Attitudes to Uncertainty and Household Decisions*

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Abstract

We comprehensively study uncertainty attitudes in a large representative household survey. Our incentivized experiments elicit various measures of risk, loss and ambiguity aversion, probability weighting parameters as well as subjective expectations and relate them to outcomes related to health prevention or financial decision making. We find that there is substantial variation across gender, age and region in these measures. Women, for example, are found to be more risk averse and loss averse, but also less ambiguity averse compared to men. These differences tend to be sizeable enough to generate significant differences in the outcomes we study. Conditional on knowing a person's risk aversion their degree of loss aversion as well as ambiguity aversion still explains an important part of the variation in economic outcomes. In terms of measurements, while lottery based measures based on price lists tend to work quite well for risk and loss aversion, a simple survey-style question works much better than our lottery based measures for ambiguity aversion.

Keywords: Uncertainty Attitudes, Subjective Expectations, Household Behaviour, Survey Design;

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1 Introduction

Over the last two decades Economics has seen a large amount research into non-standard models of decision-making (Starmer, 2000). One particular focus has been on modeling broader attitudes to uncertainty as in prospect theory with its many variants (Kahnemann and Tversky, 1979; Tversky and Kahmemann, 1992; Prelec, 1998; Wakker, 2010; Barberis, 2013) or in theories of ambiguity aversion (Gilboa and Marinacci, 2013). These models have partly been developed as a result of findings in lab experiments and experimentalists have extensively studied ways to measure these uncertainty attitudes often using choices between lotteries.[1] While these measures are well understood in the lab, there is much less evidence on how important these broader measures of uncertainty are in explaining people's everyday decisions.

Our paper aims to provide a comprehensive measurement and analysis of broader attitudes to uncertainty in a representative population. We elicited various measures of risk, loss and ambiguity aversion as well as probability weighting parameters using incentivized experiments in a large representative sample of the UK population. We then ask how well these measures can explain outcomes related to health prevention or financial decision making. In order to understand to which extent people perceive ambiguity for different events, we also comprehensively elicit subjective expectations. Our paper also has a methodological contribution. As broader uncertainty attitudes are not typically measured in general social surveys, little is known on the optimal question format for such surveys. As we elicit a variety of lottery based as well as simpler measures, our research also allows us to compare several ways of eliciting these broader attitudes in general surveys.

We find that there is substantial variation across gender, age and region in these measures. Women, for example, are found to be more risk averse and loss averse, but also less ambiguity averse compared to men. Londoners are less risk averse and ambiguity averse, but more loss averse compared to the rest of the UK. These differences tend to be sizeable enough to generate significant differences in the outcomes we study. Conditional on knowing a person's risk aversion their degree of loss aversion as well as ambiguity aversion still explains an important part of the variation in economic outcomes. In terms of measurements, while lottery based measures based on price lists tend to work quite well for risk and loss aversion, a simple survey-style question works much better than our lottery based measures for ambiguity aversion.

Our paper contributes to existing literature on how uncertainty attitudes shape household decisions. The vast majority of existing research has focused uniquely on risk attitudes (Barsky et al., 1997; Khwaja et al., 2006; Bonin et al., 2007; Guiso and Paiella, 2008; Dohmen et al., 2011) and has demonstrated that risk preferences are related to various risky decisions, including being self-employed, migrating, and holding risky assets.[2] Much less attention has been paid to other measures of uncertainty attitude. (Dimmock et al., 2016) study attitudes to ambiguity in a sample representative of the Dutch population and find that ambiguity aversion is negatively related to stock market participation, but only for people who perceive stock returns as highly ambiguous. Noussair et al. (2014) find evidence that higher order risk attitudes (referred to as "prudence" and "temperance") affect saving behaviour and portfolio choices in the same Dutch household panel. We contribute to this literature by comprehensively eliciting risk and ambiguity attitudes, loss aversion and probability weighting parameters, which enables us to ask how much more of the variation in household choices under uncertainty we can explain if we elicit their broader attitudes to uncertainty, like ambiguity

[1] See among many others Ellsberg (1961); Camerer (1989); Starmer (1992); Hey and Orme (1994); Thaler et al. (1997); Holt and Laury (2002); Schmidt and Traub (2002); Holt and Laury (2005); Halevy (2007); Harbaugh et al. (2010); Ahn et al. (2014) or Trautmann and van de Kuilen (2015)

[2] There is also some research on whether risk preferences are stable across different contexts finding mixed results (Barseghyan et al., 2011; Einav et al., 2012)

or loss aversion, in addition to their risk aversion.

Our research also contributes to literature on how attitudes to uncertainty are related to individual characteristics, such as gender, age, or sometimes cognitive ability. Existing literature has mostly focused on the determinants of risk attitudes. Dohmen et al. (2011), von Gaudecker et al. (2011) and Noussair et al. (2014) provide evidence that risk attitudes are shaped by gender and age in large representative samples in Germany and the Netherlands, respectively. Falk et al. (2017) provide evidence from a "globally representative" sample covering 76 countries. In their study women are substantially more risk averse than men, by about a fifth of a standard deviation. Croson and Gneezy (2009) summarize evidence from lab experiments and show that in a majority of studies women are more risk averse, but effect sizes are heterogeneous, and roughly 40% of studies do not find a gender difference, possibly due to small sample sizes (Niederle, 2014).

To our knowledge our study is the first to comprehensively study more general measures of uncertainty in a representative sample. Our results show that, while gender and age are also important determinants of other measures, not just risk aversion, the sign and size of the effect differs across different types of uncertainty attitude with, for example, women being more risk and loss averse than men (von Gaudecker et al., 2011), but less ambiguity averse. A second contribution is that we consider both incentivized (lottery choice based) as well as non-incentivized (survey-based) measures of these different uncertainty attitudes allowing us to understand the relationship not only between different types of uncertainty attitude, but also between incentivized and non-incentivized measures.[3] Because implementing real incentives for large representative samples is complex, the latter question has received already some attention. Dohmen et al. (2011), Noussair et al. (2014) and von Gaudecker et al. (2011) have compared incentivized and non-incentivized questions for risky choices and found no differences, while Dimmock et al. (2016) did find a difference for ambiguity attitudes. We do find differences both for risk and ambiguity attitude, but they are not large and it is not always clear whether the incentivized measure does better.

The paper is organized as follows. In Section 2 we discuss our sample, the design of the experiments and procedures. Section 3 focuses on demographics and exogenous determinants of risk attitude. Section 4 shows how uncertainty attitudes relate to household behaviour. Section 5 focuses on subjective expectations and contains our structural results and Section 6 concludes.

2 Design and Procedures

Our survey consisted of six different modules. In modules (I)-(IV) we elicited uncertainty attitudes using a variety of prominent measures from the literature, in module (V) we asked participants a number of questions on their everyday choices in situations under uncertainty and in module (VI) we elicited subjective probabilities for some of the events associated with module (V). Modules (II)-(IV) were incentivized, i.e. respondents were paid (in cash) according to the choices they made, while a fixed fee of 5GBP was paid for responses to modules (I), (V), (VI). We randomized the order in which modules appeared with the following three sequences each administered to a third of the sample: (I)-(II)-(III)-(IV)-(V)-(VI); (V)-(VI)-(I)-(II)-(III)-(IV); (V)-(VI)-(I)-(II)-(IV)-(III).[4] Within

[3]Vieider et al. (2015) also consider various measures of risk and other uncertainty attitudes in a large sample of University students. See also Haridon et al. (2017).

