Cross-Firm Variations in Portfolio Recommendations for Robo-Advisors*

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Abstract

We show that there are significant differences in the consistency of advice across robo-advisors to different investors seeking advice. By comparing the recommended portfolios for three generic investors across a large share of actors on the U.S., U.K. and Canadian markets for robo-advisors we found that the generic aggressive investor with a high level of financial literacy received largely consistent portfolio recommendations across the robo-advisors while the generic moderate investor with a moderate level of financial literacy received slightly less consistent recommendations. In turn, the generic conservative investor in our sample received much less consistent recommendations. The conservative investor also had the lowest financial literacy by our measurement. The combination of receiving high variations of portfolio recommendations in combination with low financial literacy might suggest that this conservative investor is not having his best interests sought after in the robo-advisor environment. This should be investigated further by future research. Our study also shows that the cross-firm variations across all three investors can be explained to some part by the robo-advisor's country of origin and exposure to fixed income products in their underlying offering.

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1. Introduction

Recent time's changes in the market for financial advice for individual investors has been manifested in an increasing use of automated digital advisors via Internet, henceforth called robo-advisors (Berndt et al., 2017). One of the main arguments for the use of robo-advisors is its alleged objectivity in portfolio recommendations compared to the interest of conflict-ridden traditional financial advisors (Burke et al., 2015; Baker et al., 2017). Yet, there is a pervasive cross-firm variation in portfolio recommendations in the marker for robo-advice. If the individual investor seeks various advice from several robo-advisors the recommended portfolio allocation will differ. How can this variation be explained?

While there is a lot of research on traditional advisors and their different biases (Baker et al. 2017) there is a still little research on the exploding number of robo-advisors in the world. We wanted to try and explain how and why investor with different levels of risk-aversion are being treated differently in this highly topical market. By creating our own dataset of robo-advisory portfolio recommendations for generic investor profiles and firm characteristics in the combined U.S., UK and Canadian market for robo-advice we have been able to find patterns in the data that suggest that the variation in cross-firm advice for portfolio recommendations is largest for conservative investors (investors with low risk-tolerance and no previous experience with investments) while moderate and aggressive investors in turn receive more consistent advice on average.

The most important factor for explaining the portfolio allocation weights across all observations was the individual investor's generic classifications. We have shown that our own-constructed generic investor profiles explain more than 55% of the variations in advice with high statistical significance, and over 78% when controlling for firm fixed effects (see Table 11). This is a fundamental postulate that shows that the robo-advisors are on average able to recognize the differences in risk-tolerance, financial experience and other personal characteristics of our generic investor profiles. Our finding that robo-advisors on average can categorize the different investors and give them different portfolio recommendations made it more interesting to look at the portfolio recommendations across robo-advisors for each generic investor in isolation. Especially the portfolio recommendations aimed at the generic conservative investor where the variations are the largest.

Our dataset thus invited us to further investigate the isolated investor cases which showed that, with some significance, UK robo-advisors on average gave smaller equity weights to conservative portfolios but we were unable to find statistically significant explanations for the cross-advisory variations for conservative investors when isolated. This gives reason to think that the explanation lies with some elusive investment philosophy bias. That is, the robo-advisor has some predetermined idea of how portfolio recommendations should look that is not based on investor preferences. To be able to say something about investment philosophy biases effect for individual robo-advisors we would need to have a large number of portfolio recommendations for each advisor. On average, the investors recommend a median of 5 different portfolios (range from 1 to 100 different allocations), making such a bias hard to measure. The firm fixed effect were shown to explain quite a lot of the variations (see Table 11) on the aggregate level for our generic conservative investor but we have not looked at the individual firms' philosophies themselves. Our results are merely suggesting that investment philosophy biases play a role in explaining the cross-firm variations in recommendations, especially for conservative investors.

Apart from the fundamental assumption that investor style is having a large impact on the recommended portfolio allocations we also tested hypotheses that economies-of-scale, country of origin, number of portfolios and number of questions asked in the questionnaire could explain the variations across firms.

In line with previous research by Dimmock and Kouwenberg (2010) we have been able to attribute a small portion of portfolio recommendation variations to country effects - if the firm is originating from the United Kingdom. From our results U.K. robo-advisors are on average recommending 15.2% less equity with some statistical significance. Perception of risk associated with equity varies across countries and we have seen this somewhat reflected in lower equity recommendations on average for U.K. firms compared to U.S. and Canadian firms.

