students decide to borrow, conditional on having a loan. We discuss our results in the context of recent advances to relate lab measures of ambiguity aversion and likelihood insensitivity to real economic decisions.

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1. Introduction

Since the publication of the well-known [Ellsberg paradox \(1961\)](#), ambiguity aversion has been found and replicated in many laboratory studies ([Trautmann and van de Kuilen, 2015](#)). Ambiguity aversion is a preference for risky over ambiguous prospects that are equivalent under subjective expected utility. Several theoretical models have been developed that include parameters for ambiguity aversion to explain real-life individual and market behavior and anomalies in areas such as portfolio choices ([Dow and Werlang, 1992](#); [Easley and O'Hare, 2009](#)), market microstructure ([Easley and O'Hare, 2010](#); [Ozsoylev and Werner, 2009](#)), home country bias ([Uppal and Wang, 2003](#)) and break-down of trading, which occurred during the recent financial crisis ([Guidolin and Rinaldo, 2013](#)). Although these theoretical models seem promising, the reality is that few experimental studies have found a clear relationship between individually elicited ambiguity aversion in the lab and real-life behavior ([Trautmann and van de Kuilen, 2015](#)). To a certain extent the same limitation also applies to risk prefer-

ences, where many studies provide mixed evidence for a direct link between individuals' lab-elicited risk preferences and related decision-making in real life ([Friedman et al., 2014](#); [Trautmann, 2016](#)).

Research on the predictive power of experimentally elicited ambiguity aversion is restricted to only a handful of studies. In the field of developmental economics, [Warnick et al. \(2011\)](#) find negative effects of ambiguity aversion on the adoption of new varieties of crop in Peruvian farmers and [Ross et al. \(2012\)](#) report a negative relationship between ambiguity aversion and the adoption of new variety of rice. For ambiguity aversion, as well as risk aversion, [Sutter et al. \(2013\)](#) find only a weak correlation with real-life decision-making in adolescents. [Dimmock et al. \(2016a\)](#) report a positive correlation between ambiguity aversion and stock market participation in the US, but in a very similar study in the Netherlands this relationship only holds for subjects who perceive stock returns as highly ambiguous ([Dimmock et al., 2016b](#)).

We also investigate the external validity of likelihood insensitivity, which is a modeling framework often discussed in the context of ambiguity aversion ([Abdellaoui et al., 2011](#)). Likelihood insensitivity describes people's tendency to weight probabilities non-linearly. Specifically, people tend to overweight low likelihood events, also referred to as the 'possibility effect', and underweight

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high likelihood events, which is known as the ‘certainty effect’ (Wakker, 2010). This tendency affects ambiguity preferences in opposite directions: people are generally more ambiguity seeking in the context of low likelihood events and more ambiguity averse in the context of high likelihood events. Regarding the external validity of likelihood insensitivity, a similar picture as with ambiguity aversion and risk aversion emerges: evidence for a clear relationship between lab measurements and real-life behavior is hard to find (Dimmock et al., 2016b). To the best of our knowledge, Dimmock et al. (2016b) is the only study that relates likelihood insensitivity to real economic decisions. They report a negative relation between likelihood insensitivity and stock market participation, but, interestingly, not for ambiguous situations like self-employment or private business ownership.

Overall, the link between experimentally elicited ambiguity aversion, likelihood insensitivity and decision-making in real life is mixed and findings do not seem to replicate reliably, which is a serious issue for policy recommendations. The emerging literature on the external validity of the aforementioned experimental measures shows that there is a need for more research in this area (also see Trautmann and van de Kuilen, 2015). We contribute to this literature by investigating the relationship between ambiguity aversion, risk aversion, likelihood insensitivity and student borrowing behavior of 233 students in the Netherlands. Student borrowing is an important policy instrument for the Dutch government (see next section) and elsewhere. Although a substantial share of students (35%) in the Netherlands take out student loans (Kreetz et al., 2012), the majority prefers to finance their studies with a part-time job. As part-time jobs affect the total amount of time spent on studying the average study duration in the Netherlands is nearly six years, while most curriculums are designed for four years only (Oosterbeek and van den Broek, 2009). This situation can be mitigated with student loans and is not unique to the Netherlands. Countries like UK, US and Australia face similar problems. In fact, in many of these countries students face much higher education and admission fees compared to the Netherlands, which aggravates the problem for students who want to avoid loans (Institute for Higher Education Policy, 2008).

A number of studies focus on debt aversion amongst students. Fear of debt and the prospect of accumulating debt can even influence the decision to study in the first place. This is especially prevalent among low socio-economic groups (Callender and Jackson, 2005, 2008). The majority of studies measure debt aversion and determinants for debt aversion with survey items like ‘owing money is basically wrong’, ‘there is no excuse for borrowing money’, or proxy questions like ‘do you usually pay off your credit card balances each month (conditional on having any)?’. It is not clear whether these survey questions refer to risk aversion, ambiguity aversion, or other related components. The study of Eckel et al. (2007) is a notable exception. The authors experimentally elicit debt aversion as well as risk and time preferences with Canadian adults. The authors find “no evidence that debt aversion is an important barrier to investment in postsecondary education” (p. 234). They do find, however, that risk-seeking and patient persons are more likely to take up education financing, supporting the notion that investing in education is a relatively risky choice. In this study we therefore also elicit risk preferences and analyze the relationship between risk aversion measured in the lab and student borrowing behavior.

Although we also measure risk aversion to complement previous research, our primary argument in this study is that taking out student loans is less about risk and more about ambiguity, where probabilities for possible states are not known. We argue that students’ aversion to borrow may be primarily driven by their aversion to the ambiguous conditions of a student loan. As explained in more detail in the next section, Dutch students face a multi-

tude of ambiguous elements in the decision to take out a loan. For example, the total debt outstanding cannot be precisely assessed because student loan interest rates are floating and unknown. Students are therefore uncertain if and to which extent receiving the loan will outweigh the ease and cost of repayment and benefit their study and study duration. This might explain why the majority of Dutch students prefer to have a part-time job to finance their studies. Graduation and a decent job most likely ensure that students will have no serious problem to repay their debts, but both these events – graduation and obtaining a job with a sufficient income – are several years and numerous ambiguous events away. Yet students have to decide at the start of their study program whether to take out a student loan and, importantly, how much. The higher the stakes, the more confident a student needs to be that the student loan is a worthwhile investment to finance their study and generate the expected income and career as a result (Hill, 2013). Accordingly, we expect that students who are more ambiguity averse will borrow less than other students.

In addition to the effect of ambiguity aversion we argue that likelihood insensitivity can affect borrowing behavior when students perceive the probability to benefit from taking out a loan (including ease of loan repayment) as a high likelihood event. Note that students can freely decide on the loan amount and borrow very small and easily repayable amounts, for example, as additional ‘pocket money’ when they decided to primarily finance their studies through part-time jobs. Hence, we assume that students consider it to be likely that a loan will benefit their study and that this benefit will outweigh the burden of repayment. We therefore expect that students with likelihood insensitivity will underweight the high probability that the loan will benefit them and hence overweight the costs associated with this type of student financing. Hence, we predict that students who exhibit high likelihood insensitivity will try to either refrain from borrowing completely, or borrow as little as possible.