[4]The reason why we picked three sequences was to be able to control for order effects, while at the same time ensuring a "high" expected sample size within each order. We chose the specific sequences as we wanted to have the real life outcomes sometimes first and sometimes last, the loss aversion module last at least once, as it can involve negative payments and the risk aversion modules always before the loss and ambiguity modules as they are cognitively easier to understand and will help participants gain familiarity with the "wheels of fortune" question format in a relatively simpler setting.

each module questions appeared in fixed order. Next, we now describe each of these modules in detail.

2.1 Measures of Uncertainty Attitude

(I) Simple Risk and Ambiguity Measures In the first module we elicited risk and ambiguity attitudes using simple questions as in Dohmen et al. (2011). In particular we asked participants the following questions

> On a scale from 1,...,10 with 1 being "not at all willing" and 10 being "very willing": "How willing are you to take risks, in general, *if you know the odds associated with different outcomes*?"

and

> On a scale from 1,...,10 with 1 being "not at all willing" and 10 being "very willing": "How willing are you to take risks, in general, *if you do not know the odds associated with different outcomes*?"

Based on these questions we measure risk aversion by $R_i^D = 11 - a_i^1$, where a_i^1 is i's answer to the first question and ambiguity aversion by $AA_i^D = 11 - a_i^2 - R_i^D$, where a_i^1 is i's answer to the second question. While the first question has been found to explain behaviour well in Dohmen et al. (2011), these measures do not allow to link answers to a preference structure or to make interpersonal comparisons of the type i is more/less risk averse than j. However, both Dohmen et al. (2011) and Falk et al. (2016) have found that these simple measure correlates well with incentivized measures in lab experiments. Below we will discuss how the R^D measure correlates with other measures of risk attitude we elicit in our survey.

(II) CRRA parameter from Holt and Laury (2002) Lotteries The second measure infers a CRRA parameter from a sequence of lottery choices as in Holt and Laury (2002). In particular, participants choose between two lotteries (wheels of fortune), where wheel A pays 20 GBP with probability p and 16 GBP with $1-p$ and wheel B pays 38 GBP with probability p and 1 GBP with $1-p$. Across ten questions p increases from 0.1 to 1 in steps of 0.1. From these choices we infer risk aversion parameter γ^{HL} from the following class of CRRA utility functions $u(x) = x^{\gamma}$.[5] We deal with multiple switches by averaging the γ^{HL} implied by each of them .

(III) Risk (CRRA) preferences and Loss Aversion from Tanaka et al. (2010) Lotteries The third module elicits risk attitudes by using lotteries from Tanaka et al. (2010). See Table XXX in Appendix A for details and for the precise set of lotteries used. As Tanaka et al. (2010)'s lotteries involve both gains and losses, this allows us to estimate a loss aversion parameter. Specifically, the risk aversion parameter γ is jointly identified with a probability weighting parameter α and a loss aversion parameter λ (see below) from the following class of utility functions

$$u(x) = \begin{cases} x^{\gamma} & \text{if } x > 0 \\ -\lambda(-x)^{\gamma} & \text{else} \end{cases}$$

In terms of probability weighting, we consider the following probability weighting function due to Prelec

[5] If e.g. a participant chooses wheel A in questions 1,...,5 and wheel B in questions 6,...,10, then we know that $0.59 < \gamma^{HL} < 0.81$. As an estimate of γ^{HL}, we then use the mean of this interval, i.e. in this case $\hat{\gamma}^{HL} = 0.7$.

$$\pi(p) = \left(\frac{1}{\exp(\ln \frac{1}{p})^{\alpha}} \right)^{\beta}. \quad (1)$$

Tanaka et al. (2010) assume that $\beta = 1$ and then estimate α jointly with the risk aversion parameter γ^T. If $\beta = 1$, then $\pi(p) = p$ whenever $\alpha = 1$, which corresponds to the standard case.

(IV) Ambiguity Attitudes Module (IV) elicits ambiguity attitudes following the matching probabilities procedure (see e.g. (Abdellaoui et al., 2011; Dimmock et al., 2016)). In this module, participants are presented with two types of wheels of fortune, some where the probabilities of winning are known (known wheels) and some where they are unknown (unknown wheels). The known wheels are used to estimate a CRRA parameter which is then used to estimate parameters $(\hat{\alpha}, \hat{\beta})$ for probability weighting functions $\pi(p)$. Apart from the weighting function described in (1), we also consider a linear weighting function $\pi(p) = \alpha + \beta p$. For details see Appendix A. Matching probabilities are then defined as $m(p) = \pi(p, \hat{\alpha}, \hat{\beta})$. Following Abdellaoui et al. (2011) and Dimmock et al. (2016) we can then define an agent's ambiguity aversion for different levels of p as

$$AA_p = p - m(p) \quad (2)$$

An agent is ambiguity averse $AA_p > 0$, ambiguity neutral if $AA_p = 0$ and ambiguity seeking if $AA_p < 0$. For each weighting function we have three points AA_p at $p = 0.25, 0.5, 0.75$.

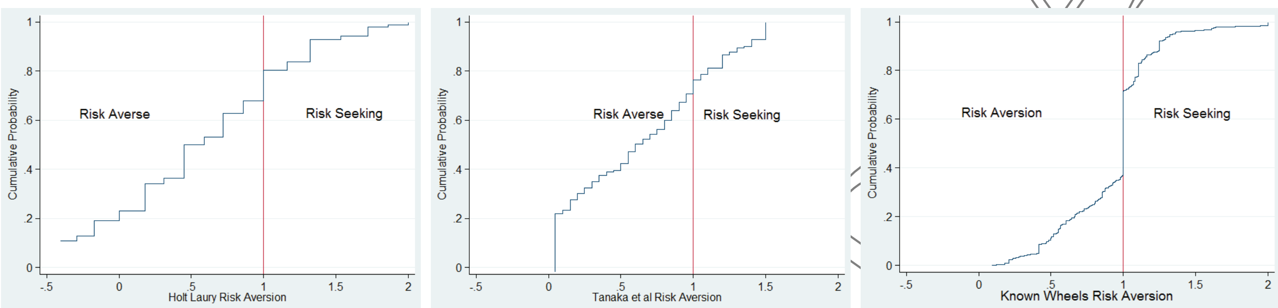
Descriptives and Correlation among Measures Table 1 shows descriptive statistics and pairwise correlation of risk measures and loss aversion. In terms of their descriptive statistics, by and large our measures are in line with previous literature. The exception is maybe the R^D measure, where we find a mean of 2.39 (sd 1.98) compared to a mean of 6.57 (sd 2.38) found by Dohmen et al. (2011). Our participants, hence indicate less risk aversion than those in Dohmen et al. (2011) on the 1,...,10 scale. One possible explanation for this difference could be that our question singles out situations with *known* odds. Indeed, when we ask participants about *unknown* odds we find a mean of 6 (sd 1.92) very much in line with Dohmen et al. (2011). This suggests that many participants could have situations with unknown probabilities in mind when they answer the question as posed in Dohmen et al. (2011). This conjecture is further supported by the fact that for the measures of risk attitude based on lottery choices (with known odds) we find measures that are very much in line with previous literature.

