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Can self-assessed financial risk measures explain and predict bank customers' objective financial risk?

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ABSTRACT

This paper evaluates risk preference measures by contrasting subjective or self-assessed risk with objective risk, as implicated by bank customers' actual portfolio allocation. Using a detailed data set of 7,234 bank customers, we find that subjective risk measures can explain and predict objective risk, but that the relationship is relatively weak. Subjective measures that uses survey questions about the customers' trade-off between risk and return is a better measure than the hypothetical lottery for explaining objective risk. Both measures are relatively weak at predicting objective risk, but perform better than using a naïve model. We also find that multiple-item variables are somewhat better than single-item variables for explaining objective risk.

1. Introduction

Risk preference is an important factor in financial decision making. In what way and to what extent investors avoid or seek risk have crucial implications for their decisions on, e.g., investment, pensions, and insurances. Financial institutions need to understand their customers' risk preferences in order to give well-targeted advice. This also applies to the expanding market of robo-advisors, in which customers' risk preferences need to be correctly determined in order to ensure that a suitable equity portfolio is provided (Tertilt and Scholz, 2017). A major challenge is to measure customers' risk preferences effectively. A number of studies discuss trade-offs when choosing methods to measure risk preference (Dohmen et al., 2011; Loomes and Pogrebna, 2014; Dave et al., 2010; Charness et al., 2013; Eckel and Grossman, 2008; Menkhoff and Sakha, 2017), e.g., in terms of the measures' explanatory and predictive power, overall validity, simplicity, and cost-effectiveness.

The overall objective of this paper is to evaluate risk preference measures by contrasting subjective or self-assessed risk with objective risk, as implicated by bank customers' actual portfolio allocation. Nosic and Weber (2007), Chang et al. (2004), and Schooley and Worden (1996) find consistency between subjective and objective risk. Households allocate their assets

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according to their attitudes toward risk. Park and Yao (2016) find that those who have financial planners more often have risk attitudes that are in line with their behavior. Some other studies come to different conclusions, and results are mixed. Marinelli et al. (2017) find inconsistencies between subjective and objective risk tolerance. They analyze the characteristics of those who either undervalue or overvalue their self-assessed risk, and those who overexpose or underexpose their objective risk according to their portfolio composition. Also, Jianakoplos (2002) and Ehm et al. (2014) conclude that there is a gap between reported customers' willingness to take risk and their actual portfolio allocation of risk. Thus, there is a need to study this research question further, e.g., by using new and extended data.

Considerations when deciding on suitable risk preference methods include whether to 1) use surveys with one-dimensional or multi-dimensional questions (MacCrimmon and Wehrung, 1986; Menkhoff and Sakha, 2017), 2) use subjective or objective measures from register data (Schooley and Worden, 1996), 3) ask context-related questions or more general questions (Dohmen et al., 2011), or 4) arrange experiments in laboratories or in the field (see, e.g., Smith, 2008, for background). Methods could include choice dilemmas (Stoner, 1961), heuristic judgements often used by practitioners (discussed in Grable and Lytton, 1999), utility theory (von Neumann and Morgenstern, 1944), or prospect theory (Kahneman and Tversky, 1979). If lotteries are used, one needs to decide if they are hypothetical or real, and if small or large stakes should be used (Holt and Laury, 2002).

When using self-assessed risk measures, researchers often use the answers from the American Survey of Consumer Finances (SCF). Respondents answer one question to rate their willingness to take risk when saving or investing. Loomes and Pogrebna (2014) argue that it is not safe to expect that one or two questions can provide a reliable measure at the individual level, since most individuals show extensive variability in their responses to questions intended to measure their risk attitudes. Therefore, several different questions should be used, or at least two different procedures, to check the sensitivity of the risk attitude parameters. In order to reduce noise in measures, Menkhoff and Sakha (2017) find that it is better to combine single-item risk measures to form multiple-item risk measures. They, and Dohmen et al. (2011), conclude that survey items perform just as well as incentivized experimental items in explaining risky behavior.

The main contribution of this paper is to explore the possibility of using and comparing bank customers' self-assessed risk preference with their objective risk preference, as shown by their actual allocation of risky and risk-free assets. Two types of subjective measures – survey questions on hypothetical lottery choices, and survey questions on risk preferences regarding the trade-off between risk and return – are compared. The questions are related to the investment and saving context. Also, building upon recent findings from Menkhoff and Sakha (2017), we compare separate single-item measures with a combination of measures. The paper uses a unique dataset of 7,234 customers in a Swedish retail bank.

Another contribution of the paper is its use of extensive multiple controls. In addition to socioeconomic and demographic characteristics, data on customers' use of, and trust in, financial advisors, customers' subjective knowledge of, and interest in, finances, and their objective financial literacy, as determined by a test, are included in the analysis. We are also able to analyze the consistency between subjective and objective measures, using a finer division of the objective risk measure. Customers' allocation of total assets, mutual fund assets, and equity assets are analyzed and compared with subjective risk measures.

Our main findings are as follows. We find that subjective risk measures can explain and predict objective risk, but that the relationship is relatively weak. We also find that the subjective measure that uses survey questions about the customers' trade-off between risk and return is a better measure than the hypothetical lottery for explaining objective risk. Both measures are relatively weak at predicting objective risk according to the root mean of the squared standard errors (RMSE), but better than a naïve model. Finally, we find that combined measures are somewhat better than single-item questions for explaining objective risk.

The rest of the paper is structured as follows. In the next section, we describe our research design, i.e., the setup of the study, the data set, and the methodology used. Regarding the construction of key variables, we discuss the characteristics of the subjective and objective risk measures. In Section 3, we analyze the results, including robustness checks and the study's limitations. Section 4 concludes with a discussion about implications for researchers and practitioners.

2. Research design

2.1. Set up of the study

The two subjective risk measures are analyzed in three ways: 1) individually, 2) combined, and 3) as an average of these two standardized risk measures. These are compared with objective risk, which is defined as the actual allocation of risk-free assets and risky assets in bank customers' portfolios. Three types of assets are analyzed: 1) total assets, 2) mutual fund assets, and 3) equity assets. Eight models of combinations of subjective risk preferences are discussed and compared for each of the three asset types, i.e., a total of 24 models are presented and discussed.

In line with Shmueli (2010), we discuss both the explanatory and predictive qualities of these models – even if the main objective is to find out how the subjective measures predict the objective measure of risk taking. Whereas academic research is more focused on explaining, practice – not least, within finance – is more focused on prediction.

From an explanatory point of view, our *first* hypothesis is that subjective risk measures can explain and predict objective risk. In line with extensive and often-cited research by Ajzen and Fishbein (see, e.g., Ajzen and Fishbein, 2005; Ajzen, 2008), a person's behavior is a function of his or her behavioral intentions, which are determined by his or her beliefs and attitudes. Indeed, Samuelson (1969) assumed that individuals with low risk tolerance would be likely to hold less risky assets.

Drawing on research by Nosic and Weber (2007), and Dohmen et al. (2011), our *second* hypothesis is that the subjective survey measure will be superior to the hypothetical lottery measure in explaining and predicting the objective risk measure.

Finally, we are interested in finding support for our *third* hypothesis, which is that it is preferable to combine single-item measures to form multiple-item risk measures (Loomes and Pogrebna, 2014; Menkhoff and Sakha, 2017).