We use recent methods to elicit ambiguity aversion, risk aversion and likelihood insensitivity in a well-controlled laboratory setting and relate it to a real financial decision, student borrowing, which has ambiguous features and is relevant for all participants in our experimental population. We elicit ambiguity aversion and likelihood insensitivity based on matching probabilities of three uncertain events with the following likelihoods: 0.1, 0.5 and 0.9 (Abdellaoui et al., 2011; Dimmock et al., 2016b; Dimmock et al., 2016a). After this elicitation procedure, students answer a variety of questions concerning their borrowing behavior. We find both ambiguity aversion and likelihood insensitivity in our sample. 33% of our participants have a student loan, which is in line with representative samples (Biermans and Budil-Nadvorníková, 2003; van den Broek and van de Wiel, 2005; Oosterbeek and van den Broek, 2009). Our main finding is that ambiguity aversion, likelihood insensitivity and risk aversion are not related to the decision to take out a student loan nor to the amount they decide to borrow conditional on borrowing. In the last section of this paper we discuss the implications of these findings.

2. Student loans in the Netherlands

In the Netherlands, students can get two kinds of financial support from the government: a basic scholarship and a student loan. Most students receive a basic government scholarship. The exact amount depends on the individual’s and family’s wealth and income level. Students receive the basic scholarship for up to four years, because the majority of curriculums are set up as four-year programs (three years bachelor; one year master). Next to this scholarship, almost all students are able to take out student loans that are subsidized and issued by the government. Students can borrow up to €301.27 per month. After four years of study, when

the basic scholarship ends, students can borrow up to €916.96 per month for three more years.¹ As the student loans by the government have more favorable terms than individual bank loans, the latter are rarely used by Dutch students for secondary education (Kreetz et al., 2012).

Practically every student is eligible for the full loan amount and application is very easy. All that a student needs to do is visit the webpage of DUO (the relevant governmental agency of the Dutch Ministry of Education) and enter the required information. The website is very transparent and accessible and no additional mailings or requirements are needed. A student who decides to take out a student loan will receive the first loan payment within a month.

If a student graduates within ten years, the basic scholarship will be awarded as a gift. The student loan has to be repaid. The interest rate on government student loans are based on the current government interest rate and are therefore much lower than the interest rate a bank would issue on loans. While studying, students already incur interest costs based on the current interest rate. Two years after a student graduates, the repayment period starts and the graduate has to repay a fixed monthly amount. During the repayment period, interest costs on the remaining loan are still incurred. The graduate will be informed about this interest rate at the start of the repayment period. Every five years this interest rate is adjusted for a new period of five years. The repayment period has a maximum of 15 years, but graduates can choose to repay faster.

A student who decides to take out a student loan has information on the current interest rate, but she is uncertain about the different interest rates that will apply in the following years of study and during the various repayment periods. On its web page, DUO and the Ministry of Education offer calculation modules to estimate future loan repayments. The estimated monthly repayment amounts are provided for four different possible interest rates that could apply in the future. There is no information provided about the consequences when a student is unable to repay her loans.

A student, who decides to borrow now, can do so with a few mouse clicks. Yet she does not know the exact amount that she needs to repay in the future. She does not know the exact interest rate that will apply. She does not know what actions can be taken if she will be unable to repay in the future. Overall, there is substantial ambiguity about the consequences of the decision to take out a student loan at this moment in time.

3. Experimental design

3.1. Measuring ambiguity aversion and likelihood insensitivity

We use a simple and tractable method known as probability matching. The idea is to elicit probability equivalents of a specific uncertain prospect by allowing participants to simultaneously choose between an event with unknown probabilities and an event with known probabilities. Using a multiple choice list format, a subjective probability 'mp' is elicited from the participants for which they are indifferent between the unknown event E and a gamble where outcome 1 is realized with probability mp. For instance, tomorrow it might rain (outcome 1) or not (outcome 0). This unknown event E can be described as $1E0$. If there exists a number mp such that $1E0 \sim 1mp0$, we call mp the matching probability of E (Wakker, 2010, p. 120). The difference between the underlying likelihood of an unknown event and the matching probability can be taken as an index of ambiguity aversion

(Jaffray, 1989; Kahn and Sarin, 1988; Wakker, 2010).² In this study, we estimated individual's ambiguity aversion based on matched probabilities of three uncertain events with underlying likelihoods: 0.1, 0.5 and 0.9.

The unknown and the risky events in our experiment are operationalized via the standard Ellsberg urn setup (1961). The unknown urn was composed of 100 colored chips in an unknown composition. If the underlying likelihood of the unknown urn was 0.5 (henceforth U2), all chips in U2 were of one of two colors: yellow or green. The colors but not the compositions were known to the subjects. The risky (known) urn (K2), had a known composition of yellow and green chips.

With a multiple choice list procedure, we asked participants to indicate their preference for a draw from either urn U2 or K2. See Fig. A1 in Appendix A for a visualization of this setup. At the start of the experiment, before instructions had been distributed, subjects selected one color: either yellow or green. The number of X chips in urn K2, defined in terms of the participant's selected color, increased in each row (option B), whereas the composition of urn U2 remained unknown and fixed (option A). Each row $i \in (1, 2, \dots, 20)$ in this list was a separate binary choice between urn U2 and K2. In other words, in each row participants had to choose from which urn they would like to draw a chip: from urn U2 (option A) or from urn K2 (option B). If the chip from the preferred urn was of their selected color, participants won € 15, else nothing (if this choice was randomly selected at the end of the experiment to be played out for real).

The switching point from option A to option B indicates when a subject prefers a draw from urn K2 with X chips in their selected color over a draw from urn U2. If a subject switched to Option B in row i , we take the midpoint between X_{i-1} and X_i chips as an estimate of subjects' matching probability of urn U2. The earlier a participant switches from option A to option B the more ambiguity averse she is.

We refer to an individual's matched probability in the two-color urn setup as $m(0.5)$. For instance, if $m(0.5)$ is 0.38, then a subject indicated to be indifferent between a draw from urn U2 and a draw from urn K2 which is composed of 38 chips in the participant's selected color and 62 chips of the other color. If $m(0.5)$ has a value below 0.5, which is the ambiguity neutral probability of urn U2, ambiguity aversion is expressed. A value of $m(0.5)$ higher than 0.5 indicates ambiguity loving behavior.

We also elicited the matched probabilities $m(0.1)$ and $m(0.9)$, corresponding to the underlying likelihoods of 0.1 and 0.9, by using a 10-color urn (see Figs. A2 and A3 in Appendix A for these setups). To elicit $m(0.1)$, the unknown urn (U10), contained 100 chips in an unknown composition of 10 colors. Urn K10 on the other hand consisted of a known composition of 100 chips with 10 colors. With the same multiple choice list procedure as before, we measured $m(0.1)$ by letting the participant choose between a draw from urn U10 (option A) or urn K10 (option B). Again, participants knew that they could win € 15 if the chip they draw from their preferred urn was of their selected color, else they won nothing. In each row $i \in (1, 2, \dots, 20)$ the amount (X) of chips in the participant's selected color in urn K10 increased. The minimum amount of chips in row 1 (X_1) was 2 chips, and the maximum amount of chips (X_{20}) was 40 chips. The switching point from option A to option B in row i indicated when subjects preferred a draw from urn K10 with X_i chips in their selected color over a draw from urn U10. We again take the midpoint of tokens before and at the switching point, $X_{i-1} + \frac{1}{2}(X_i - X_{i-1})$, as the value of $m(0.1)$. For example, when

¹ This was the current situation when we conducted our experiment and the scheme that applied to our experimental population. In the discussion we explain that from 2015 onwards the financial support solely relies on student loans.

² One of the merits of matching probabilities is that ambiguity aversion is directly measured relative to risk preferences and does not require the additional elicitation of utility or probability weighting (Wakker, 2010).