The mean value of our measure $1 - \gamma^{HL}$ is 0.431 with a median of 0.480, while Holt and Laury (2002) find that $1-\gamma$ is "centered around the $0.3-0.5$ range" (p. 1649) across their three treatments. The mean value of γ^T we obtain is $\gamma^T = 0.647$ and the median is 0.6 ($n = 818$).[6] Tanaka et al. (2010) obtain a mean value of 0.59 in one part and 0.63 in another part of their sample. Our estimates are, hence, well in line with what previous literature has found. The mean value of $1 - \gamma^K$ is somewhat lower, though it should be noted that it correlates well with the other measures. Pairwise correlations among other measures of risk aversion are all positive and highly statistically significant with coefficients ranging between 0.0571 to 0.2603. While these are not very high, they are line with correlations identified in prior literature. Figure 1 illustrates the cdfs of our measures γ^{HL}, γ^T and γ^K. According to all measures 20-25 percent of respondents are classified as risk-seeking and a further 5-10 percent as risk-neutral according to γ^{HL}, γ^T with almost 40 percent behaving in a risk-neutral manner according to γ^K.

[6] We can also estimate γ^T under standard EU assumptions, i.e. by assuming that $\alpha = 1$. In this case we obtain a mean of 0.585 (median 0.55).

	Descriptive Statistics				Pairwise correlation			
	n	mean	median	SD	R^D	$1-\gamma^{HL}$	$1-\gamma^{T}$	$1-\gamma^{K}$
R^D	877	2.939	2	1.98	1			
$1-\gamma^{HL}$	872	0.431	0.480	0.61	0.2603***	1		
$1-\gamma^{T}$	818	0.353	0.400		0.0571	0.0970***	1	
$1-\gamma^{K}$	863	0.076	0		0.1384***	0.1747***	0.0622***	1
λ	826	2.984	1.170	3.76				
α^T	874	0.754	0.800					

Table 1: Descriptive Statistics and pairwise correlation of risk measures, loss aversion and probability weighting parameters.



(a) γ^{HL} (b) γ^{T} (c) γ^{K}

Figure 1: CDF of risk aversion parameters γ^{HL}, γ^{T} and γ^{K} .

For the loss aversion parameter λ we find a mean of 2.984 (median 1.170) based on 826 observations. Tanaka et al. (2010) find a mean λ of 2.63 and Tversky and Kahmemann (1992) found a mean of 2.25. Our estimate is hence slightly higher than those. For the probability weighting parameter α Tanaka et al. (2010) find a mean of 0.74 compared to our 0.754. Figure 3 in Appendix C illustrates a probability weighting function based on this value of α.

Table 2 summarizes information on our measures of ambiguity. The mean of the simple measure elicited in module (I) is 2.74 and 78% of participants are classified as ambiguity averse according to this measure. Since this is a new measure we introduce, there are no comparisons to existing literature for these numbers. Ambiguity aversion elicited in module (IV) changes with the ambiguity neutral probability p. While for $p = 0.25$ most people are classified as ambiguity seeking, for $p = 0.75$ most are classified as ambiguity averse. For $p = 0.5$ there are somewhat more ambiguity averse than ambiguity seeking people, but the difference is smaller than with $p = 0.75$. For comparison Dimmock et al. (2016), using the linear probability weighting function, obtain mean values of $(AA_{0.1}, AA_{0.5}, AA_{0.9}) = (-0.12, 0.10, 0.21)$ with SD of $(0.25, 0.24, 0.33)$. In terms of the share of ambiguity averse people they find that $(0.33, 0.68, 0.53)$ percent, respectively, are classified as ambiguity-averse in their three cases and $(0.49, 0.22, 0.35)$ as ambiguity-seeking with the remainder classified ambiguity-neutral. This is in line with our findings. In terms of the pairwise correlation between the different measures of ambiguity aversion we find that the measures elicited via matching probabilities are all strongly correlated among each other, while the measure based on the simple question shows only a weak, but still positive correlation with the former.

2.2 Outcomes and Subjective Probabilities

(V) Outcomes Module (V) elicited information on participants' real life choices under risk/ambiguity in the following areas: (i) health prevention, in particular whether they smoke, got a flu vaccine or a Cervical Screening, (ii) insurance choices for car, health and home insurance and (iii) gambling, in

	AA^D		Share who are Ambiguity...			Correlation with...		
	Mean	SD	Averse	Neutral	Seeking	$AA_{0.5}$ (Lin)	$AA_{0.5}$ (PR1)	$AA_{0.5}$ (PR2)
AA^D	2.74	2.15	0.78	0.18	0.04	0.0631*	0.0764**	0.0566*
	$AA_{0.25}$		Share who are Ambiguity...			Correlation with...		
	Mean	SD	Averse	Neutral	Seeking	$AA_{0.5}$ (Lin)	$AA_{0.5}$ (PR1)	$AA_{0.5}$ (PR2)
$p = 0.25$								
Linear	-0.16	0.15	0.16	0.01	0.84	0.9635***	0.8691***	0.6323***
Prelec I	-0.03	0.07	0.37	0.09	0.53	0.4635***	0.9389***	0.4321***
Prelec II	-0.13	0.20	0.42	0.05	0.52	0.2277***	0.4503***	0.8553***
	$AA_{0.5}$		Share who are Ambiguity...			Correlation with...		
	Mean	SD	Averse	Neutral	Seeking	$AA_{0.5}$ (Lin)	$AA_{0.5}$ (PR1)	$AA_{0.5}$ (PR2)
$p = 0.5$								
Linear	0.03	0.15	0.55	0.08	0.37	1	-	-
Prelec I	0.03	0.07	0.53	0.08	0.37	0.8932***	1	-
Prelec II	0.00	0.21	0.50	0.05	0.45	0.6292***	0.7800***	1
	$AA_{0.75}$		Share who are Ambiguity...			Correlation with...		
	Mean	SD	Averse	Neutral	Seeking	$AA_{0.5}$ (Lin)	$AA_{0.5}$ (PR1)	$AA_{0.5}$ (PR2)
$p = 0.75$								
Linear	0.25	0.22	0.86	0.00	0.14	0.9443***	0.8328***	0.5621***
Prelec I	0.13	0.20	0.54	0.09	0.37	0.8737***	0.9959***	0.7812***
Prelec II	0.13	0.25	0.53	0.05	0.41	0.7956***	0.8731***	0.9274***

Table 2: Mean and SD of ambiguity aversion measure for different probability weighting functions and ambiguity neutral probabilities p.

particular about their engagement in sports betting, the national lottery and their participation in the stock market. In addition we asked them whether they would accept a free holiday to Tunisia, as the questionnaire was fielded shortly after the 2015 Tunisia terror attack which was heavily covered in British media. The precise list of questions can be found in Appendix A.

(VI) Subjective Probabilities We also elicited subjective probabilities for some outcomes as follows. We first asked participants how likely they thought an event was. After they indicated a probability we asked them whether they meant this more as an exact probability or whether they had a "range in mind". If they indicated the latter, then we also asked them to specify what range approximately (see Giustinelli and Pavoni (2017) for a similar methodology).

The events we elicited subjective probabilities for were (i) the chance to get the flu in the next 12 months, (ii) the chance that someone in your family is at fault of a car accident ever (iii) the chance to get cervical cancer in the next 15 years (women only) (iv) the chance of a man (woman) to get lung cancer if he smokes at least one cigarette a day for 20 years (v) the chance that the FTSE 100 Index of the London Stock Exchange will have grown by 5 percent or more one year from now (vi) how likely it is to win the lottery if you buy a national lottery ticket (vii) how likely is it to win some money if you engage in [....] betting (only those who indicated to bet on certain sports). The precise list of questions can be found in Appendix A. Across questions between 37 percent (lottery) to 50 percent (car accident) of participants indicated that they meant the probability indicated as an exact probability. The rest indicated ranges.