By collecting both subjective and objective data, the relationship between subjective risk measures (intentions, attitudes, beliefs) and objective risk measures (behavior) can be tested empirically. Thus, we analyze the correlations between subjective and objective risk measures, and we compare the size of the standardized coefficients in the ordinary least square regressions, so that the variables are measured on the same scale, with the aim of finding out the change in the mean of the objective risk measure, given a one-standard-deviation change in the explanatory variable. Also, the variable's importance is evaluated by comparing the increase in R-squared when moving from using only the control variables in the model to adding the explanatory variable. This gives us the possibility of tracking the amount of unique variance that the explanatory variables explain above and beyond the other variables in the model. Using an R-squared form of the F-statistic, we can find out if the change in R-squared is statistically significant (Wooldridge, 2006, p.158). The variable that has the largest standardized coefficient and shows the largest significant change in R-squared is the preferred variable to use when explaining the objective risk taking.

In predictive modelling, the priority is to generate accurate predictions of new observations. Hence, we use the predicted measures from the original data set, and then test it on a new data set (out of sample). We agree with Shmueli (2010) that the predictive power cannot be inferred from the explanatory power; thus the evaluation needs to involve the out-of-sample testing. Since our sample is sufficiently large, we divide it and use one half as in sample and the other half as out of sample.

We also evaluate the models by comparing the models' Akaike information criterion (AIC) and Bayesian information criterion (BIC), which are estimators of the relative quality of the models (Burnham and Anderson, 2004). According to Sober (2002), the in-sample AIC measures predictive accuracy, while the BIC measures goodness of fit and relates more to explanatory power.

In addition to the statistical criteria, the costs of providing the financial institutions with customer data and using the models are discussed. The models with register data only are less costly than the models using extensive survey data about the person's interest, skills, and life situation. Thus, we present models using with and without survey data control variables.

2.2. Data collection

Objective data sampled from a bank's register are combined with subjective data from answers received from a questionnaire sent out to the same sample of customers. The data are cross-sectional.

From the register of one of Sweden's largest banks, 90,520 customers were randomly sampled, representing a population of 2,254,420 bank customers aged 18 and over. The bank is one of four large retail banks in Sweden, which altogether represent 75 % of Swedish banks' deposits or loans. The bank has a similar structure as the other three large banks, and it has a large customer size and a broad geographical coverage. The register data were provided in March 2013 and gave us – on an individual customer basis – sociodemographic information about age, gender, and geographical location, as well as financial information on debt, assets, and annual net income.

These data were combined with answers from a postal survey undertaken in April-May 2013. The survey data provided us with information on family status, home ownership, work status, education, and financial literacy, as well as risk attitudes, confidence and interest in and knowledge about finances, and the use of, and trust in, financial advisors provided by the bank.

From the postal survey, which did not include reminders, we received 16,050 responses. The figure represents a response rate of 18 %. This is lower than most surveys using face-to-face interviews or telephone interviews, such as American Survey of Consumer Finances (SCF) produced by the Federal Reserve with a response rate above 60 %. However, it is about the same or higher than most internet or e-mail surveys, e.g., Kramer (2016) who obtained a response rate of 10.8 %, and Lusardi et al. (2011) who obtained response rates between 7.5 and 19 % depending on the country. It is lower than some other postal surveys, covering research about similar sensitive issues, such as Ameriks et al., (2007) who used the American TIAA-CREF database and reached 30.7 %, but about the same as Jonsson et al., (2017), who got a response rate of 17.3 %, and Lea et al., (1995), who got response rates of 21.5, 17.5 and 9.5 % from non-debtors, mild debtors and serious debtors, respectively. Since our response rate is relatively low, we acknowledge that the study uses a convenience sample. Comparing register and survey data (see Table 1), we find that the sample used in the models has wealthier and older clients, and that it is not entirely representative of all of the bank's customers. However, the data are unique and steps have been taken to limit the problem of selection bias. We use group analysis to find differences in predictability, depending on age, gender, wealth, debt, financial literacy, and the use of a financial advisor (see robustness and group analysis in Section 3.2).

Only customers using this particular bank–and no other banks–are included in the sample, in order to minimize the problem of customers having financial assets and liabilities in other banks. This restriction lowered the number of respondents from 16,050 to 9,460. Furthermore, as the respondents did not answer all the questions, the models were evaluated using 7,324 observations.

Table 1
Descriptive statistics.

Variable explained:	Register data		Used sample						
	Mean	Std.dev	Mean	Std.dev	Min.	Max.	ARP	MRP	ERP
Asset ratio (ARP)	0.392	0.376	0.495	0.353	0	1			
Mutual fund ratio (MRP)	0.163	0.265	0.218	0.275	0	1			
Equity ratio (ERP)	0.039	0.129	0.058	0.146	0	1			
Explanatory:									
1. Hypothetical Lottery Risk Preference (LRP)			1.382	0.634	1	3			
2. Low risk or “risk averse”			0.701	0.458	0	1			
Medium risk or “neutral risk”			0.216	0.411	0	1			
High risk or “risk taker”			0.083	0.276	0	1			
3. Survey “I can accept to lose part of saving if the chance of getting a good return is great” (A)			3.020	1.767	1	7			
4. Survey “I think one has to take risk in order to gain something” (B)			3.524	1.797	1	7			
5. Survey “I would like to increase the risk involved in my saving because I think the return is too low” (C)			2.665	1.609	1	7			
6. Survey Risk Preference (SRP), a factor constructed of A, B, C			−0.011	1.248	1.975	2.796			
8. Average of standardized LRP and SRP (Multi)			−0.048	0.790	−1.121	2.319			
Controls:									
Age	49.746	18.495	54.628	17.111	18	100			
Gender (male = 1)	0.491	0.500	0.468	0.499	0	1			
Men							0.486	0.203	0.073
Women							0.503	0.231	0.045
Urban - Four large city areas	0.795	0.403	0.850	0.357	0	1			
Monthly income (net of income tax)	14,075	12,980	17,262	12,671	0	366,957			
Investment Volume	317,146	871,251	454,413	807,219	0	1.80E + 07			
Debt	19,600	131,232	20,184	119,131	0	4.90E + 06			
Use financial advisor	0.667	0.471	0.827	0.378	0	1			
Have advisor							0.543	0.232	0.065
Do no have advisor							0.264	0.150	0.025
Trust in advisor (subjective)			1.106	2.289	−2.741	3.831			
Interest in finances (subjective)			−0.188	1.531	−2.325	3.094			
Knowledge in finances (subjective)			−0.024	0.791	−2.134	1.504			
Family status									
Single - w/o children			0.227	0.419	0	1	0.475	0.247	0.064
Singe - w children			0.040	0.196	0	1	0.523	0.153	0.025
Couple - w/o children			0.274	0.446	0	1	0.468	0.241	0.064
Couple - w children			0.435	0.496	0	1	0.527	0.191	0.056
Other			0.023	0.151	0	1	0.347	0.269	0.012
Housing									
Rental apartment			0.223	0.416	0	1	0.383	0.184	0.034
Tenant-owned apartment			0.192	0.394	0	1	0.512	0.241	0.071
House			0.541	0.498	0	1	0.535	0.221	0.063
Farmhouse			0.044	0.205	0	1	0.494	0.254	0.066
Workstatus									
Full time			0.449	0.497	0	1	0.508	0.174	0.044
Part time			0.104	0.306	0	1	0.522	0.191	0.034
Retired			0.316	0.465	0	1	0.504	0.295	0.096
Long-term sick			0.039	0.193	0	1	0.452	0.168	0.066
Student			0.043	0.202	0	1	0.356	0.273	0.017
Unemployed			0.050	0.218	0	1	0.408	0.173	0.027
Education									
No finalized education			0.098	0.298	0	1	0.446	0.251	0.061
Pregymnasial education (Lower secondary school)			0.119	0.323	0	1	0.475	0.257	0.071
Gymnasium (Upper secondary school)			0.293	0.455	0	1	0.496	0.193	0.0494
Postgymnasial education, < 3 yrs			0.201	0.400	0	1	0.513	0.217	0.061
Postgymnasial education, > = 3 yrs			0.289	0.453	0	1	0.504	0.217	0.059
FinKnow									
0 right			0.227	0.419	0	1	0.383	0.169	0.034
1 right			0.256	0.437	0	1	0.527	0.243	0.036
2 right			0.174	0.379	0	1	0.496	0.214	0.054
3 right			0.138	0.345	0	1	0.531	0.240	0.070
4 right			0.103	0.304	0	1	0.526	0.242	0.073
5 right			0.065	0.247	0	1	0.562	0.232	0.122
6 right			0.037	0.189	0	1	0.603	0.193	0.174