$m(0.1)$ is 0.16, this indicates that the subject is indifferent between gambling on a draw from urn K10 that is composed of 16 chips in their selected color versus gambling on a draw from urn U10. A matched probability above (below) the ambiguity neutral probability of 0.1 implies ambiguity loving (averse) behavior.

To elicit $m(0.9)$ we run the same protocol as discussed before, only now there are nine winning colors, defined as the nine colors that were not selected by the participant (the complement of urn U10 with 1 winning color). Here X_1 was 60 chips and X_{20} was 98 chips. When $m(0.9)$ is 0.7, for instance, the participant indicated to be indifferent between a draw from urn K10 filled with 70 chips, colored by any of the nine winning colors, versus a draw from urn U10.

For all three list procedures, we designed the program in such a way that participants could only switch once. Subjects who immediately ‘switched’ to option B in row 1 received the amount of chips in row 1 as their matching probability. At the other extreme, subjects who never switched to Option B received the amount of chips in row 20 as their matching probability. We classified a participant as ambiguity neutral if (s)he switched from option A to option B when the risky urn was in line with the ambiguity neutral probability (for the two-color urn U2 this is row 10 in Fig. A1 in Appendix A).

AAp refers to the degree of ambiguity aversion for each uncertain event with ambiguity-neutral probability p . We compute the AAp with each individual’s matched probability as follows:

$$AA0.1 = 0.1 - m(0.1)$$

$$AA0.5 = 0.5 - m(0.5)$$

$$AA0.9 = 0.9 - m(0.9)$$

We use the method developed by Abdellaoui et al. (2011) to extract two indices: ambiguity aversion and likelihood insensitivity. For each participant we estimate the best-fitting line between p and $m(p)$, by means of OLS on the open interval (0,1). We refer to the intercept with c , and the slope with s . Finally, we compute $d = 1 - c - s$, which is the distance from 1 at the regression line where $p = 1$. Based on these three parameters, we define:

Index $a = 1 - s (= c + d)$, which is the index of likelihood insensitivity, and

Index $b = 1 - s - 2c (= d - c)$, which is the index of ambiguity aversion.

Index b is an anti-index of the average height of the curve and refers to a global index of ambiguity aversion. Index a on the other hand is an anti-index of the steepness of the curve and it reflects the neglect to sufficiently differentiate between intermediate levels of likelihood (Wakker, 2010; Abdellaoui et al., 2011; Dimmock et al., 2016b). The most common behavioral pattern is a combination of both ambiguity aversion and likelihood insensitivity (Wakker, 2010).

3.2. Consistency

In order to test the consistency of participants’ preferences elicited in the multiple choice list, we also administer a direct binominal choice between each of the three ambiguous likelihood events and a risky urn defined by their respective ambiguity neutral probabilities of 0.1, 0.5 and 0.9. Please see Fig. A4 (in Appendix A) for an illustration of the consistency check for the two-color ambiguous urn U2.

This binominal choice was elicited *before* participants were confronted with the choice list procedure. For a consistent decision-maker, identical preferences should emerge in the direct choice (Fig. A4 in Appendix A) as in the row from the choice list where the risky urn was in line with the ambiguity neutral probability

(row 10 in Fig. A1 in Section 1 of the Appendix). The direct comparison between the ambiguous and risky urn allows us to assess the robustness of participants’ preferences.

The consistency rates (in percentages of the total participant pool) are 81.97%, 76.39% and 94.42% for the three likelihoods of 0.5, 0.1 and 0.9, respectively. Our consistency rates are higher than Dimmock et al. (2016b) and Dimmock et al. (2016a), and in line with Kocher et al. (2015). Overall, 69.66% ($n = 136$) of our participants showed a consistent pattern for all three likelihoods (henceforth ‘consistent sample’). For robustness we rerun all our analyses on our consistent sample (see Models 5 and 6 in Table C3 in Appendix C).

3.3. Risk aversion

We also measure individuals’ risk preferences. Within the same framing as above (see Fig. A5 in Appendix A) we elicited subjects’ certainty equivalent to a draw from a two-color risky urn (equivalent to K2 with 10 chips and a probability of 0.5). Participants are informed that a drawn chip corresponding to their selected color (yellow or green) would lead to a gain of € 15, else they win nothing.

Participants had to select, in each row in a choice list format of 20 rows in total, their preference between drawing a chip from the risky urn and receiving a sure payoff. The sure payoff increased with each row and reached a maximum amount of € 15 at row 20. At some point participants switched from choosing the risky urn to the sure option. We take the midpoint of the two sure payoffs before and at the switching point as each participant’s certainty equivalent (CE). As a measure of individual risk aversion we use: $r = 1 - CE/15$ (Wakker, 2010). A value of r larger (smaller), than 0.5, indicates risk aversion (risk seekingness).

3.4. Questionnaire

After we elicited participants’ matching probabilities and their preference towards risk, we administered a questionnaire. We specifically asked if they were familiar with DUO before they answered subsequent questions. All students were well aware of the existence of DUO.

The questionnaire consisted of three parts. Part 1 of the questionnaire dealt with questions concerning their borrowing behavior. The main questions we use for our analyses ask whether or not they borrow, and if so, how much they borrow. In part 1 we also conducted a cognitive reflection test (Frederick, 2005) and a financial literacy test (Lusardi and Mitchel, 2011). Both these tests contained three questions and each participant received a normalized score between 0–1 depending on the amount of correct answers.

Part 2 of the questionnaire included demographic questions such as age, gender, living situation, study year and study topic.

The last part of the questionnaire, part 3, was the life orientation test, which measured general optimism and pessimism (Scheier and Carver, 1985; Scheier et al., 1994). Participants indicated on a 5-point Likert scale (scored with a range from 0–4) if they totally (dis)agreed with the statement being posed. A maximum score of 24, respectively 0, means an extremely optimistic and pessimistic view on life.³

³ We added this part to the questionnaire as we were interested to study if the optimism and pessimism scores from this life orientation test would correlate with the optimism and pessimism labels used to describe overweighting of low likelihoods, respectively underweighting of high likelihood events (See Table C1 in Appendix C). As scores on the life orientation test had no relationship with borrowing behavior, likelihood insensitivity and ambiguity aversion we do not report them in our main results section.

3.5. Procedures

The experiments were conducted at NSM laboratory (Nijmegen School of Management) at the Radboud University Nijmegen and ELSE (Experimental Laboratory for Sociology and Economics) at the University of Utrecht in March 2014. 233 participants - 130 females and 103 males - participated in our study. The experiments were computerized using the software z-Tree (Fischbacher, 2007). All participants had to answer comprehension questions before each task. We checked their answers and, in case of mistakes, privately explained the correct answer before all participants were allowed to start the task.

There was a fixed order of tasks. The matched probabilities were elicited in the following order: $m(0.5)$, $m(0.1)$ and $m(0.9)$. This is in line with procedures from Dimmock et al. (2016b) and Dimmock et al. (2016a). Subsequently we elicited participants' risk preferences. Finally, participants filled in the questionnaire before any feedback was given on the results and payment of the experimental tasks.

Participants received a sure amount of €4 as show-up fee. At the end of each session the computer would randomly select one choice from one of the four experimental tasks: one row from one of the choice lists used to elicit the matching probabilities of the ambiguous likelihood events of 0.1, 0.5 and 0.9 and participants' risk preferences. This randomly selected choice was played out for real by letting participants select a chip from either urn U2, urn U10 or from a risky urn. If a participant would have to draw a chip from the risky urn, we would compose an 'urn' in front of their eyes by filling it with the amount of chips in their selected color (corresponding to the selected row).