2.3 Procedures and Sample Properties

Invitations to participate in our survey were sent to all potential respondents from the IP8 wave in November 2015. Those are 2378 people. Potential participants were sent 5GBP in cash with the original invitation. This has been shown to increase the chances of survey completion **(REF)**. They were also sent three reminders between November 2015 - January 2016 to complete the survey, which closed in February. In total 886 people (37%) responded. Table 3 shows some characteristics of respondents and non-respondents. Respondents differ from non-respondents in terms of their marital status and their ethnicity, but not in terms of gender or age. Both sample are also largely similar in terms of decisions under risk (including a lottery based measure of risk attitude elicited in IP8) with the exception of smoking where the sample of respondents contains more non-smokers. Conditional on initiating the survey, the response rates across the different parts of the questionnaire range between 91% (Loss Aversion segment) to 98% (real-life questions). Not all of these answered all questions in each segment. The number of participants who answered all questions in the entire survey is xxxx.

	Non Respondents	Respondents	p-value
Basic Demographics			
Gender	0.534	0.526	0.707
Age	44.84	45.88	0.175
Pensioner	0.202	0.178	0.145
Marital Status			
Single	0.349	0.270	0.008
Married	0.443	0.613	0.001
Divorced	0.109	0.074	0.006
Number of Children	0.694	0.599	0.036
Ethnicity			
White/British	0.798	0.880	0.100
Black	0.112	0.069	0.001
Attitudes			
Financial Situation	2.355	2.013	0.001
Life Satisfaction	6.613	6.771	0.186
Left/Right Political	5.006	5.131	0.183
Geographical Area			
Rural Area	1.226	1.250	0.190
London Area	0.122	0.082	0.003
Decisions			
Self Employed	0.122	0.106	0.354
Interest Savings	284.57	361.66	0.280
Non-Smoker	0.809	0.912	0.001
Risk Preference	8.566	9.184	0.291

Table 3: Sample properties of non respondents and respondents.

After the survey ended we drew 100 participants at random. For each participant drawn we then picked one of the questions at random. If a question from modules (I), (V) or (VI) was drawn they received an additional 5 GBP if they had answered that question. If a question from modules (II)-(IV) was drawn they were paid according to their choice. Participants were informed about this procedure in the invitation letter. Overall payments ranged from 5GBP (for those who were not selected) to 92 GBP. Conditional on being selected average payments were ≈ 31 GBP and the overall average payment was ≈ 7.90 GBP.

3 Determinants of Uncertainty Attitude

3.1 Exogenous determinants of uncertainty attitude

Tables 1 and 2 in Section 2.1 revealed substantial heterogeneity in individual attitudes towards risk, ambiguity and in loss aversion. In this section we try to uncover whether some of the heterogeneity in attitudes to uncertainty is systematic and could thus leading to differences in economic decisions across different types of individuals. We focus on the impact of four personal characteristics: gender, age, ethnicity and religion. These characteristics are plausibly exogenous with respect to individual attitudes towards uncertainty, and thus allow us to give a causal interpretation to correlations and regression results. There are also important implications if these characteristics have an impact on uncertainty attitudes. For example, a gender difference in risk attitudes could be part of the explanation for gender differences in social behavior and economic outcomes that have been widely documented (Goldin and Rouse, 2000; Leibbrandt and List, 2015)

	(1) R^D	(2) R^D	(3) R^D	(4) $1-\gamma^{HL}$	(5) $1-\gamma^{HL}$	(6) $1-\gamma^{HL}$
female	0.736***	0.443***	0.466***	0.118***	0.103**	0.103**
	(0.136)	(0.114)	(0.114)	(0.041)	(0.042)	(0.044)
age	0.020***	0.024***	0.019***	0.007***	0.007***	0.007***
	(0.004)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
white	0.255	0.244	0.411*	-0.046	-0.033	-0.060
	(0.229)	(0.203)	(0.223)	(0.079)	(0.078)	(0.091)
anglican	0.368	0.151	0.224	-0.0560	-0.0406	0.106**
	(0.232)	(0.191)	(0.144)	(0.0889)	(0.0891)	(0.0534)
catholic	0.229	0.244	0.352*	0.131	0.120	0.131
	(0.245)	(0.188)	(0.192)	(0.0841)	(0.0842)	(0.0840)
other relig	0.281	0.188	-0.024	-0.002	-0.002	-0.057
	(0.248)	(0.220)	(0.244)	(0.095)	(0.094)	(0.111)
AA^D		-0.529***	-0.525***			
		(0.0251)	(0.0261)			
$AA_{0.5}(PR1)$					-0.621**	-0.583**
					(0.268)	(0.275)
Constant	1.179***	2.763***	3.412***	0.196	0.205*	0.267
	(0.370)	(0.332)	(0.442)	(0.124)	(0.123)	(0.171)
Observations	877	876	843	851	842	810
Additional Controls	NO	NO	YES	NO	NO	YES
R-squared	0.067	0.384	0.415	0.053	0.061	0.078

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: The table presents results from OLS estimations of risk attitude on a number of demographic characteristics. Additional Controls include region fixed effects for 11 government office regions as well as additional dummies for religion, education, marital status, the number of children and a dummy for whether a person lives in a rural area or not.

We run OLS regressions, where we regress our various measures of uncertainty attitude on demographic explanatory variables. All estimation results report robust standard errors. The only sample restriction is the omission of individuals with missing values for the variables in a given regression. Table 4 focuses on our measures of risk aversion R^D and $1-\gamma^{HL}$, while Table 5 focuses on the risk aversion measure $1-\gamma^{HL}$ as well as our measure of loss aversion λ. In columns (1) and (4) of each table, our baseline specification, we regress our measures of uncertainty attitude on gender, age, ethnicity and religion, which to us are all plausibly exogenous. Other columns control additionally for measures of ambiguity elicited in the same module[7] as well as possibly additional demographics which could potentially be endogenous, such as geographic location, education, marital status or the number of children (columns (3) and (6) in Table 4 and columns (3) and (5) in Table 5).

In line with a substantial body of evidence from lab experiments (Eckel and Grossmann, 2008; Croson and Gneezy, 2009) as well as some previous survey measures (Dohmen et al., 2011) and experiments in household panels (von Gaudecker et al., 2011), we uncover substantial gender differences. Women tend to be more risk averse according to all of our measures, though the effect is only statistically significant for the R^D and $1-\gamma^{HL}$ measures. For these measures, though, the effect is very robust appearing for both sets of control variables as well as when ambiguity attitude is controlled for. Importantly, the effect is also quantitatively significant. Given that one standard

[7]For the HL measure we control for the $AA_{0.5}(PR1)$ measure elicited in module (IV). Results are qualitatively the same and quantitatively very similar if we control for other measures of ambiguity aversion.