Table 2
Measurement model - result of confirmatory factor analysis and reliability measures.

Risk Preference (SRP) Construct	Mean	Factor Loading	Measurement Error	z value	Item Reliability (R2)	Composite Reliability	AVE
A. I can accept to lose part of my saving capital is the chance of getting a good return is great	2.994	0.83	0.006406	130.19	0.70	0.99	0.98
B. I think one has to take risk in order to gain something	3.494	0.81	0.006382	126.88	0.66		
C. I would like to increase risk since the return is too low	4.975	0.50	0.007019	71.69	0.25		

Data are presented and analyzed on an individual level, but there is a complication – married couples could have divided their total assets unevenly. However, since Swedish couples are taxed as individuals, the problem is likely to be less severe than in countries where joint taxation is used. In addition, family status is used as a control variable.

2.3. The construction and description of variables

2.3.1. The explained variables – the objective risk preference measures

In a financial context, relating the risky assets to total financial assets gives an objective measure of an investor's tolerance for risk. Schooley and Worden (1996) find that those who stated that they were willing to take substantial risk to earn higher return had, indeed, riskier portfolios, compared with those who were not willing to take any financial risk.

The purpose in this paper is to analyze how subjective measures of risk preferences explain the share of risky assets of bank customers' portfolios. Thus, our main explained variable is the bank customer's risky assets in relation to his or her total financial assets. The overall and *first* objective measure is the asset risk preference (ARP). In this measure, all financial assets, such as mutual funds, shares, as well as capital insurances – often related to retirement plans with a mixture of mutual funds and shares – are included. The scale extends from 0 to 1, where 0 corresponds to having no risky assets in the bank customer's portfolio and only deposits in risk-free saving accounts, while 1 corresponds to a portfolio consisting of risky assets and no deposits in risk-free saving accounts. The mean of ARP is 0.495, and 20 % have no risky assets at all.

The *second* objective measure is the mutual fund risk preference (MRP). The mean is 0.219 and 40 % have no mutual funds at all. Wärneryd (1996) classifies savings according to low risk (saving account, check accounts, saving certificates, and employer-sponsored saving schemes), medium risk (bonds and mutual investment funds), and high risk (growth funds, shares, and options). If data had been provided, we would have liked to divide the mutual funds into different risk classes, but instead they are treated as risky, in line with shares.

The *third* objective measure is the equity risk preference (ERP). The mean is 0.057, and 70 % have not shares at all. In ERP, the shares contributed by capital insurance are not included, and, in MRP, the funds contributed by capital insurance are not included.

In our definition of assets, we have excluded home equity, consumption goods, social security, public pensions, and human capital. Gross financial assets are analyzed, rather than net assets. In Sweden, debt is usually linked to home equity, and a minor share of the customers' debt is related to consumption goods. Nevertheless, debt is included in our model as a control variable. Table 1 shows the descriptive statistics and the distribution of the explained risk measures ARP, MRP, and ERP.

2.3.2. The explanatory variables – the subjective risk preference measures

Two subjective measures are used in this study, and then combined in different ways to obtain single and multiple measures: 1) lottery risk preference (LRP) is based on a hypothetic gamble involving getting money from a lottery versus choosing a smaller certain amount; and 2) survey risk preference (SRP) is based on three survey questions on customers' subjective views on their trade-off between risk and possible return on savings.

2.3.2.1. Lottery risk preference (LRP). Risk attitude measures are often based on lottery choices (Kahneman and Tversky, 1979; Holt and Laury, 2002; see also, e.g., Wärneryd, 1996). In its simplest form, the individual makes a choice between two alternatives of the form (v, p), where p is the probability of winning, v is an amount of money, and $1\text{-}p$ is the probability of winning nothing. The expected utility of such alternatives is $pu(v)+(1\text{-}p)u(0)$, where u is the utility function for money. The individual is assumed to select the alternative with the greatest expected value. "Risk aversion is defined as a preference for a sure outcome over a prospect with an equal or greater expected value... Risk seeking is exhibited if a prospect is preferred to a sure outcome with equal or greater expected value" (Wärneryd, 1999, p. 234, referring to Tversky and Fox, 1995, p. 269). The lottery risk preference measure used in this paper does not involve real payoffs and is, therefore, hypothetical. It was tested by asking the respondents to choose between receiving an amount of money with total certainty or participating in a lottery:

- *I choose either to get 1,000 SEK with 100 % probability, or take part in a lottery and get 2,000 SEK with 40 % probability (and nothing with 60 % probability).*
- *I choose either to get 1,000 SEK with 100 % probability, or take part in a lottery and get 2,000 SEK with 60 % probability (and nothing with 40 % probability).*

In line with Wärneryd (1999), who referred to Tversky and Fox (1995), the respondents were coded in the following way:

- high risk – chooses lottery in both cases (a prospect is preferred to a sure outcome with equal or greater expected value);
- medium risk – chooses 1,000 SEK in the first case, and lottery in the second case (the alternative with the greatest expected value is preferred); and
- low risk – chooses 1,000 SEK in both cases (a preference for a sure outcome over a prospect with an equal or greater expected value).

In Table 1, the distribution among these three types of risk attitudes as measured by risk tolerance is shown. A majority of bank customers take low risks (70.6 %), followed by medium risk (21.2 %), and high risk (8.2 %). Compared with Dohmen et al. (2011), the share of high risk is similar, but the share of low risk is somewhat smaller, while the share with medium or neutral risk behavior is somewhat larger. Similarly, Holt and Laury (2002) note that, with normal laboratory payoffs, most subjects (or experiment participants) are risk averse and few are risk seeking. They observe that 81 % of the subjects are risk averse, 13 % risk neutral, and 6 % risk seeking.[1]

Men are more risk seeking, according to our survey: 10.8 % of the men take high risks while only 6.6 % of the women do. This finding is in line with Dohmen et al. (2011), but contrary to Harrison et al. (2007), who find no gender effect on risk preferences.

Regarding the validity of this measure, the face validity is satisfactory, and the content validity includes all four elements, as discussed by MacCrimmon and Wehrung (1986), i.e., it includes the probability and amount of both gains and losses. The criterion validity is also satisfactory, as we find a positive correlation between the risk preference measure and the holding of risky assets.