Subjects were paid, in cash and in private, €12.15 on average (including show-up fee) for a session lasting about one and a half hour

The production of the unknown urns U2 and U10 was explained very carefully at the start of the experiment. We used four different production methods to construct urns U2 and U10, namely 'human', 'compound', 'unknown' and 'nature'.⁴ During the whole experiment urn U2 and urn U10 were visibly placed in the laboratory so that any suspicion participants could have had with regard to potential manipulation of the ambiguous urns was eliminated.

4. Results

4.1. Sample descriptives

We excluded five participants from our total set of 233 participants. Three participants turned out not to be a student in violation of our selection criteria. Two participants did not report their income, which we use as a control variable in our analyses. All analyses are conducted with the remaining 228 participants.

Table 1 shows that 33% of our subjects borrow money at DUO on a monthly basis. The average amount borrowed is €388.16 per month.⁵ Both these figures are very consistent with findings

⁴ The four production methods were implemented as four separate treatments randomized over 17 different sessions in a between-subjects design. In a companion paper we focus on the question if ambiguity aversion and likelihood insensitivity are influenced by the construction of an ambiguous urn. All results in this paper remain qualitatively valid when including dummies for either sessions or for production methods in our statistical models. Please see Appendix B for a more detailed explanation of the production methods and Appendix C for the results of the robustness analyses (Table C4).

⁵ This amount is higher than the maximum of €301.27 per month, because many students study longer than four years, after which they can borrow up to €916.96 (see Chapter 2 of this paper).

Table 1

Characteristics of borrowers vs non-borrowers.

Variables:	Borrowers	Non-borrowers	Overall
N (proportion)	76 (32.62%)	157 (67.38%)	233 (100%)
Income	€ 661.04	€ 556.88	€ 602.10
Age	21.92	21.05	21.68
Siblings	1.83	1.61	1.67
Female	56.58%	55.41%	55.79%
Economics study	9.21%	24.20%	19.31%
Live on own	85.53%	70.70%	75.54%
Study years	2.47	1.88	2.08
Living expenses	€ 568.42	€ 426.64	€ 473.90
Amount borrowed	€ 388.16	€ 0	€ 126.61

Table 2

Descriptives ambiguity, likelihood insensitivity and risk.

Variable	Mean	Std. Dev.	Min	Max
$m(0.1)$	0.142	0.064	0.02	0.40
$m(0.5)$	0.475	0.083	0.23	0.8
$m(0.9)$	0.738	0.110	0.60	0.98
AA0.1	-0.042	0.065	-0.30	0.08
AA0.5	0.025	0.083	-0.30	0.27
AA0.9	0.162	0.110	-0.08	0.3
Index b (ambiguity aversion)	0.097	0.110	-0.45	0.31
Index a (likelihood insensitivity)	0.254	0.169	-0.2	0.89
Risk aversion	0.547	0.134	0	0.925

Table 3

Ambiguity preferences.

Likelihood	0.1	0.5	0.9
Ambiguity averse	13 (6%)	87 (38%)	197 (86%)
Ambiguity neutral	59 (26%)	76 (33%)	20 (9%)
Ambiguity seeking	156 (68%)	65 (29%)	11 (5%)

from much larger representative samples (Biermans and Budil-Nadvorníková, 2003; van den Broek and van de Wiel, 2005; Oosterbeek and van den Broek, 2009; Kreetz et al., 2012). Table 1 also shows that borrowers live more frequently on their own, have higher living expenses, more siblings, are further progressed in their study (in terms of study years), and older than non-borrowers ($p < 0.05$, two-sample t -test). Also, the total amount of income is higher for borrowers than for non-borrowers; this may indicate that borrowers need to offset higher living expenses.

4.2. Ambiguity aversion and likelihood insensitivity

Table 2 shows that, on average, subjects have matching probabilities below the ambiguity neutral probabilities of 0.5 and 0.9 and overweight the ambiguity neutral probability of 0.1. This pattern is both consistent with ambiguity aversion (mean index b value of 0.097, which is significantly higher than 0: $t(227) = 13.235$, $p < 0.001$ two-tailed) and likelihood insensitivity (mean index a value of 0.254, which is significantly higher than 0: $t(227) = 22.712$, $p < 0.001$ two-tailed). Finally, participants can be characterized as risk averse (mean value of 0.547, which is significantly higher than 0.5: $t(227) = 5.35$, $p < 0.001$ two-tailed). For the consistent sample, the mean values of index b , a and risk aversion are respectively 0.110, 0.244 and 0.542 and these values are significantly different from 0 and 0.5 ($p < 0.001$ two-tailed).

In Table 3 the percentages of participants who can either be classified as ambiguity averse, neutral or seeking are distinguished for the three different likelihoods. In coherence with a positive value of likelihood insensitivity, the percentage of ambiguity averse

Table 4
Determinants of borrowing behavior (logistical regression; 1 = yes, I borrow).

Do you borrow	1	2	3	4	5	6
Index b	0.657 (1.424)	0.424 (1.481)			2.080 (2.351)	
Index a	0.176 (0.941)	0.145 (0.956)			−0.150 (1.294)	
AA0.1			−1.419 (2.473)	−1.939 (2.514)		−2.841 (3.784)
AA0.5			2.007 (1.946)	2.211 (1.972)		5.900* (3.234)
AA0.9			0.070 (1.396)	−0.278 (1.463)		−0.334 (2.014)
Risk aversion		−1.108 (1.143)		−1.111 (1.148)	−1.188 (1.519)	−0.270 (1.546)
Financial literacy		−.449* (0.257)		−0.487* (0.261)	−.415 (0.345)	−0.447 (0.351)
Cognitive reflection test		−0.126 (0.449)		−0.094 (0.451)	−1.070* (0.543)	−1.073 (0.664)
Income	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Study years	0.049 (0.062)	0.051 (0.063)	0.051 (0.062)	0.053 (0.063)	0.057 (0.089)	0.053 (0.092)
Female	0.021 (0.305)	−0.056 (0.317)	0.031 (0.306)	−0.048 (0.319)	−0.769* (0.447)	−0.791* (0.456)
Economic study	−1.070** (0.450)	−0.803* (0.470)	−1.067** (0.451)	−0.788* (0.470)	−1.543** (0.713)	−1.512* (0.713)
Siblings	0.095 (0.122)	0.073 (0.126)	0.083 (0.122)	0.058 (0.126)	−0.047 (0.169)	−0.058 (0.170)
Live on own	0.704* (0.406)	0.732* (0.414)	0.728* (0.408)	0.762* (0.415)	1.603*** (0.611)	1.728*** (0.622)
Constant	−1.694 (0.538)	0.020 (0.984)	−1.710 (0.541)	0.074 (0.992)	−1.556 (0.699)	0.074 (1.305)
Observations	228	228	228	228	136	136
Consistent sample	0	0	0	0	1	1
LR Chi2	chi2(8) = 17.26	chi2(11) = 21.90	chi2(9) = 18.13	chi2(12) = 23.20	chi2(8) = 18.61	chi2(11) = 23.50
Prob > Chi2	0.0276	0.0251	0.0337	0.0261	0.0171	0.0150
Pseudo R-squared	0.0595	0.0755	0.0624	0.0799	0.135	0.0799

Standard errors reported in parentheses.

*** Significant at the 0.01.

** Significant at the 0.05.

* Significant at the 0.1.