	(1) $1-\gamma^T$	(2) $1-\gamma^T$	(3) $1-\gamma^T$	(4) λ	(5) λ
female	0.020	0.046	0.054	0.829***	0.812***
	(0.034)	(0.033)	(0.034)	(0.269)	(0.287)
age	0.002*	0.001*	0.002*	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.008)	(0.010)
white	0.094	0.090	0.059	-0.004	-0.119
	(0.071)	(0.069)	(0.082)	(0.531)	(0.750)
anglican	-0.050	-0.059	0.042	0.008	0.276
	(0.060)	(0.059)	(0.044)	(0.603)	(0.378)
catholic	-0.009	-0.009	-0.014	0.115	0.181
	(0.068)	(0.067)	(0.068)	(0.581)	(0.576)
other relig	-0.090	-0.101	-0.108	-0.500	-0.558
	(0.078)	(0.077)	(0.087)	(0.568)	(0.648)
λ		-0.033***	-0.033***		
		(0.004)	(0.004)		
Constant	0.207**	0.301***	0.196	2.799***	3.364***
	0.016	0.085	0.108	0.015	0.036
Observations	804	792	761	812	780
Additional Controls	NO	NO	YES	NO	YES
R-squared	0.014	0.083	0.106	0.014	0.035

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: The table presents results from OLS estimations of risk attitude (columns (1)-(3)) and loss aversion (columns (4)-(5)) on a number of demographic characteristics. Additional Controls include region fixed effects for 11 government office regions as well as additional dummies for religion, education, marital status, the number of children and a dummy for whether a person lives in a rural area or not.

deviation for the risk measure R^D is about 1.98 (Table 1), the gender effect corresponds to about a quarter of a standard deviation (once ambiguity attitude is controlled for). This is in line with findings by (Dohmen et al., 2011). Without controlling for ambiguity, the effect size is even bigger, about a third of a standard deviation. For the Holt and Laury (2002) measure measure the effect size is somewhat smaller, but still substantial. Given a standard deviation of 0.61 for $1-\gamma^{HL}$ the gender effect corresponds to about one sixth of a standard deviation. In section 4.1, where we relate risk attitudes to different important behaviors under uncertainty, we return to a discussion of the economic significance of these effect sizes.

Our study also provides new evidence on gender differences in loss aversion. Women are substantially more loss averse compared to men. This effect is very robust with a virtually identical effect size for both sets of controls (columns (4) and (5) in Table 5). The effect is also substantial. Given a standard deviation of λ of 3.6, the gender effect is again about a quarter of a standard deviation. Similar effects have been found in some lab experiments (Schmidt and Traub, 2002; Rau, 2014). von Gaudecker et al. (2011) also found that women are more loss averse in a representative sample of the Dutch population, even though the effect is somewhat imprecisely estimated.[8]

Interestingly women are also found to be less ambiguity averse than men according to all our measures (though for the AA^D measure the effect is no longer statistically significant once risk aversion is controlled for (Table 6). Effect sizes are somewhat smaller here, but the direction and size of effect is in line with some previous evidence from lab-in-the-field experiments. Specifically, Borghans et al. (2009) found that women are less ambiguity averse for "small" degrees of ambiguity in a sample of Dutch high school students. By contrast Sutter et al. (2013) in a sample of children and Dimmock et al. (2016) find little relation between gender and ambiguity attitude in the lottery based measure.

Our results demonstrate substantial and comprehensive differences in uncertainty attitudes across

[8] Johnson et al. (2006) find no gender differences in loss aversion in a sample of auto buyers. They use a slightly different definition of loss aversion which makes it hard to compare these effects.

genders. They also show that gender differences in uncertainty attitudes are more complex than assumed in much of the previous literature which is focused uniquely on risk aversion. While women are more risk averse and more loss averse, they appear less ambiguity averse than men. This suggests that women should not generally be expected to avoid uncertainty more than men do in economic decisions. If a choice situation involves a large degree of ambiguity women might be willing to accept more uncertainty than men. In Section 4.1 we will ask to which extent this can be the case.

	(1) AA^D	(2) AA^D	(3) AA^D	(4) $\mathrm{AA}_{0.5}(L)$	(5) $\mathrm{AA}_{0.5}(L)$	(6) $\mathrm{AA}_{0.5}(L)$
female	-0.558***	-0.0828	-0.0330	-0.0899***	-0.0851***	-0.0888***
	(0.151)	(0.125)	(0.129)	(0.0182)	(0.0185)	(0.0197)
age	0.00823*	0.0212***	0.0156***	-0.000979*	-0.000636	-0.000461
	(0.00481)	(0.00400)	(0.00491)	(0.000573)	(0.000596)	(0.000708)
white	-0.118	0.147	0.112	0.0569	0.0618	0.0553
	(0.299)	(0.266)	(0.293)	(0.0395)	(0.0386)	(0.0435)
anglican	-0.406*	-0.170	-0.0612	0.0362	0.0339	-0.00151
	(0.245)	(0.202)	(0.186)	(0.0333)	(0.0333)	(0.0222)
catholic	-0.306	-0.0494	-0.000375	-0.0210	-0.0349	-0.0608
	(0.339)	(0.269)	(0.310)	(0.0447)	(0.0459)	(0.0379)
other relig	-0.175	0.00575	-0.0244	-0.0203	-0.0121	-0.0177
	(0.278)	(0.247)	(0.278)	(0.0383)	(0.0377)	(0.0438)
R^D		-0.644***	-0.649***			
		(0.0264)	(0.0269)			
$1-\gamma^{HL}$					-0.0370**	-0.0345**
					(0.0149)	(0.0155)
Constant	2.745***	3.530***	4.100***	0.0371	0.0302	0.0576
	(0.363)	(0.318)	(0.491)	(0.0473)	(0.0464)	(0.0789)
Observations	876	876	843	860	838	827
Additional Controls	NO	NO	YES	NO	NO	YES
R-squared	0.025	0.357	0.376	0.041	0.049	0.075
	(7) $\mathrm{AA}_{0.5}(PR1)$	(8) $\mathrm{AA}_{0.5}(PR1)$	(9) $\mathrm{AA}_{0.5}(PR1)$	(10) $\mathrm{AA}_{0.5}(PR2)$	(11) $\mathrm{AA}_{0.5}(PR2)$	(12) $\mathrm{AA}_{0.5}(PR2)$
female	-0.0291***	-0.0276***	-0.0280***	-0.0679***	-0.0657***	-0.0600***
	(0.00536)	(0.00545)	(0.00565)	(0.0146)	(0.0149)	(0.0155)
age	-0.000257	-0.000166	-0.000125	-0.000351	-0.000320	-0.000356
	(0.000167)	(0.000173)	(0.000204)	(0.000467)	(0.000482)	(0.000557)
white	0.0213*	0.0221**	0.0199	0.0476	0.0473	0.0572
	(0.0113)	(0.0112)	(0.0122)	(0.0316)	(0.0318)	(0.0353)
anglican	0.000936	0.00229	0.00238	-0.0199	-0.0173	-0.0181
	(0.00932)	(0.0108)	(0.00683)	(0.0245)	(0.0294)	(0.0196)
catholic	-0.0170*	-0.0171*	-0.0191*	-0.0269	-0.0245	-0.0273
	(0.00997)	(0.0102)	(0.0105)	(0.0272)	(0.0276)	(0.0283)
other relig	-0.00188	-0.000798	-0.00257	-0.0280	-0.0274	-0.0305
	(0.0118)	(0.0119)	(0.0137)	(0.0320)	(0.0327)	(0.0374)
$1-\gamma^{HL}$		-0.0102**	-0.00951**		-0.00785	-0.00739
		(0.00442)	(0.00452)		(0.0121)	(0.0123)
Constant	0.0487***	0.0478***	0.0471**	0.0123	0.0126	-0.0142
	(0.0132)	(0.0131)	(0.0227)	(0.0364)	(0.0366)	(0.0626)
Observations	864	842	831	864	842	831
Additional Controls	NO	NO	YES	NO	NO	YES
	0.046	0.053	0.082	0.036	0.035	0.058

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: The table presents results from OLS estimations of ambiguity attitude on a number of demographic characteristics. Additional Controls include region fixed effects for 11 government office regions as well as additional dummies for religion, education, marital status, the number of children and a dummy for whether a person lives in a rural area or not.