2.3.2.2. Survey risk preference (SRP). Previous research has shown that a questionnaire measure should be used as a complement to the lottery choice measure, at least when investigating trusting behavior in a laboratory context. Lönnqvist et al. (2015) compare the Holt and Laury (2002) lottery choice measure, using experiments, with the questionnaire measure developed by Dohmen et al. (2011), using the Berg et al. (1995) trust game as the criterion variable. The questionnaire measure is found to have good construct validity. This measure also has reasonable predictive power and very good test-retest stability over time (one year). By contrast, Lönnqvist et al. (2015) show that the lottery choice measure has no construct validity, almost no predictive power on trusting behavior, and, most important, no test-retest stability. Contrary to Dohmen et al. (2011), who find high correlation between the questionnaire measure and a hypothetical lottery (from a survey), Lönnqvist et al. (2015) find that the two measures are virtually uncorrelated. They argue that the high degree of noise is specific to the behavioral measurement of individual risk attitudes by the lottery choice task, using small stakes, as proposed by Holt and Laury (2002).

Risk preferences are often measured by using survey questions. Grable and Lytton (1999) developed a multidimensional tool consisting of 20 (later reduced to 13) items. Unfortunately, the tool lacked simplicity and seemed to be administratively burdensome. Dohmen et al. (2011) took the opposite position and developed a simple and low-cost measure of risk; they asked only one question about respondents' willingness to take risks "in general," using an eleven-point scale. They find 78 % of their participants to be risk averse; 13 % are risk neutral; and 9 % of the subjects show a risk-taking behavior. Compared with context-specific questions, the general risk question is seen as the best all-round predictor. However, asking about risk attitudes in a more specific context gives a stronger measure for that context. Responses to the general risk question are found to be highly correlated with choices in the hypothetical lottery question, indicating that the general risk question has explanatory power for choices in financial lotteries. The hypothetical lotteries are strong predictors for financial decisions, in the sense that they predict holding stocks (Dohmen et al., 2011).

The American Survey of Consumer Finances (SCF), used by many American academics, poses the following question: Which of the statements on this page comes closest to the amount of financial risk that you and your (spouse/partner) are willing to take when you save or make investments?[2]

1) take substantial financial risks expecting to earn substantial returns;
2) take above-average financial risks expecting to earn above-average returns;
3) take average financial risks expecting to earn average returns; or
4) not willing to take any financial risks.

Grable and Lytton (2001) assess the reliability and validity of the question used in the SCF. Since the same question has been used since 1983, the tool is regarded as relatively reliable and stable. Over time, the share of respondents for each alternative has changed somewhat. Those who answered "no risk," accounted for 43 % in 1983, 50 % in 1992, and 39 % in 1998. One reason for these differences could be that validity is impaired by volatility, which confuses individuals

[1] Holt and Laury (2002) test whether results change if payoffs are scaled up by factors of twenty, fifty, and ninety; when payoffs are hypothetical, the differences are small. In a later study Holt and Laury (2005), they find the differences statistically insignificant when possible order effects in their experiments are eliminated. Their main finding, however, is that the subjects become sharply more risk averse when payoffs are real and actually paid out in cash.

[2] The option, "take below-average financial risk expecting to earn below-average return," is not available.

Table 3
Correlation matrix of subjective and objective risk measures.

	1(LRP)	Q.A	Q.B	Q.C	6 (SRP)	8 (multi-item)	ARP	ERP	MRP
1(LRP)	1.0000								
Q.A	0.2619	1.0000							
Q.B	0.2666	0.6826	1.0000						
Q.C	0.2033	0.4293	0.4236	1.0000					
6 (SRP)	0.2881	0.8762	0.9426	0.4619	1.0000				
8 (multi-item)	0.8027	0.7089	0.7532	0.4143	0.8023	1.0000			
ARP	0.0640	0.1731	0.1584	0.1093	0.1880	0.1570	1.0000		
ERP	0.0562	0.1203	0.1235	0.0728	0.1368	0.1203	0.2807	1.0000	
MRP	−0.0139	0.0483	0.0337	0.0148	0.0491	0.0182	0.5437	−0.0309	1.0000

Notes: Model 2, not shown, is an extended version of model 1, with factor variables. Q.A, Q.B., and Q.C., are used in Models 3,4, and 5. Model 7, not shown, is a combination of Models 1 and 6.

when they think about risk tolerance (ibid.). Even so, the authors argue that the risk question in the SCF passes the face validity and the construct validity, but fails the content validity. This is because the four distinct elements present when making risky choices, such as 1) the probability of gains, 2) the probability of losses, 3) the amount of potential gains, and 4) the amount of potential losses (MacCrimmon and Wehrung, 1986) – are not included in the measure in a concurrent way (Grable and Lytton, 2001). Even though the authors view the criterion validity to be sufficient, compared with their 13-item questionnaire, they argue that the SCF question may be a relatively good measure for investment risk tolerance, or as a measure of financial expertise.

Our questions (Q.A., Q.B., and Q.C.) measure risk preferences, and is tested by responding to a survey about the trade-off between risk and return (c.f. Wärneryd, 1996). The variable SRP is built up from three questions raised (see Table 2), with a Likert-type scale ranging from 1 (= Totally disagree) to 7 (= Totally agree):

A confirmatory factor analysis (CFA) is conducted in order to evaluate the measure of the explanatory variable SRP, providing a test for unidimensionality (Gerbing and Anderson, 1988). The factor loadings are at or above 0.5, as suggested by Bollen (1989). Item reliability (R-squared) measures show values above the recommended 0.5 (Bollen, 1989), except for the third statement, where the R-squared is lower. However, composite reliability for the construct is high, exceeding the recommended level of 0.70 (Hair et al., 1998). The average variance extracted is above 0.5 (Fornell and Larcker, 1981). The high reliability is due to very small indicator measurement errors. The score of the construct varies between −1.975 and 2.796, with a mean of −0.011.

In line with the assessment of Grable and Lytton (2001), the risk preference, as developed above, is likely to be more related to investment choices than risk in general. However, compared with the SCF questions, this measure has a higher content validity, since both gains and losses are included in the question. By correlating the measure with risky assets, including stock holdings and investments in mutual funds, we can establish satisfactory criterion validity.

2.3.2.3. Multi-item risk measures. A combination of LRP and SRP is tested in one of the models, Model 7. In addition, an average of the standardized LRP and SRP makes up a multi-item measure, used in Model 8. This multi-item variable varies between −1.121 and 2.319, and the mean is −0.048.

2.3.3. Correlation of subjective and objective risk measures

The correlation between the explanatory variables LRP and SRP is positive (0.28). The correlations between the three questions used in SRP are higher (between 0.42 and 0.68). Between the explanatory and the explained variables, the correlations are higher for the three survey questions used for SRP, and SRP, along with ARP, MRP, and ERP, than for LRP. Note that the correlation between LRP and MRP is negative. Those who take high risk, according to the lottery questions, seem more likely to invest in equity than in mutual funds (c.f. Dohmen et al., 2011).

2.3.4. Control variables

The variables age, gender, urban residence (the four large-city areas), income, financial assets, and debt are included as control variables. In addition, the use of, and trust in, financial advisors is included, together with knowledge of, and interest in, financial matters. Also, family status, work status, house type, education, and financial literacy are controlled for.