(seeking) participants increases (decreases) in the ambiguity neutral probability.⁶

4.3. Lab-elicited measures and borrowing behavior

In order to test if our experimental measures from the laboratory relate to the decision to take out a student loan, we first run a logistical regression model with the borrowing decision as dependent variable. This dependent variable is a dichotomous variable, with 1 indicating if a student borrows, irrespective of how much, and 0 indicating when a student does not borrow. We find marginally significant ($p < 0.1$) trends of financial literacy, studying economics, and whether one lives on her own on the decision to borrow (Table 4). Neither ambiguity aversion nor likelihood insensitivity nor risk aversion, however, are associated with the decision to take out a student loan.⁷

Please recall from Table 1 that 33% of our subjects borrow money monthly at DUO. We therefore also analyze the role between our experimental measures and the amount borrowers in our student population borrow, given that students took out a loan ($n = 76$). A Pearson product-moment correlation shows a significant negative correlation between ambiguity aversion (index b) and the amount a student borrows ($r = -0.233$, $p < 0.05$). We perform several additional analyses to test the validity of this pairwise correlation. Firstly, we run an OLS regression on the group of borrowers ($n = 76$) with the amount borrowed (on a monthly basis) as dependent variable (see Appendix C, Table C3). The previously found negative bivariate relationship between borrowers' ambiguity aversion and the amount they borrow remains significantly valid in a multivariate setting (see models 1–4 in Table C3 in Appendix C). This result is not influenced when we perform the same analyses and control for session effects and production methods (see Appendix C, Table C4).

Importantly, however, when we run the same models with the consistent sample ($n = 46$, see models 5 and 6 in Table C3 in Appendix C), the significant effect of borrowers' ambiguity aversion on the amount they borrow monthly vanishes. Also, we cannot confirm our previously found result when we run a Tobit regression on the whole sample and model the null-borrowers as left-censored observations (see Appendix C, Table C5).

This led us to more carefully look at our sample of borrowers. We found one extreme outlier (see Fig. C6 in Appendix C) who was at the same time highly ambiguity seeking and who belonged to the highest 5% percentile of amount borrowed (and was not part of the consistent sample). When we reran our OLS models (see Table C3 in Appendix C) and removed this one outlier, the earlier reported relationship between ambiguity aversion and amount borrowed was not present anymore. Although we have low power, insignificance is not driven by large standard error, but rather by an absence of an effect.

In Sections 1 and 2 of this paper we argue that there is ambiguity over the exact interest rates for the student loan. Yet, students who take out a loan late in their studies, e.g. shortly after the last adjustment of the interest rates, should have better information to assess the future debt they have to pay off than others and hence suffer from less ambiguity. To check whether the missing relationship is driven by students in higher years, we reran all our regressions with first- and second-year students only (unreported). The sample size was $n = 159$ (original $n = 228$), which shows that the large majority of students in the original sample were quite far from graduation and loan repayment. The results of all our robustness checks (both logit and OLS) are near to identical to the reported results.

Hence, overall, we can therefore conclude that our results show no relationship (a) between the decision to borrow and ambiguity or risk measures and (b) between the amount borrowed and our ambiguity and risk measures (conditional on borrowing and after eliminating a single outlier).

⁶ Please see Tables C1 and C2 in Appendix C for more descriptive data on ambiguity aversion and likelihood insensitivity.

⁷ Ambiguity aversion at $p = 0.5$ in Model 6 is the only exception, but is only weakly significant at the 10% level.

5. Discussion and conclusion

This study is part of a relatively new stream in decision research that attempts to relate experimentally elicited ambiguity aversion and likelihood insensitivity to real life decision-making outside the laboratory. We used advanced methods to elicit ambiguity aversion and likelihood insensitivity in a well-controlled laboratory setting and relate it to Dutch students' borrowing behavior in our experimental population.

Dutch students face a multitude of ambiguous elements in the decision to take out a loan, including uncertain interest rates. We hypothesized that students who are more ambiguity averse will not borrow or borrow less than other students. Furthermore, we hypothesized that students who exhibit high likelihood insensitivity will underweight the probability that the loan will benefit them and overweight the cost and ease of repayment. Altogether, this would aggravate the relationship between ambiguity aversion and borrowing behavior even more.

Our results indicate no relationship between ambiguity aversion, risk aversion, likelihood insensitivity and students' borrowing behavior. Our parameters of interest do not influence the decision to take out a loan or the amount borrowers are willing to loan. Contrary to previous results (Eckel et al., 2007; Oosterbeek and van den Broek, 2009) we find no relationship between individuals' risk aversion and borrowing behavior.

As discussed in Section 2 of this paper, the cohort of students that participated in our study received a basic scholarship from the government along with the possibility to take out a study loan. As the Dutch government faces pressures to reduce costs, fewer resources are allocated to education. One of the recent consequences is that new cohorts of Dutch students who started as of September 2015 will receive no monthly basic scholarship anymore and will have to exclusively rely on student loans.

From countries with higher educational fees, results show that students, who are reluctant to borrow, choose more frequently to work part-time, opt for a lower cost institution, or study part-time (Institute for Higher Education Policy, 2008). These are all factors that increase the risk of study dropout. Next to this potential risk of higher dropout rates, a 2.1% decline in the amount of Dutch students pursuing higher education is predicted as a consequence of this new policy (Berkhout and van der Werff, 2014).

Not surprisingly, the decision to take out a student loan appears to be primarily driven by financial constraints. We find that borrowers live more frequently on their own, have higher living expenses, more siblings, are further progressed in their study (in terms of study years), and older than non-borrowers. What is

somewhat surprising, however, is that risk and ambiguity aversion from the lab are unable to detect any additional effects in students' borrowing behavior. Irrespective of students' lab-elicited preferences for risk and ambiguity, some students have no alternative but to take out a student loan in order to attain education. And vice versa, some students are not restricted to borrowing, and will not do so, even if they appear to be more risk and ambiguity seeking in the lab.

A limitation in our study setup is that we have restricted the elicitation of ambiguity aversion and likelihood insensitivity to the gain domain. If students' decision to take out a study loan is driven by a fear of not being able to repay their study debts in the future, our null-finding between likelihood insensitivity and student borrowing may have come from the fact that we did not elicit matching probabilities for an ambiguous prospect in the loss domain. Previous research has shown that the common pattern of over- and underweighting of low respectively high likelihood events in the gain domain is completely reversed in the loss domain (Di Mauro and Maffioletti, 2004; Vieider et al., 2012). In the Netherlands the default rate on student loans was 11% in 2009 and 15.63% in 2013 (Dutch Ministry of Education, 2014) and in the United States the 2013 national cohort default rate was 11% (Federal Student Aid, 2016). Hence, more research is needed to investigate how the expectation of defaults relates to ambiguity aversion and likelihood insensitivity in the loss domain.

Overall, the results of this study and other experimental evidence regarding the external validity of lab-measured ambiguity aversion and likelihood insensitivity remain mixed and unconvincing. For risk measurements Friedman et al. (2014) argued that the definition, modelling and elicitation of risk does not (yet) adequately relate to the perceived risk that people face in their daily lives. We extend this argument to measures of ambiguity aversion and likelihood insensitivity in the lab in combination with student borrowing behavior in the field.

Acknowledgment

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Appendix A



Fig. A1. Table setup for eliciting $m(0.5)$. Screenshot from our zTree program. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)



Fig. A2. Table setup for eliciting $m(0.1)$. Screenshot from our zTree program. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

Task 2 Part 2

Remember: there are 100 chips in each urn.
Also remember in each line the amount of chips for Urn K10 correspond to your nine selected colors.