In terms of other demographics, risk aversion also increases with age according to all our measures. This is in line with findings by Dohmen et al. (2011), von Gaudecker et al. (2011) and Dohmen et al. (2017), but not with Noussair et al. (2014) who found that older people are less risk averse. Loss

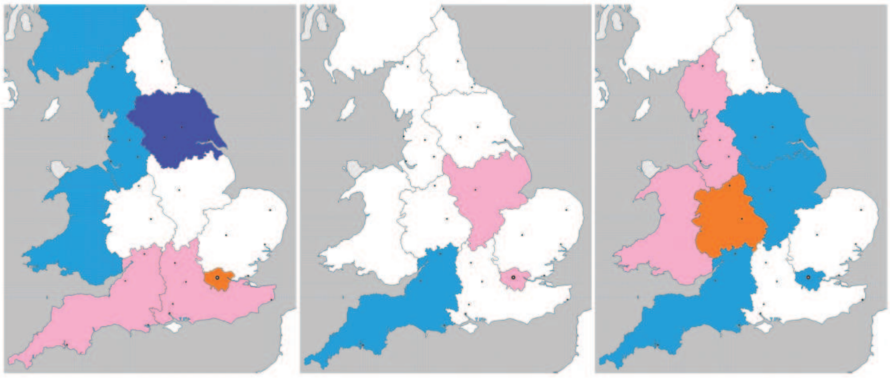


Figure 2: Regional distribution of uncertainty attitudes. The left panel shows the distribution of risk aversion R^D, the middle panel ambiguity aversion AA^D and the right panel loss aversion λ. We standardize all measures to mean zero and standard deviation one. White regions are within 0.05 SD of the mean. Pink regions are between 0.05-0.10 and orange regions between 0.1-0.2 SD below the mean. Blue regions are between 0.1-0.2 SD and dark blue regions more than 0.2 SD above the mean.

aversion and ambiguity attitude, by contrast, seem largely unaffected by age. This is interesting as it could suggest that these latter measures are more stable over the life-cycle.[9]

Figure 2 illustrates the distribution of some uncertainty attitudes across government office regions.[10] Risk aversion seems to be higher in the northern regions of England and lower in the South, with people living in London being least risk averse and people in Yorkshire most risk averse (measure R^D in the left panel of Figure 2). Differences in ambiguity attitudes (AA^D, middle panel) and loss aversion (λ, right panel) seem less systematic, but London emerges as clearly different from surrounding areas with Londoners less ambiguity averse and more loss averse than the rest of the country on average. These differences point to interesting patterns of sorting along uncertainty attitudes. People with different uncertainty attitudes seem to choose different areas where to live.[11] It is open question whether different regional conditions also affect uncertainty attitudes differentially in the absence of migration (Diamond, 1997; Page et al., 2014; Calo-Blanco et al., 2017). Other controls, like religion, education or marital status are not systematically correlated with any of the uncertainty attitudes.

3.2 Relation between different types of uncertainty attitude

Our evidence also allows to ask how different types of uncertainty attitudes (e.g. risk aversion and ambiguity aversion) correlate among each other. Table 4 shows that risk aversion and ambiguity aversion are negatively related. The effect is substantial and highly statistically significant. It is true for both the Dohmen et al. (2011) measures of risk and ambiguity aversion (columns (2) and (3)) as well as when we relate the Holt-Laury measure of risk aversion with the measure elicited in the wheels (columns (5) and (6) in Table 4 and colums (5), (6), (8),(9), (11) and (12) in Table 6). The negative relationship appears both when we control for the larger as well as the smaller set of controls. It is true for both men ($\rho = -0.4988$, Dohmen measures) and women ($\rho = -0.6103$, Dohmen measures) and across a range of other demographics (e.g. age and education). The negative relation between

[9] Our current data do not allow us to distinguish this hypothesis from an alternative hypothesis according to which loss aversion and ambiguity aversion vary with age but in a non-systematic way across individuals.

[10] There are 11 government office regions in the UK, the North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, South East, South, South West, London, Wales and Scotland.

[11] The extent of migration greatly differs across regions with an estimated 45% of Londoners are foreign-born compared to only around 5% in Wales (`ons.gov.uk/peoplepopulationandcommunity/populationandmigration`).

risk and ambiguity aversion is also found in Dimmock et al. (2016). We also identify a negative relationship between risk aversion and loss aversion (columns (2) and (3) in Table 5), which is also very robust appearing for both sets of controls.

4 Attitudes to Uncertainty and Household Behaviour

We now ask to which extent different uncertainty attitudes matter in explaining household choices under uncertainty. We start by discussing the behavioral validity of the different measures of risk attitude, i.e. to which extent these measures can explain choices under uncertainty (subsection 4.1). We then ask to which extent broader measures of uncertainty attitude can explain choices over and above an agents' risk attitude. In other words we ask how much is gained in terms of the ability to predict households' behaviour under uncertainty by eliciting an agent's loss aversion (Section 4.2) or degree of ambiguity aversion (Section 4.3) if risk attitude is already known. Our data will also allow us to compare multiple risk or ambiguity measures in terms of their explanatory and predictive power. Throughout this section the focus will be on identifying correlations in the reduced form.

To answer these questions we will use all the behaviours under uncertainty elicited in module (V) of our survey. We committed to these outcomes at the time of designing the study and are not adding or dropping any outcomes ex post. The following variables are constructed. The variable `Flu Vaccine` is a binary variable that indicated whether the respondent got a flu vaccine this season.[12] `Smoking` indicates whether the respondent smokes, whereby smoking of e-cigarettes is coded as non-smoking. The variable `Cervical Screening` is set to missing for all men. For women it indicates whether the respondent indicated that she had a Cervical Screening in the last 3 years. `Insurance` is a variable that indicates whether the respondent held any of five possible insurance policies (items I1-I5 in Table 11). `Sports Betting` indicates whether a respondent engages in sports betting and `Lottery participation` whether they buy tickets in the national lottery. `Stock market participation` indicates whether respondents hold stocks and `Free Holiday Tunisia` asks whether people would go to Tunisia if given a free one-week all-inclusive holiday for themselves and their family.

4.1 Risk Attitudes

Table 7 compares our three measures of risk attitude, R^D, $1-\gamma^{HL}$ and $1-\gamma^{T}$ in terms of their ability to explain these choices under uncertainty. Each column shows a a separate logit regression where the coefficients show the effect of a one-unit increase in the respective risk measure on the probability to engage in the outcome in question.