The six financial literacy questions that are asked are relatively difficult and different from other literacy surveys, (see Lusardi, 2012; Almenberg and Widmark, 2011), but they are relevant in the Swedish financial context, where it is common to save in mutual funds and shares, instead of bonds, and where most households borrow with variable interest rates. That is why it is important to know that the Riksbank has an inflation target. It is also important to know when the Riksbank increases or decreases its repo rate, and to understand what the real interest rate, an equity-linked security, and the P/E-ratio are. Most bank customers also need to know that mutual funds have different risk levels, and that saving in equity funds is riskier than saving in balanced or fixed-income funds. Nevertheless, despite the importance of knowing these answers, about half of the respondents had only 0 or 1 right, and only 20 % had more than 3 right answers.

2.4. Methodology

We use multiple regression analysis, with the purpose of explaining and predicting objective risk taking by subjective risk measures as explanatory or predictor variables, and with the addition of control variables to make the model more realistic. The models is described by the following eight equations for ARP (similar models for MRP and ERP can be constructed):

$$\mathrm{ARP} = \beta_0 + \beta_1 \mathrm{LRP} + \beta_2 x_2 \ldots + \beta_k x_k + \mu \quad (1)$$

$$\mathrm{ARP} = \beta_0 + \beta_1 \mathrm{LRP} + \beta_2 x_2 \ldots + \beta_k x_k + \mu \quad (2)$$

$$\mathrm{ARP} = \beta_0 + \beta_1 \mathrm{QA} + \beta_2 x_2 \ldots + \beta_k x_k + \mu \quad (3)$$

$$\mathrm{ARP} = \beta_0 + \beta_1 \mathrm{QB} + \beta_2 x_2 \ldots + \beta_k x_k + \mu \quad (4)$$

$$\mathrm{ARP} = \beta_0 + \beta_1 \mathrm{QC} + \beta_2 x_2 \ldots + \beta_k x_k + \mu \quad (5)$$

$$\mathrm{ARP} = \beta_0 + \beta_1 \mathrm{SRP} + \beta_2 x_2 + \ldots + \beta_k x_k + \mu \quad (6)$$

$$\mathrm{ARP} = \beta_0 + \beta_1 \mathrm{LRP} + \beta_2 \mathrm{SRP} + \beta_3 x_3 \ldots + \beta_k x_k + \mu \quad (7)$$

$$\mathrm{ARP} = \beta_0 + \beta_1 (\mathrm{LRP} + \mathrm{SRP})/2 + \beta_2 x_2 \ldots + \beta_k x_k + \mu \quad (8)$$

where ARP is objective risk taking as a share of risky assets ($\geq 0, \leq 1$), β_0 is the intercept, β_1 is the parameter associated with the first explanatory variable, β_2 is the parameter associated with the second explanatory variable (if used in the model; otherwise associated with the first control variable), and β_3 (or β_2) to β_k are the parameters associated with the *k* control variables. The variable μ is the error term. Model 2 includes LRP as a factor variable. Model 7 is a combination of LRP and SRP, while Model 8 uses an average of the standardized beta values of LRP and SRP.

To address the potential problems of selection bias, we test the two subjective measures LRP and SRP with regard to age, gender, wealth, debt, financial literacy, and the use of financial advisor (see Section 3.2 about robustness and group analysis).

3. Results

3.1. Overall results

In Table 4, Model 1 (using LRP) and Model 6 (using SRP) are presented, with ARP as the explained variable. With all the control variables, the models explain close to 20 % of the ratio between risky assets and total financial assets of bank customers. Model 6 has a larger standardized coefficient (0.132) than Model 1 (0.036), thus indicating higher explanatory power.

Analyzing the control variables, the "Use of financial advisor, the "Trust" in the advisor, and the "Investment volume" (or total financial assets) are the variables with the highest explanatory power. "Family status" and "Work status" are not statistically significant variables, and, in the case of Model 6, the "Interest" in finances is also not significant. The relationship between ARP and income, as well as between ARP and debt, is negative. The higher the income and debt, the lower is the risky asset ratio. One explanation could be that the more debt a customer has, the more of his or her income is needed to pay debt service, and the possibilities for investing in risky assets decrease.

In Table 5, all eight models are presented for each objective measure, i.e., for ARP, MRP, and ERP. The focus here is to summarize the independent variables' contribution to regression effects, as well as to compare the models in terms of explanatory power and evaluate the models' predictive power.

We find support for the hypothesis that subjective risk measures can explain and predict objective risk measures. However, the correlations and beta values are relatively low. Thus, the models show that other factors have higher beta values when explaining objective risk. For example, as seen in Table 4, having an advisor (0.151–0.155) and trusting him or her (0.184–0.196) is more strongly related to objective risk. Apart from the control variables discussed above, developments regarding the stock exchange and the housing market could be important. These markets were performing relatively well at the time of the survey (spring of 2013). For some customers, a strong stock market could imply selling and keeping the money in a risk-free savings account, and, for others, it could suggest that it is preferable to buy more shares. Buying and selling houses and apartments could also imply more or less money in the risk-free savings accounts. Longitudinal studies, adding stock market and real estate price data, are needed to shed more light on the importance of these factors.

Table 4
OLS regression for models 1 and 6, presenting coefficients for control variables.

	ARP (only register data controls)			ARP (register + survey data)			ARP (only register data controls)			ARP (register + survey data)		
	Coeff.	p-values	St.Coeff.	Coeff.	p-values	St.Coeff.	Coeff.	p-values	St.Coeff.	Coeff.	p-values	St.Coeff.
Independent:												
1. Hypothetical Lottery Risk Preference (LRP)	0.0286	0.000	0.051	0.0202	0.001	0.036						
6. Survey Risk Preference (SRP)							0.0451	0.000	0.161	0.0375	0.000	0.132
Control (register data):												
Age	0.0006	0.019	0.028	0.0013	0.000	0.063	0.001	0.000	0.055	0.002	0.000	0.089
Gender	−0.0441	0.000	−0.062	−0.0487	0.000	−0.069	−0.061	0.000	−0.087	−0.056	0.000	−0.079
Urban - large cities	0.0498	0.000	0.050	0.0410	0.000	0.041	0.050	0.000	0.051	0.040	0.000	0.040
Monthly income (net of income tax)	4.0E-07	0.179	0.014	−6.8E-07	0.045	−0.024	5.4E-08	0.855	0.002	−7.9E-07	0.020	−0.027
Investment Volume	8.2E-08	0.000	0.187	6.8E-08	0.000	0.155	7.3E-08	0.000	0.167	6.5E-08	0.000	0.150
Debt	−4.4E-08	0.128	−0.015	−6.1E-08	0.027	−0.021	−4.7E-08	0.100	−0.016	−5.9E-08	0.016	−0.022
Use financial advisor	0.2425107	0.000	0.259	0.1450	0.000	0.155	0.230	0.000	0.246	0.144	0.000	0.151
Control (survey data):												
Trust in advisor (subjective)				0.0303	0.000	0.196				0.028	0.000	0.184
Interest in finances (subjective)				0.0123	0.000	0.053				0.003	0.301	0.015
Knowledge in finances (subjective)				−0.0342396	0.000	−0.077				−0.037	0.000	−0.082
Family status												
Compared with Single - w/o children												
Singe - w children				0.0229	0.263	0.013				0.023	0.260	0.013
Couple - w/o children				−0.0368	0.001	−0.046				−0.036	0.001	−0.046
Couple - w children				−0.0018	0.871	−0.002				−0.004	0.741	−0.005
Other				0.0061	0.834	0.003				0.008	0.786	0.003
Housing												
Compared with Rental apartment												
Tenant-owned apartment				0.0303	0.015	0.034				0.028	0.024	0.031
House				0.0362	0.001	0.051				0.036	0.001	0.050
Farmhouse				0.0249	0.213	0.014				0.027	0.170	0.016
Workstatus												
Compared wtih Full time												
Part time				0.0092	0.490	0.008				0.011	0.411	0.009
Retired				−0.0443	0.001	−0.058				−0.040	0.003	−0.052
Long-term sick				−0.0407	0.054	−0.033				−0.035	0.095	−0.019
Student				0.0221	0.343	0.013				0.021	0.377	0.012
Unemployed				−0.0426	0.021	0.026				−0.044	0.015	−0.027
Education												
Compared with No finalized education												
Pregymnasial education (Lower secondary school)				−0.0069	0.678	−0.006				−0.005	0.766	−0.004
Gymnasium (Upper secondary school)				0.0237	0.120	0.031				0.026	0.087	0.033
Postgymnasial education, < 3 yrs				0.0158	0.321	0.018				0.017	0.284	0.019
Postgymnasial education, > = 3 yrs				0.0016	0.916	0.002				0.004	0.809	0.005