Choice	Option A Urn U10	Your choice	Option B Urn K10
1	<p style="text-align: center;">Urn U10</p>	A <input type="radio"/> B	€ 15: 60 chips, € 0 otherwise
2		A <input type="radio"/> B	€ 15: 62 chips, € 0 otherwise
3		A <input type="radio"/> B	€ 15: 64 chips, € 0 otherwise
4		A <input type="radio"/> B	€ 15: 66 chips, € 0 otherwise
5		A <input type="radio"/> B	€ 15: 68 chips, € 0 otherwise
6		A <input type="radio"/> B	€ 15: 70 chips, € 0 otherwise
7		A <input type="radio"/> B	€ 15: 72 chips, € 0 otherwise
8		A <input type="radio"/> B	€ 15: 74 chips, € 0 otherwise
9		A <input type="radio"/> B	€ 15: 76 chips, € 0 otherwise
10		A <input type="radio"/> B	€ 15: 78 chips, € 0 otherwise
11		A <input type="radio"/> B	€ 15: 80 chips, € 0 otherwise
12		A <input type="radio"/> B	€ 15: 82 chips, € 0 otherwise
13		A <input type="radio"/> B	€ 15: 84 chips, € 0 otherwise
14		A <input type="radio"/> B	€ 15: 86 chips, € 0 otherwise
15		A <input type="radio"/> B	€ 15: 88 chips, € 0 otherwise
16		A <input type="radio"/> B	€ 15: 90 chips, € 0 otherwise
17		A <input type="radio"/> B	€ 15: 92 chips, € 0 otherwise
18		A <input type="radio"/> B	€ 15: 94 chips, € 0 otherwise
19		A <input type="radio"/> B	€ 15: 96 chips, € 0 otherwise
20		A <input type="radio"/> B	€ 15: 98 chips, € 0 otherwise

Confirm

Fig. A3. Table setup for eliciting $m(0.9)$. Screenshot from our zTree program. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

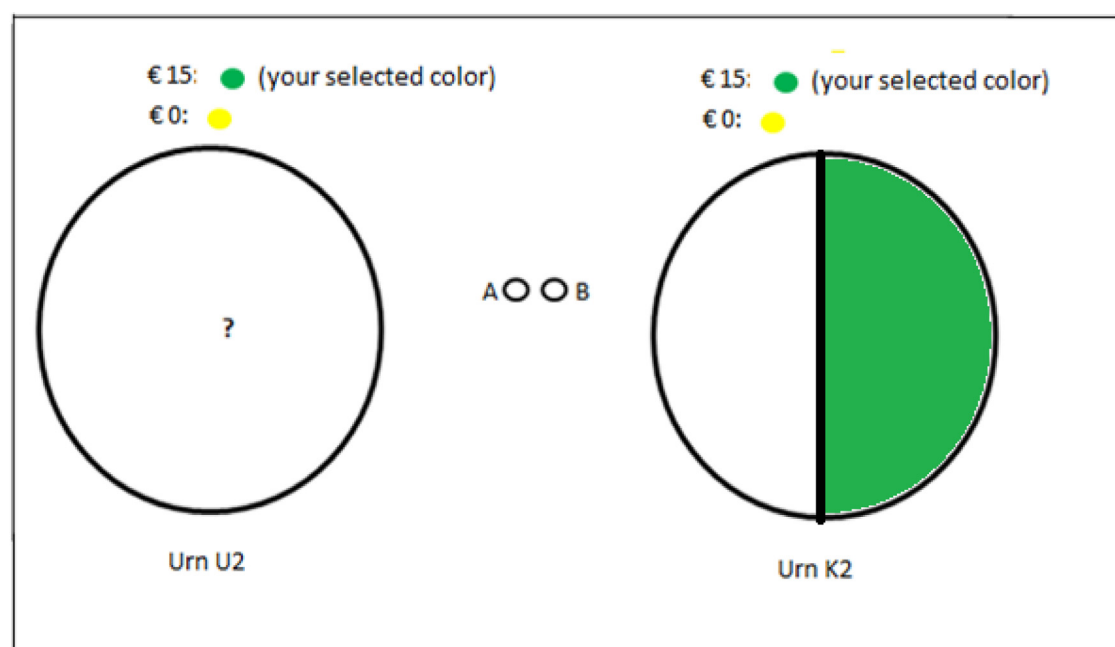


Fig. A4. Choice screen 'consistency check' (with green as illustration). (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

Task 4

Remember: Option B is an urn filled with 10 balls: 5 yellow balls and 5 green balls. You win 15 euro if the chosen ball is of color green, or else you win nothing.

	Option A	Your choice	Option B
1	I choose the certain amount of €0.75	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
2	I choose the certain amount of €1.50	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
3	I choose the certain amount of €2.25	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
4	I choose the certain amount of €3.00	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
5	I choose the certain amount of €3.75	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
6	I choose the certain amount of €4.50	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
7	I choose the certain amount of €5.25	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
8	I choose the certain amount of €6.00	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
9	I choose the certain amount of €6.75	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
10	I choose the certain amount of €7.50	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
11	I choose the certain amount of €8.25	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
12	I choose the certain amount of €9.00	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
13	I choose the certain amount of €9.75	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
14	I choose the certain amount of €10.50	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
15	I choose the certain amount of €11.25	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
16	I choose the certain amount of €12.00	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
17	I choose the certain amount of €12.75	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
18	I choose the certain amount of €13.50	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
19	I choose the certain amount of €14.25	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball
20	I choose the certain amount of €15.00	A <input type="radio"/> B <input type="radio"/>	I choose to draw a ball

Confirm

Fig. A5. Table setup for eliciting risk preferences. Screenshot from our zTree program.

Appendix B

In this study we used four different production methods to construct urns U2 and U10. These production methods were implemented as four separate treatments, randomized over 17 different sessions. In a companion paper we focus on the question if ambiguity attitudes are influenced by the construction of an ambiguous urn via a between-subjects design. For internal use, we labeled the production methods as: ‘unknown’ ($n = 54$), ‘human’ ($n = 55$), ‘compound’ ($n = 64$) and ‘nature’ ($n = 60$).

Before participants indicated their choices in the multiple list procedure, but after participants had selected their color, we explained the production method and produced urns U2 and U10. After the urns were composed, they were placed in front of the laboratory where all participants could see them throughout the whole session. In this way we removed any suspicion that the urns could be manipulated by the experimenters after they were produced.

In the **unknown production method** we, the experimenters, composed both ambiguous urns before the session started without telling participants how the urns were composed.

For the remaining three production methods we asked a randomly drawn participant (the ‘producer’) to compose both ambiguous urns U2 and U10. The instructions we gave the producer of the urns were publicly explained to all participants. The producer then composed these urns in private. Hence, both the experimenters and the participants were unaware of the composition of the urns. After the producer composed the urns, she was excused from the session.

The **human production method** implied that the randomly selected participant produced urns U2 and U10 in any preferred combination of two colors (for urn U2) or ten colors (for urn U10). Hence, the human production method was very similar to the unknown production method with the exception that not the experimenters but a participant composed the urn.

In the nature and compound production method, the producer was required to compose the urns based on temperatures (for nature) and randomly drawn numbers (for compound). After the sessions participants were able to check whether the producer adhered to this procedure and this was openly communicated to everybody in the room (including the producer).