The simple measure R^D explains some of the variation in sports betting, lottery participation, stock market participation and the free holiday in Tunisia question. Respondents who indicate a higher degree of risk aversion as measured by R^D are less likely to engage in any of these behaviours. Effect sizes are substantial showing the economic significance of this measure. For example, with respect to stock market participation the marginal effect of a 1% increase in R^D is a 1.7% decrease in the propensity to participate in the stock market. Dohmen et al. (2011) have correlated this measure with stock market participation, smoking, whether a person is active in sports and whether they are self-employed and found economically and statistically significant relation between the R^D measure and all of these. While our results on stock market participation are in line with theirs, we do not find a significant effect on smoking. Going back to the main survey data we can also check for whether R^D relates to self-employment (a variable "active in sport is only available for part of our sample"). While we do not find a statistically significant relationship between self-employment and R^D we do find that the simple measure of ambiguity aversion is a significant predictor of self-employment (see Section 4.3 for more detail).

[12] Remember that our survey was fielded in November, hence shortly after the start of the flu season in the UK.

	Flu Vaccine			Smoking			Cervical Screening			Insurance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
R^D	0.007			-0.001			-0.006			-0.003		
	(0.008)			(0.005)			(0.011)			(0.004)		
$1-\gamma^{HL}$		-0.005			0.006			-0.014			-0.019	
		(0.026)			(0.018)			(0.038)			(0.015)	
$1-\gamma^{T}$			0.000			0.047**			-0.014			0.000
			(0.037)			(0.022)			(0.056)			(0.021)
α			0.039			-0.107**			0.059			-0.069
			(0.074)			(0.044)			(0.117)			(0.043)
Observations	875	849	800	876	850	801	459	446	414	769	747	703
Pseudo R2	0.141	0.140	0.138	0.0466	0.0435	0.0675	0.00173	0.00219	0.00347	0.186	0.185	0.192
McFadden Adj. R-squared	0.126	0.124	0.120	0.0124	0.00804	0.0262	-0.0272	-0.0275	-0.0321	0.132	0.130	0.127
AIC	1030	1003	948.7	519.6	503.3	471.6	638.3	621.3	578.8	290.6	279.4	266.1
BIC	1073	1046	995.6	562.6	546	518.4	671.3	654.1	615	327.7	316.4	307.1
	Sports Betting			Lottery participation			Stock market participation			Free Holiday Tunisia		
	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)	(8b)	(9b)	(10b)	(11b)	(12b)
R^D	-0.030***			-0.026***			-0.017**			-0.015*		
	(0.007)			(0.008)			(0.008)			(0.008)		
$1-\gamma^{HL}$		-0.057**			0.031			-0.026			-0.057**	
		(0.025)			(0.026)			(0.025)			(0.026)	
$1-\gamma^{T}$			-0.012			0.033			-0.026			-0.017
			(0.034)			(0.039)			(0.036)			(0.037)
α			-0.040			0.010			0.125*			-0.042
			(0.073)			(0.082)			(0.072)			(0.079)
Observations	871	845	798	871	845	798	737	713	676	875	849	800
Pseudo R2	0.0604	0.0505	0.0499	0.0290	0.0225	0.0200	0.104	0.0976	0.0994	0.0754	0.0760	0.0692
McFadden Adj. R-squared	0.0422	0.0317	0.0279	0.0130	0.00611	0.000604	0.0806	0.0740	0.0714	0.0593	0.0594	0.0496
AIC	945	928.1	882	1115	1090	1032	720.7	705.3	664.5	1052	1018	968.4
BIC	988	970.7	928.8	1157	1133	1079	762.1	746.5	709.7	1095	1061	1015

Table 7: The table presents marginal effects of LPM estimations of outcomes on various measures of risk attitude. All columns control for gender, age, ethnicity and religious affiliation.

The lottery based measure $1-\gamma^{HL}$ also has a substantial and statistically significant effect on sports betting behaviour and respondents' willingness to take the trip to Tunisia. While it explains fewer outcomes than the R^D measure, it has a substantially better fit for the two outcomes for which it is statistically significant. Based on AIC, for example, the simple measure R^D is at most 0.2% as likely to minimize the information loss as the model using the lottery based measure $1-\gamma^{HL}$.[13] The measure based on the (Tanaka et al., 2010) lotteries, where γ is jointly elicited with α explains even fewer outcomes than $1-\gamma^{HL}$. While it usually has a higher R^2 and better values of AIC and BIC compared to the other measures, this is due to the information gained from probability weighting.

These results also highlight how important the exogenous determinants of risk attitudes discussed in Section 3 are through the channel of changing risk attitudes. For the outcome of stock market participation, for example, we find a direct gender effect of ≈ -0.035, which is very imprecisely estimated, though. The indirect effect via the channel of a changed attitude to risk amounts to -0.013 which is about one third of the direct effect. In terms of age, we find a direct positive effect on stock market participation of 0.008, which is also highly statistically significant and an indirect effect of -0.0003, which is only around 5% of the direct effect. Hence while, the direct effect of age on stock market participation clearly outweighs the indirect effect, the indirect gender effect is substantial.

4.2 Loss Aversion

This subsection focuses on loss aversion and its impact on behaviour. The question we aim to answer is whether loss aversion can explain behaviour in our decision situations under uncertainty over and above what is already explained by peoples' risk attitude. Answering this question will (i) create insights into how we should think of loss aversion as a preference parameter and (ii) help survey specialists to assess how important it is to include measures of loss aversion in general household surveys.

Table 8 shows the results. Conditional on risk aversion, more loss averse respondents are more likely to buy insurance and less likely to engage in sports betting or to accept free travel to Tunisia. The effects are sizable with a 1% increase in λ being associated e.g. with a 1% decrease in sports betting or a 0.6% increase in the propensity to buy insurance. The effect is hence between a third (sports-betting) or half (insurance) of the very imprecisely estimated effect of a 1% increase in risk aversion. These results show that loss aversion is an important preference parameter that affects choices under uncertainty over and above a respondent's risk aversion. Including loss aversion into the regression also substantially increases the pseudo-R2 compared to regressions based on the risk aversion parameter alone (Table 7). In the case of `Insurance`, for example, the pseudo-R2 increases by around 10% once loss aversion is included and the AIC suggests that the model without loss aversion is only 0.09% as likely to minimize the information loss as the model that includes loss aversion.

Again these results show the importance of the exogenous determinants of loss aversion discussed in Section 3. There is, for example, no direct effect of gender on `Insurance`. The indirect effect of gender on insurance choice, which operates via loss aversion, however means that in expectation women are 0.3% more likely to hold insurance compared to men.

4.3 Ambiguity Aversion

In this section we ask whether our measures of ambiguity aversion affect household decisions on top of any effect that operates via risk aversion. This will tell us how important it is to understand

[13] This is based on $\exp \frac{928-945}{2} \approx 0.0002$ for sports betting

	Flu Vaccine (1)	Smoking (2)	Cervical Screening (3)	Insurance (4)
$1-\gamma^T$	-0.014	0.038*	-0.002	0.011
	(0.035)	(0.041)	(0.037)	(0.039)
α	-0.026	0.014	0.125*	-0.047
	(0.073)	(0.083)	(0.073)	(0.079)
λ	-0.009**	0.001	0.004	-0.007*
	(0.005)	(0.005)	(0.004)	(0.004)
Observations	790	791	410	694
Pseudo R-squared	0.140	0.0749	0.00282	0.211
McFadden Adj. R-squared	0.120	0.0289	-0.0367	0.136
AIC	937.4	463.9	575.5	252.5
BIC	988.8	515.3	615.6	297.9

	Sports Betting (1)	Lottery (2)	Stock Market (3)	Tunisia (4)
$1-\gamma^T$	-0.032	0.039	-0.015	-0.027
	(0.198)	(0.185)	(0.242)	(0.191)
α	-0.146	0.061	0.815*	-0.234
	(0.409)	(0.375)	(0.473)	(0.390)
λ	-0.054**	0.003	0.028	-0.036*
	(0.026)	(0.021)	(0.028)	(0.021)
Observations	788	788	670	790
Pseudo R-squared	0.0547	0.0210	0.102	0.0733
McFadden Adj. R-squared	0.0300	-0.000587	0.0710	0.0516
AIC	863.9	1021	659.6	957.3
BIC	915.3	1073	709.2	1009

Table 8: The table presents marginal effects of LPM estimations of outcomes on loss aversion. All columns control for gender, age, ethnicity and religious affiliation.

respondents' ambiguity aversion in order to predict their choices under uncertainty.