(*continued on next page*)

Table 4 (*continued*)

	ARP (only register data controls)			ARP (register + survey data)			ARP (only register data controls)			ARP (register + survey data)		
	Coeff.	p-values	St.Coeff.	Coeff.	p-values	St.Coeff.	Coeff.	p-values	St.Coeff.	Coeff.	p-values	St.Coeff.
FinKnow												
Compared with 0 right												
1 right				0.0831	0.000	0.103				0.080	0.000	0.099
2 right				0.0448	0.000	0.048				0.041	0.001	0.044
3 right				0.0764	0.000	0.075				0.069	0.000	0.068
4 right				0.0648	0.000	0.056				0.058	0.000	0.050
5 right				0.0998	0.000	0.070				0.088	0.000	0.062
6 right				0.1207	0.000	0.065				0.103	0.000	0.055
Constant	0.1424	0.000		0.1455	0.000		0.1864	0.000		0.1561	0.000	
Observations	7324			7324			7324			7324		
F-stat	122.47			55.35			167.88			62.27		
R-Squared	0.134			0.1885			0.154			0.2002		
AIC	4516			4087			4342			3981		
BIC	4579			4321			4404			4215		

Regarding how well the subjective risk measures explain ARP, Model 6 has the highest beta value (0.132). In addition, the direct correlation with ARP (0.188) and the F-test of the model (62.3) show the highest values, while the BIC value is the lowest (4215). On the other hand, Model 7 has the R-squared F-test (124.05). Furthermore, Model 7 has the lowest values for AIC (3973). Thus, the models with the highest explanatory power are the ones where SRP is used as the only variable, and where LRP and SRP are combined. Using LRP only, i.e., Models 1 and 2, is a suboptimal solution. Thus, our results support the findings of Menkhoff and Sakha (2017), i.e., that survey items perform just as well as incentivized experimental items, and that multi-item variables perform better than single-item variables in explaining risk tolerance.

The explanatory power for ERP is similar to that for ARP, but in terms of beta values and the F-test of the model, Model 6 is similar to Model 8, i.e., the average of the standardized coefficients for LRP and SRP. Analyzing MRP, Model 6 shows the highest indicator for the F-test (29.11), while Model 7 shows the largest R-squared F-test (40.20). In addition, Model 7 has the lowest values for the information criteria (AIC = 1054; BIC = 1302).

In order to test the models' predictive power, we ran the regressions for half of the sample, and then used the predicted values in the other half of the sample to be able to compare the results with the actual values. The mean of the predicted standard errors (MSE) and the root mean of the squared standard errors (RMSE) are used to compare the models. The best predictive power, i.e., the lowest values of MSE and RMSE, is found for ERP (RMSE = 0.13), followed by MRP (0.26) and ARP (0.32).

Regarding ARP, the RMSE shows that the predictive power supports the explanatory power. Model 7 shows the highest predictability, and Model 6 the second highest. The same applies for MRP. For ERP, the best predictive power is represented by Models 1 and 2, i.e., the models using LRP. The information criterion, AIC, which often is used to show predictive power, does not support the RMSE results. Instead, AIC gives more support to Models 1 and 2. However, the differences among all the models are marginal; therefore, in terms of predictive power, the models seem to be similarly weak, but better than naïve models.

3.2. Robustness and group analysis

All models are statistically significant, based on analysis of their F-values. The subjective risk measures alone do not explain more than 4 % of the variance in the explained variable. Adding the control variables, the models explain up to 20 % of the variance. The p-values are based on heteroscedasticity robust variance.

Using cross-sectional data, there is a risk that a customer's asset allocation in a certain month differs from other months, e.g., because of specific investments or consumption expenditures resulting in changes in the normal risk preference. We have data also for January 2013, and use this to calculate objective risk preferences for January to compare with the March data used. The correlation is 0.93, resulting in similar results regarding the beta values for SRP and LRP, the F-statistics, and the R-squared values. We conclude that the models used are robust in terms of using two different objective risk preferences, although the data points are very near in time.

With relatively low R-squared and adjusted R-squared values, there is a risk that omitted variables, had they been included in the model, would have contributed to other results. In particular, variables other than subjective risk attitudes could drive the objective risk ratio. Nosic and Weber (2007) discuss how risk taking can be influenced by events such as obtaining a university degree or having children. Also, stock exchange developments could cause either optimism or pessimism, thus influencing the behavior of risk taking. More research is needed to analyze the omitted variables and their influence on the consistency between subjective and objective risk measures.

Another common problem of endogeneity is reverse causality. In line with theory, we assume that attitudes and beliefs should feed into intentions and, thereafter, behavior. But what if behavior would cause different intentions and attitudes –

Table 5
Measuring the explanatory and predictive power of subjective risk measures.

	B	βxy	βx	βy	*t*-test	F-test	*r*	F-test (ΔR2) F-test (ΔR2)	β * rβ * r	MSE	RMSE	AIC	BIC
1. Hypothetical Lottery Risk Preference (LRP)	0.020	0.036	0.013	0.057	3.349	55.35	0.064	11.68	0.0023	0.0309	0.3191	4087	4321
2. Hypothetical Lottery Risk Preference(LRP)						54.49		8.54		0.0313	0.3190	4084	4325
Risk averse vs Risk neutral	−0.037	−0.048	−0.017	−0.106	−4.01								
Risk taker vs Risk neutral	−0.013	−0.010	−0.004	−0.037	−0.86								
3. I can accept to loose part of my saving if the chance of getting a good return is great	0.023	0.113	0.040	0.064	9.53	60.53	0.173	94.50	0.0196	0.0303	0.3172	3986	4220
4. I think one has to take risk in order to gain something	0.021	0.106	0.038	0.059	8.75	59.66	0.158	80.72	0.0168	0.0303	0.3171	4161	4397
5. I would like to increase the risk involved in my saving because I think the return is too low	0.013	0.058	0.020	0.036	5.10	54.91	0.109	17.08	0.0063	0.0305	0.3183	4048	4283
6. Survey Risk Preference (SRP) Factor of B, C, D	0.038	0.132	0.047	0.106	10.75	62.27	0.188	118.50	0.0248	0.0208	0.3165	3981	4215
7. Hypothical Lottery Risk Preference (LRP)								124.05		0.0316	0.3163	3973	4228
Risk averse vs Risk neutral	−0.021	−0.028	−0.010	−0.061	−2.27	59.48							
Risk taker vs Risk neutral	−0.023	−0.018	−0.006	−0.065	−1.51	59.48							
Survey Risk Preference (SRP)	0.037	0.129	0.046	0.103	10.17	59.48							
8. Average of standardized LRP and SRP (Multi)	0.046	0.104	0.037	0.131	8.810	59.52	0.157	78.00	0.0162	0.0308	0.3175	4921	4256