In the **nature** production method condition, the producer had to look up the actual temperatures in the cities Sydney and Warschau for urn U2 and 10 other publicly revealed cities around the world for urn U10 (via the website Weatherbug, which updates current temperatures every 5 minutes). Urn U2 was produced based on the first number behind the comma of the current temperatures in Sydney and Warschau. For example, if it was 34.6 and 8.2 °C in Sydney respectively Warschau, then the randomly selected participant was instructed to compose urn U2 with 62 green chips ($6 + 2$) and 38 yellow chips ($100 - 62$). For Urn U10, the first number behind the comma of the temperatures in the 10 cities had to be summed up. Then each of the ten numbers had to be divided by the sum and rounded to the nearest integer. These ten rounded percentages determined the number with which each chip color was represented in urn U10.

Finally, the **compound** production method was very similar as the nature production method, only that the numbers did not stem from temperatures, but were randomly drawn from envelopes. The producer had to draw one number from an envelope filled with numbers from 0 to 100. The number she drew determined the number of green chips and the remainder the number of red chips in urn U2. For urn U10 the randomly drawn participant had to draw ten numbers from ten separate envelopes filled with numbers between 0–9. These ten numbers were summed before each number separately had to be divided by the sum and rounded. Again, these ten rounded numbers determined the number with which each chip color was represented in urn U10.

Appendix C

In the section below we provide additional descriptive analyses and perform robustness analyses as also explained in the results section of this paper.

Table C1 shows correlations between our most important experimental variables. Similar to previous research we also find quite some correlations between our measures (Dimmock et al., 2016b; Dimmock et al., 2016a). The indices of ambiguity aversion and likelihood insensitivity are significantly positively correlated. Risk is positively correlated with ambiguity aversion, and weakly with

Table C1
Correlation matrix.

Variable	Index b	Index a	AA0.1	AA0.5	AA0.9	Risk
Index b	1					
Index a	0.321***	1				
AA0.1	0.471***	−0.598***	1			
AA0.5	0.732***	−0.059	0.354***	1		
AA0.9	0.674***	0.881***	−0.148**	0.136**	1	
Risk	0.132**	0.108*	0.019	0.056	0.145**	1
Optimism	−0.074	−0.034	−0.038	−0.033	−0.064	−0.076
Financial Literacy	−0.191***	−0.122*	−0.081	−0.055	−0.198**	0.065
Cognitive reflection test	−0.234***	−0.129**	−0.054	−0.172***	−0.190***	0.086

*** Significant at the 0.01.

** Significant at the 0.05.

* Significant at the 0.1.

Table C2
Ambiguity preferences and likelihood insensitivity explained by demographic variables (OLS estimation).

	Index b	Index a	AA0.1	AA0.5	AA0.9
Risk aversion	0.136** (0.055)	0.157* (0.088)	0.011 (0.034)	0.056 (0.043)	0.136** (0.055)
Financial literacy	−0.026** (0.012)	−0.022 (0.019)	−0.009 (0.007)	−0.003 (0.010)	−0.026** (0.012)
Cognitive reflection test	−0.065*** (0.021)	−0.052 (0.033)	−0.008 (0.012)	−0.040** (0.016)	−0.050** (0.021)
Optimism	−0.002 (0.002)	−0.001 (0.003)	−0.000 (0.001)	−0.001 (0.001)	−0.001 (0.002)
Income	−0.000 (0.000)	0.000			
(0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)		
Age	0.001 (0.003)	−0.003 (0.004)	0.001 (0.001)	−0.001 (0.002)	−0.001 (0.003)
Female	0.009				
(0.015)	0.010 (0.024)	0.002 (0.009)	0.003 (0.012)	0.009 (0.015)	
Economics study	−0.003				
(0.019)	−0.033 (0.031)	0.011 (0.012)	−0.001 (0.015)	−0.015 (0.019)	
Siblings	0.007 (0.006)	0.007			
(0.010)	−0.002 (0.004)	0.008* (0.005)	0.004 (0.006)		
Living expenses	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Constant	0.120 (0.078)	0.321 (0.124)	−0.038 (0.048)	−0.001 (0.061)	0.219 (0.078)
Observations	228	228	228	228	228
F-test	F(10,217) = 2.89	F(10,217) = 1.24	F(10,217) = 0.42	F(10,217) = 1.17	F(10,217) = 2.54
Prob > F	0.0021	0.2675	0.9376	0.3132	0.0066
R-squared	0117	0054	0019	0057	0105

Standard errors reported in parentheses.

*** Significant at the 0.01.

** Significant at the 0.05.

* Significant at the 0.1.

Table C3
Explaining borrowing behavior for conditional borrowers (OLS estimation).

Amount borrowed	(1)	(2)	(3)	(4)	(5)	(6)
Index b	−651.405*** (230.864)	−576.834** (248.701)			−93.108 (411.278)	
Index a	112.304 (164.915)	108.64 (170.088)			−88.776 (225.407)	
AA0.1			−30.131 (402.437)	75.690 (420.903)		450.383 (623.931)
AA0.5			−901.552*** (287.343)	−873.240*** (295.381)		−431.400 (461.175)
AA0.9			−72.901 (244.777)	−14.371 (258.063)		−15.524 (327.719)
Risk aversion		−92.178 (193.437)		−134.070 (190.353)	−149.005 (244.914)	−164.144 (245.414)
Financial literacy		26.995 (41.188)		33.399 (83.634)	41.166 (56.112)	44.910 (56.2444)
Cognitive reflection test		47.927 (85.191)		33.431 (83.634)	109.054 (109.502)	85.050 (112.135)
Income	−0.184** (0.089)	−0.187 (0.093)	−0.195** (0.087)	−0.206** (0.091)	−0.209 (0.137)	−0.217** (0.137)
Study years	30.205*** (10.340)	29.907*** (10.741)	32.192*** (10.194)	32.590*** (10.591)	23.840 (15.793)	29.175* (16.678)
Female	−24.947 (56.652)	−10.677 (60.846)	−58.411 (58.256)	−45.954 (62.117)	−27.280 (76.701)	−50.668 (80.223)
Economic study	235.786** (89.953)	226.395** (94.031)	227.506** (88.329)	215.275** (92.130)	236.018* (139.412)	245.113* (139.727)
Siblings	45.599** (20.585)	45.540** (22.339)	45.483** (20.190)	43.977** (21.861)	3.887 (29.445)	2.775 (29.469)
Live on own	183.045** (80.231)	193.947** (82.583)	156.483** (79.906)	164.034** (82.165)	114.886 (126.482)	91.122 (128.727)
Constant	224.010 (102.863)	168.184 (192.215)	271.896 (103.950)	242.220 (195.501)	281.451 (260.794)	324.803 (264.431)
Observations	76	76	76	76	46	46
Consistent sample	0	0	0	0	1	1
F test	F(8,67) = 4.19	F(11,64) = 3.06	F(9,66) = 4.28	F(12,63) = 3.26	F(11,34) = 1.04	F(12,33) = 1.04
Prob > F	0.0000	0.0024	0.0002	0.0011	0.4354	0.4416
Adjusted R-squared	0.254	0.232	0.282	0.265	0.0096	0.0094

Standard errors reported in parentheses.

*** Significant at the 0.01.

** Significant at the 0.05.

* Significant at the 0.1.

Table C4

Robustness checks for production method (for conditional borrowers).