Table 9 shows the results of this exercise. It contains two columns for each outcome. In odd columns we add the simple ambiguity measure AA^D on top of the simple risk aversion measure R^D. In even columns we add the lottery-based ambiguity measure $AA_{0.5}(PR1)$ on top of the lottery-based measure of risk aversion $1-\gamma^{HL}$.[14]

The table shows that the simple ambiguity aversion measure has a substantial effect on respondents' decisions to smoke, to have cervical screening, to engage in sports betting and to accept the free holiday in Tunisia, even once risk aversion has been controlled for. Respondents are less likely to smoke, engage in sports betting or to accept the free holiday and they are more likely to have a cervical screening the more ambiguity averse they are. In those cases where ambiguity aversion matters, effect sizes are substantial with marginal effects ranging from $\approx 50\%$ (sports betting) to $\approx 200\%$ (cervical screening) of the effect of a marginal increase in risk aversion. Interestingly, for some behaviours like e.g. the decision to have a cervical screening risk aversion does not have a statistically significant effect, but ambiguity aversion does have a substantial and statistically significant effect. For smoking, risk aversion does not have a significant effect if entered in the regression alone (Table 7), but both risk and ambiguity aversion do have a substantial and statistically significant effect if entered together, with the effect of ambiguity aversion being $\approx 45\%$ stronger. This seems intuitive as both these health prevention behaviours involve uncertainty with presumably very ambiguous probabilities (the chance to have lung or cervical cancer). It is also noteworthy, that while ambiguity aversion has a strong negative effect on sports betting, where the odds of winning are not precisely known, it has no effect on participation in the national lottery, where the odds are exactly known. Finally, we also related the simple measure of ambiguity aversion to a dummy variable that indicates

[14] Using any of the other lottery-based measures of ambiguity aversion discussed in Section 2.1 yields qualitatively and quantitatively very similar results.

whether a participant is self-employed (taken from the main survey). This is an outcome for which Dohmen et al. (2011) found that the simple risk question is an important predictor. We do not find an effect of the simple risk measure on self-employment, but we do find that - controlling for risk aversion - the simple ambiguity measure has substantial and significant impact on men's decision to become self-employed. All these results suggest that the simple measure of ambiguity aversion AA^D captures important aspects of ambiguity aversion that are linked to behaviour in decision situations with a substantial degree of ambiguity.

	Flu Vaccine		Smoking		Cervical Screening		Insurance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R^D	0.010		-0.012**		0.017		-0.003	
	(0.010)		(0.005)		(0.014)		(0.005)	
AA^D	0.003		-0.017***		0.033**		-0.001	
	(0.009)		(0.005)		(0.013)		(0.004)	
$1-\gamma^{HL}$		-0.006		0.007		-0.016		-0.017
		(0.026)		(0.018)		(0.039)		(0.015)
$AA_{0.5}(PR1)$		-0.021		0.010		-0.282		0.041
		(0.201)		(0.123)		(0.313)		(0.100)
Observations	874	840	875	841	459	440	768	739
Pseudo R-squared	0.141	0.137	0.0693	0.0440	0.0112	0.00337	0.186	0.180
McFadden Adj. R-squared	0.124	0.119	0.0313	0.00447	-0.0209	-0.0300	0.127	0.117
AIC	1032	998.8	509.5	503.4	634.4	614.8	292.4	277.8
BIC	1080	1046	557.3	550.8	671.5	651.5	334.2	319.3
	Sports Betting		Lottery Participation		Stock Market Participation		Free Holiday Tunisia	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R^D	-0.045***		-0.032***		-0.016*		-0.027***	
	(0.009)		(0.010)		(0.010)		(0.010)	
AA^D	-0.024***		-0.010		0.001		-0.019**	
	(0.008)		(0.009)		(0.008)		(0.008)	
$1-\gamma^{HL}$		-0.062**		0.026		-0.023		-0.057**
		(0.025)		(0.027)		(0.025)		(0.026)
$AA_{0.5}(PR1)$		-0.055		-0.209		0.434**		-0.121
		(0.192)		(0.216)		(0.192)		(0.203)
Observations	870	836	870	836	737	708	874	840
Pseudo R-squared	0.0700	0.0495	0.0299	0.0233	0.104	0.103	0.0803	0.0779
McFadden Adj. R-squared	0.0498	0.0284	0.0122	0.00483	0.0781	0.0763	0.0624	0.0592
AIC	937	919.9	1115	1078	722.6	701.2	1047	1006
BIC	984.7	967.2	1162	1125	768.7	746.8	1094	1053

Table 9: The table presents marginal effects of LPM estimations of outcomes on various measures of ambiguity attitude. All columns control for gender, age, ethnicity and religious affiliation.

The lottery based measure of ambiguity aversion has no significant effect on any of the outcomes, with the exception of a positive effect on stock market participation. The latter outcome has been extensively studied in Dimmock et al. (2016) who found that a specific measure related to ambiguity aversion called a-insensitivity as well as differences in education are particularly important for this outcome. They also conjecture that reference dependence might be particularly important for stock market participation. Our data from the loss aversion module allow us to partly assess this conjecture and indeed it seems that probability weighting could be important for this outcome (Table 8). Overall, these results suggest that, while the lottery based measure of ambiguity aversion can work reasonably well to explain financial decision-making, the simple measure works better in terms of explaining other outcomes. This is in line with Sutter et al. (2013), who also found only a weak relationship between a lottery-based measure of ambiguity aversion and outcomes of children.

5 Conclusions

We elicited various measures of risk, loss and ambiguity aversion as well as probability weighting parameters in a representative sample of the UK population and relate them to outcomes related to health prevention or financial decision making. In order to understand to which extent people perceive ambiguity for different events, we also comprehensively elicit subjective expectations. Our second main contribution in this paper is methodological. As broader uncertainty attitudes are not typically measured in general social surveys, little is known on the optimal question format for such surveys. As we elicit a variety of lottery based as well as simpler measures, our research also allows us to compare several ways of eliciting these broader attitudes in general surveys.

We find that there is substantial variation across gender, age and region in these measures. Women, for example, are found to be more risk averse and loss averse, but also less ambiguity averse compared to men. Londoners are less risk averse and ambiguity averse, but more loss averse compared to the rest of the UK. These differences tend to be sizeable enough to generate significant differences in the outcomes we study. Conditional on knowing a person's risk aversion their degree of loss aversion as well as ambiguity aversion still explains an important part of the variation in economic outcomes. In terms of measurements, while lottery based measures based on price lists tend to work quite well for risk and loss aversion, a simple survey-style question works much better than our lottery based measures for ambiguity aversion.

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