Mutual Fund Risk Preference (MRP)	B	βxy	βx	βy	*t*-test	F-test	*r*	F-test (ΔR2) F-test (ΔR2)	β * rβ * r	MSE	RMSE	AIC	BIC
1. Hypothetical Lottery Risk Preference (LRP)	0.001	0.002	0.000	0.003	0.15	26.08	−0.020	0.00	0.0000	0.0251	0.2584	1120	1354
2. Hypothetical Lottery Risk Preference(LRP)						25.88		5.72		0.0254	0.2582	1110	1351
Risk averse vs Risk neutral	−0.021	−0.035	−0.010	−0.076	−2.72								
Risk taker vs Risk neutral	−0.039	−0.039	−0.011	−0.141	−3.33								
3. I can accept to loose part of my saving if the chance of getting a good return is great	0.009	0.055	0.015	0.031	4.54	28.74	0.048	21.28	0.0027	0.0248	0.2582	1136	1372
4. I think one has to take risk in order to gain something	0.008	0.049	0.014	0.027	4.01	28.44	0.034	18.81	0.0017	0.0248	0.2580	1133	1369
5. I would like to increase the risk involved in my saving because I think the return is too low	0.005	0.028	0.008	0.017	2.34	27.21	0.015	3.26	0.0004	0.0248	0.2580	1139	1375
6. Survey Risk Preference (SRP) Factor of B, C, D	0.015	0.066	0.018	0.053	5.25	29.11	0.049	28.67	0.0032	0.0248	0.2580	1125	1360
7. Hypothical Lottery Risk Preference (LRP)						26.48		40.20		0.0258	0.2573	1054	1302
Risk averse vs Risk neutral	−0.014	−0.023	−0.006	−0.051	−1.77								
Risk taker vs Risk neutral	−0.043	−0.043	−0.012	−0.155	−3.66								
Survey Risk Preference (SRP)	0.016	0.071	0.020	0.057	5.35								
8. Average of standardized LRP and SRP (Multi)	0.014	0.041	0.011	0.052	3.46	26.75	0.018	10.62	0.0007	0.0251	0.2577	1079	1315

(*continued on next page*)

Table 5 (*continued*)

Equity Risk Preference (ERP)	B	βxy	βx	βy	*t*-test	F-test	*r*	F-test (ΔR2) F-test (ΔR2)	$\beta * r\beta * r$	MSE	RMSE	AIC	BIC
1. Hypothetical Lottery Risk Preference (LRP)	0.008	0.034	0.005	0.053	2.82	26.12	0.056	9.71	0.0019	0.0132	0.1301	−8693	−8459
2. Hypothetical Lottery Risk Preference(LRP)						25.42		4.86		0.0134	0.1301	−8691	−8450
Risk averse vs Risk neutral	−0.008	−0.024	−0.004	−0.053	−1.91								
Risk taker vs Risk neutral	0.008	0.015	0.002	0.054	1.10								
3. I can accept to loose part of my saving if the chance of getting a good return is great	0.004	0.052	0.008	0.029	4.10	26.15	0.120	22.12	0.0063	0.0131	0.1303	−8685	−8450
4. I think one has to take risk in order to gain something	0.005	0.058	0.008	0.032	4.49	26.21	0.124	24.78	0.0072	0.0131	0.1304	−8683	−8448
5. I would like to increase the risk involved in my saving because I think the return is too low	0.003	0.028	0.004	0.017	2.32	25.76	0.073	−6.17	0.0020	0.0131	0.1304	−8635	−8400
6. Survey Risk Preference (SRP) Factor of B, C, D	0.008	0.064	0.009	0.051	4.80	26.31	0.137	26.56	0.0088	0.0130	0.1302	−8711	−8476
7. Hypothical Lottery Risk Preference (LRP)						25.04		31.00		0.0137	0.1303	−8711	−8462
Risk averse vs Risk neutral	−0.005	−0.015	−0.002	−0.032	−1.16								
Risk taker vs Risk neutral	0.006	0.011	0.002	0.041	0.83								
Survey Risk Preference (SRP)	0.007	0.058	0.009	0.047	4.29								
8. Average of standardized LRP and SRP (Multi)	0.011	0.062	0.009	0.078	4.792	26.47	0.120	27.44	0.0075	0.0132	0.1302	−8711	−8476

Table 6
Testing age, gender, wealth, debt, financial literacy, use of financial advisor as interactive variabels with the subjective risk measures.

Interacting with LRP	ARP		MRP		ERP	
	β	p-value	β	p-value	β	p-value
LRP w/o interactive variables	**0.0371**	**0.001**	−0.0011	0.920	**0.0331**	**0.006**
Age						
Low Age	**0.0547**	**0.000**	0.0079	0.554	**0.0316**	**0.010**
Diff High Age	**−0.0379**	**0.027**	−0.0194	−0.258	0.0032	0.853
Gender						
Female	**0.0417**	**0.008**	**0.0292**	**0.057**	0.0045	0.787
Diff Male	−0.0114	0.693	−0.0139	0.639	0.0097	0.756
Wealth						
Low Wealth	**−0.0332**	**0.008**	−0.0022	0.856	**−0.0764**	**0.000**
Diff High Wealth	**0.1720**	**0.000**	**0.1841**	**0.000**	**0.0862**	**0.000**
Debt						
No debt	**0.0284**	**0.010**	0.0151	0.179	**0.0345**	**0.005**
Diff Have debt	**0.0506**	**0.000**	**−0.0937**	**0.000**	−0.0080	0.549
Financial literacy						
Low financial literacy	**0.0436**	**0.000**	−0.0056	0.643	**0.0335**	**0.006**
Diff High financial literacy	−0.0219	0.232	−0.0153	0.423	−0.0014	0.949
Financial advisor						
Not using financial advisor	**0.0786**	**0.009**	0.0280	0.322	0.0281	0.249
Diff Using financial advisor	−0.0607	0.126	−0.0426	0.263	0.0073	0.829
Interacting with SRP	ARP		MRP		ERP	
	β	p-value	β	p-value	β	p-value
SRP w/o interactive variables	**0.1358**	**0.000**	**0.0656**	**0.000**	**0.0638**	**0.000**
Age						
Low Age	**0.1069**	**0.000**	**0.0733**	**0.000**	**0.0378**	**0.012**
Diff High Age	**0.0358**	**0.041**	−0.0097	0.585	**0.0322**	**0.083**
Gender						
Female	**0.1111**	**0.000**	**0.0604**	**0.000**	0.0111	0.486
Diff Male	**0.0356**	**0.016**	0.0074	0.635	**0.0761**	**0.000**
Wealth						
Low Wealth	**0.1270**	**0.000**	**0.0939**	**0.000**	**0.0307**	**0.027**
Diff High Wealth	0.0122	0.433	**−0.0392**	**0.015**	**0.0458**	**0.008**
Debt						
No debt	**0.1371**	**0.000**	**0.0648**	**0.000**	**0.0581**	**0.000**
Diff Have debt	−0.0037	0.757	0.0020	0.843	0.0159	0.192
Financial literacy						
Low financial literacy	**0.1302**	**0.000**	**0.0797**	**0.000**	**0.0310**	**0.024**
Diff High financial literacy	0.0097	0.471	**−0.0245**	**0.085**	**0.0568**	**0.001**
Financial advisor						
Not using financial advisor	**0.1445**	**0.000**	**0.1222**	**0.000**	0.0241	0.316
Diff Using financial advisor	−0.0010	0.719	**−0.0616**	**0.022**	**0.0432**	**0.083**