Amount borrowed	(1)	(2)	(3)	(4)
Index b	–613.915** (233.867)	–560.591** (254.354)		
Index a	100.326 (164.116)	95.398 (170.500)		
AA0.1			71.876 (423.340)	197.463 (449.591)
AA0.5			–917.825*** (303.666)	–915.562*** (312.127)
AA0.9			–37.339 (249.630)	23.737 (266.746)
Risk aversion		–88.363 (195.025)		–155.937 (192.966)
Financial literacy		16.142 (42.405)		21.694 (41.427)
Cognitive reflection test		18.676 (86.785)		6.709 (84.805)
Income	–0.180** (0.088)	–0.187** (0.093)	–0.189** (0.087)	–0.204** (0.091)
Study years	29.316*** (10.400)	29.825*** (10.893)	32.577*** (10.322)	34.288*** (10.841)
Female	–16.350 (58.769)	–11.271 (62.381)	–43.884 (59.274)	–42.353 (62.680)
Economic study	230.031** (92.339)	227.968** (96.620)	229.095** (90.416)	227.383** (94.191)
Siblings	45.832** (20.764)	44.288** (22.507)	48.634** (20.383)	45.039** (21.944)
Live on own	175.738** (80.483)	179.904** (83.597)	140.288* (80.903)	138.629* (83.953)
Human	–48.204 (74.433)	–43.716 (77.498)	–99.288 (77.505)	–100.250 (80.441)
Compound	63.635 (72.164)	56.123 (74.685)	8.859 (76.107)	–6.741 (79.021)
Nature	75.287 (71.303)	75.137 (73.500)	38.243 (72.389)	36.555 (74.090)
Constant	201.406 (106.168)	198.881 (202.591)	–38.243 (72.389)	–95.480 (67.075)
Observations	76	76	76	76
F test	F (11,64) = 3.44	F (14,61) = 2.63	F (12,63) = 3.60	F (15,60) = 2.86
Prob > F	0.0008	0.0048	0.0004	0.0020
Adjusted R-squared	0.264	0.233	0.294	0.271

Standard errors reported in parentheses.

*** Significant at the 0.01.

** Significant at the 0.05.

* Significant at the 0.1.

Table C5

Determinants of the amount borrowed (tobit estimation on the whole sample).

Amount borrowed	(1)	(2)	(3)	(4)	(5)	(6)
Index b	–77.230 (399.671)	–111.847 (412.021)			360.405 (539.352)	
Index a	80.024 (266.513)	87.697 (266.519)			–37.476 (300.325)	
AA0.1			–225.876 (704.009)	–323.850 (706.123)		–387.479 (826.781)
AA0.5			16.901 (537.625)	52.573 (540.235)		914.905 (679.145)
AA0.9			21.870 (398.635)	–15.120 (410.830)		–70.057 (464.488)
Risk aversion		–331.274 (318.681)		–329.767 (319.189)	–197.933 (348.017)	–218.331 (348.259)
Financial literacy		–106.101 (71.246)		–108.391 (71.825)	–71.780 (80.824)	–80.812 (81.211)
Cognitive reflection test		–29.084 (128.532)		–27.249 (128.793)	–143.465 (150.865)	–128.924 (150.645)
Income	0.028 (0.128)	0.037 (0.128)	0.028 (0.128)	0.036 (0.128)	–0.072 (0.141)	–0.217** (0.137)
Study years	27.167 (17.703)	28.225 (17.576)	27.162 (17.712)	28.213 (17.592)	20.416 (21.231)	17.103 (21.376)
Female	–23.499 (88.599)	–45.872 (90.540)	–22.358 (89.009)	–44.049 (90.897)	–165.160 (104.788)	–156.401 (104.444)
Economic study	–228.236* (124.048)	–159.302 (127.675)	–227.922* (124.112)	–157.934 (127.838)	–295.130* (157.415)	–288.963* (156.849)
Siblings	51.054 (34.885)	42.521 (35.128)	50.563 (35.056)	41.563 (35.325)	–7.293 (40.522)	–9.889 (40.533)
Live on own	303.805** (119.483)	301.967** (118.981)	305.268** (119.991)	304.773** (119.594)	388.097*** (144.050)	405.551 (145.059)
Constant	–576.797 (165.834)	–122.016 (281.865)	–578.419 (166.415)	–121.561 (282.327)	–20.731 (315.521)	–1.645 (316.192)
Observations	228	228	228	228	136	136
Consistent sample	0	0	0	0	1	1
LR chi2	chi2(8) = 21.31	chi2(11) = 25.05	chi2(9) = 21.33	chi2(12) = 25.13	chi2(11) = 18.80	chi2(12) = 20.23
Prob > chi2	0.0064	0.0090	0.0113	0.0142	0.0649	0.0628
Pseudo R2	0.016	0.019	0.016	0.019	0.0237	0.0255

Standard errors reported in parentheses.

*** Significant at the 0.01.

** Significant at the 0.05.

* Significant at the 0.1.

likelihood insensitivity. As financial literacy and scores on the cognitive reflection test are both negatively correlated with ambiguity aversion and likelihood insensitivity, ambiguity attitudes can somewhat be explained as a cognitive bias (as also put forward by Wakker (2010)). Surprisingly general optimism and pessimism do not correlate with matching probabilities of 0.1, respectively 0.9. This indicates that general optimism and pessimism are different from the optimism and pessimism labels we use when we refer to participants, that respectively overweight and underweight likelihoods of 0.1 and 0.9.

Table C2 shows that bivariate correlations between ambiguity aversion (index b) and risk, financial literacy and scores on the cognitive reflection test hold when controlling for other demographic variables. Only the effect of risk remains prevalent,

however, when explaining likelihood insensitivity in a multivariate model.

Secondly, we perform several robustness checks to validate initial findings between ambiguity aversion and the amount students were willing to borrow. These initial reported findings are shown in Table C3. We controlled for production method (Table C4) of the ambiguous urn and session effects.

In Table C4 we reran our main OLS regression model with three dummy variables relating to the production methods (we left the unknown production method out as benchmark). We also reran the same model by adding all sessions as separate dummy variables (unreported). The results from Table C4 remain qualitatively valid.

However, when we control for consistency in decision-making (models 5–6 in Table C3) and run a Tobit regression (Table C5), our

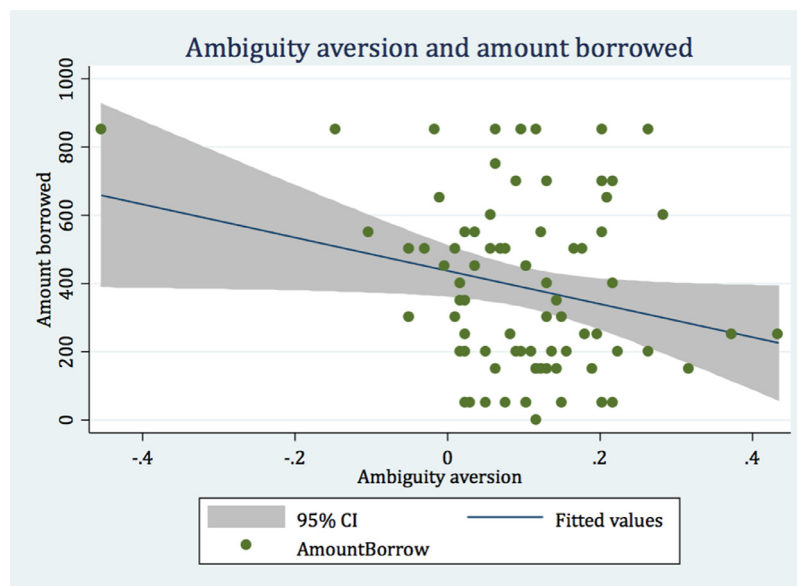


Fig. C6. Scatter plot ambiguity aversion and amount borrowed within sample of borrowers ($n = 76$).

results do not hold anymore. Please see Fig. C6 for a huge outlier which affected our initial findings reported in Table C3.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.socrec.2016.12.001](https://doi.org/10.1016/j.socrec.2016.12.001).

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