Notes: All control variables are included in the models. Bold figures indicate significant variables if p-values are below 0.10 (10 % level).

i.e., reverse causality were in effect? In such a case, the bank would have an impact on their customers' risk behavior, e.g., by actively trying to either reduce or increase risk in their portfolios. We would need longitudinal data in order to analyze how the bank over time could influence customers' allocation and/or attitudes. Future research, adding data on the bank's advice and its customers' behavior and intentions, would contribute to a better understanding of possible reverse causality; in this paper, however, the objective is to test the assumption that subjective risk preferences guide objective risk behavior, and to compare how well these subjective measures predict the objective risk measure.

We include interactive variables to test the models' results for certain groups of the sample. Relevant variables to test, based on selection bias, are age, gender, wealth, debt, and the use of financial advisor, since we find sample differences between register data and survey data. Because those who have high financial literacy could be assumed to show higher consistency between subjective and objective risk taking, we also test this variable. Age and wealth are divided into high and low, i.e., above and below the median of the sample. Financial literacy is divided into low – only 0, 1, or 2 right quiz answers – and high – more than 2 right quiz answers. Gender, debt, and use of financial advisors are dummies (male = 1, having debt = 1, use of financial advisor = 1). We interact them one by one with SRP and LRP and run the regressions for the explained variables ARP, ERP, and MRP. The results are shown in Table 6.

Analyzing first the LRP measure in respect to ARP, we see significant differences between low and high age, wealth, and debt. Older customers have lower beta values, thus indicating a weaker relationship between subjective and objective risk. On the other hand, the relationship is stronger for the wealthier and the more indebted customers. We cannot find significant differences regarding gender, financial literacy, or the use of a financial advisor. Having high wealth means significantly higher beta values for MRP, and significantly lower (negative values) if customers have debt. Regarding LRP in relation to

ERP, there are significant differences between low and high wealth. When the regressions are run with all the interactive variables at the same time (not shown in Table 6) i.e., the base case – a relatively young female person with low wealth and financial literacy, and with no debt, and without a financial advisor – all the interactive variables are significant, except gender for ARP, and except gender and financial literacy for MRP. Only wealth is significant for ERP.

Analyzing the SRP measure in respect to ARP, there are significant differences between low and high age and between men and women. The older customers and men have higher beta values, indicating a stronger relationship between subjective and objective risk. The other interactive variables are not significant for ARP. One reason seems to be that, while the beta values are significantly higher regarding ERP for wealthier customers and more literate customers using financial advisors, the corresponding beta values are lower (negative values) for MRP. The wealthier, advised, and more literate customers may prefer investing in the stock market to investing in mutual funds. Again, when the regressions are run with all the interactive variables at the same time, only age and gender are significantly different for ARP, no differences are noted for MRP, and, for ERP only gender and financial literacy are significantly different.

There are significant differences between some of the analyzed groups of the sample. Still, the beta values are generally higher for SRP, except for the wealthier customers, for whom LRP has higher beta values than SRP.

4. Conclusion and discussion

Our results support our first hypothesis, i.e., that subjective risk measures can explain and predict objective risk. Similar to Nosic and Weber (2007), Schooley and Worden (1996), and Chang et al. (2004), we find consistency between subjective and objective risk preferences. However, the correlations between the subjective and objective measures are relatively low. There are other factors with higher correlations between bank customers' self-assessed risk preferences and the way they actually allocate their risk and financial assets in their portfolios. Moreover, the relationship is weaker for mutual funds than for investments in shares.

Analyzing the different models, we find support for our second hypothesis – that the survey questions about the trade-off between risk and return are superior in terms of explaining objective risk compared to the survey questions using a hypothetical lottery (cf. Nosic and Weber, 2007; Dohmen et al., 2011). In terms of predicting objective risk, using the RMSE, the differences between the models are marginal, and their predictive power seems to be about the same. The best predictive power is found for the analysis of equity risk, followed by mutual fund risk, and last, the overall allocation of risky assets.

We also find support for the third hypothesis – that it is preferable to combine single-item questions to form multiple-item risk measures. This is in line with findings of Menkhoff and Sakha (2017) and Loomes and Pogrebna (2014). The construct subjective risk preference (SRP), used in Model 6, shows a higher explanatory power than the single-item questions used in Models 3, 4, and 5. Furthermore, the combination of the lottery risk preference (LRP) and SRP in Model 7 shows a larger change in R-squared than Model 6. However, Model 6 has higher values for beta and the F-test of the models than Model 7. Still, Models 6–8, where single-items are combined into multi-item variables, perform better than Models 1–5, using single-item variables.

We can also show that there are significant differences between the analyzed groups of the sample, and that they differ between LRP and SRP. Interacting group variables with SRP, for example, shows significant differences between low and high age, and between women and men. However, importantly, we do still find SRP to have stronger explanatory power than LRP. The wealthy customers are the exception, where LRP shows higher beta values than SRP. This indicates a need to further study wealthy customers and their risk preferences. In contrast to Park and Yao (2016), we do not find significant differences in consistency between subjective and objective risk measures for customers with and without financial advisors.

For practitioners, our findings indicate the following: Bank customers who say they are willing to take risk to gain something and are willing to lose part of their saving capital if the chance of getting a good return is great, have riskier portfolios. This also applies to the hypothetical lottery, albeit the relationship is weaker. Those who prefer a prospect to a sure outcome with equal or greater expected value, and those who choose in accordance with the expected value, have riskier portfolios than those who prefer a sure outcome over a prospect with an equal or greater expected value. A bank, interested in monitoring its customers' subjective risk assessments, can start with the survey questions focused on the trade-off between risk and return. The explanatory power increases when combining these questions with the lottery, but the benefits are marginal. When costs of surveying customers are included, the conclusion to focus primarily on the survey on the trade-off becomes even stronger. This study found that the bank customer's use of, and trust in, the financial advisor has a positive relationship with his or her objective risk, but that this factor made no difference regarding the consistency between subjective and objective risk. Hence, there is potential for financial institutions to improve this consistency. For those who take more or less risk in objective terms than can be assessed subjectively, the bank can mitigate the unintended outcomes by, in the first case, reducing, and, in the second, increasing risky assets. By selling financial products that are in line with the customers' risk profile, the bank can both expand business opportunities and deliver products that are better adjusted to customers' life context and risk tolerance.

Not least, financial institutions using robo-advisors need to ensure that risk preferences are measured as accurately as possible, in order to provide portfolios that are in line with the intentions of their customers. Unlike a physical advisor, the robo-advisor does not ask follow-up questions; it is also more difficult for the robo-advisor to judge if the information provided by the customer is reliable (Sweden's financial supervisory authority, Finansinspektionen, 2016). Furthermore, financial institutions need to ensure that legal obligations are fulfilled, such as Markets in Financial Instruments Directive (MiFID II) in Europe. Understanding how to measure bank customers' risk preferences is crucial in order to deliver well-targeted products.

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