The hypothesis that robo-advisory firms give varying portfolio recommendations because of an economies-of-scale rationale has support in previous research by Baker and Dellaert (2018) and we have been able to find a slightly significant effect that firms that have specialized in investing in fixed income assets are more likely to give portfolio recommendations with more fixed income weight on average. We found no significant correlation showing that robo-advisors originating in each different nation of the experiment had any fixed specialization effect. If, say, U.S. robo-advisors on average were more specialized towards equity, this could harm the regression by introducing multicollinearity (the robo-advisor being from the U.S. would have both an effect on the firm's exposure towards equity which affects the recommendation as well as through the independent country variable).

One other plausible hypothesis to explain the variation in recommendations across advisors was be the difference in questions asked in the questionnaire. The questionnaire is the foundation for the recommendation and we have been able to show that the robo-advisors are, on average, correctly managing to give different advice to different investors based on the answers provided by these questionnaires. The hypothesis was that the more question the robo-advisor is asking, the more it can specialize its offering and channel the investor towards a more customized portfolio. This would suggest that firms with a small number of questions would be closer to some sort of default portfolio, and the more questions asked, the more the firm can deviate from the default. This hypothesis does not, however, hold in our experiment. First of all, we found almost no correlation between the number of questions and the number of portfolios offered (see Figure 1.a. and 1.b.). This is also in line with previous research (Tertilt & Scholz, 2017). There is also no support for this hypothesis in our regression analysis; the number of questions and the number of portfolios are explaining close to nothing of the variation. The number of questions asked and portfolios offered have close to no effect in the isolated case for the generic conservative investor (see Table 11).

Our best model is able to explain 67.4% of the variations in portfolio recommendations on the aggregate level. It is unable to significantly explain why our generic conservative investor is facing so much higher variance in their portfolio recommendations compared to our generic moderate and aggressive investor respectively. We can however show with significance that the variance within each generic investor style subset is somewhat significant, meaning that there is support in suggesting that conservative investors are really facing a higher variance in recommendations on average. While explanations such as country effects, robo-advisors' specializations, number of questions asked in the questionnaire or the number of different portfolios offered are not able to explain more than 67.4% there is reason to look closer at the generic conservative investor, since the variation here is significantly larger and thus carries the largest portion of the overall variation. The conservative investor faced a standard deviation of 0.22 compared to 0.17 for moderate and aggressive investors in their portfolio recommendations.

Previous research by Fisch et al. (2015) and Mandell (2008) have shown that investors with lower levels of financial literacy share a higher risk of taking poor financial decisions, leading to unnecessary fees as well as failure while trying to take advantage of diversification effects. Our constructed conservative investor profile has consistently reported low levels of previous investment and/or financial experience (see Appendix A). While this does not exactly translate into levels of financial literacy, as measured by e.g. OECD it has acted as a proxy for financial literacy for the analysis of our results. This means that the conservative investor is also, to a high degree, showing low levels of financial literacy. The effect of low financial literacy could explain the variation because of investment philosophy bias from the robo-advisory firm. Financially illiterate investors have a lower ability to assess the portfolio recommendations provided and are also less likely to compare their recommendations across robo-advisors (Fisch et al, 2015). This investment philosophy bias is, as mentioned before, elusive and it has been beyond the scope of this paper to investigate it at proper length. Our results suggest that this bias, measured as a firm fixed effect, plays a substantial part of explaining the variations in recommendations. We leave a suggestion to further research in this field to more accurately try and measure this bias. It is in the interest of consumers of robo-advisory services as well as the providers of these same services to understand the disparity in recommendations for, especially conservative, investors discovered in our paper.

1.1 Related literature

The academic literature on robo-advisors is scarce which is something we have been experiencing along with Tertilt and Scholz (2017). While there is a large recent literature discussing the benefits and downsides of traditional financial advice such as Chalmers & Reuter (2015) and Bhattacharya et al (2012) there is apparently little research on the quality of robo-advisors' advice. This is odd given the recent time's criticism of traditional advice in favor for the more transparent and cost-efficient robo-advisors (Transparency Market Research, 2017). One of the authors on the subject, Fein (2015), has shown that robo-advisors are not necessarily providing recommendations that are cost-minimizing, free of conflicts of interest, nor in the best interest of the client. Fein is approaching robo-advisors from a legal standpoint, looking at the user agreements between robo-advisors and their clients. She also finds that it's hard to argue that robo-advisors are giving personal advice at all since the recommendations *"may be based on incorrect assumptions, incomplete information, or circumstances not relevant to the user."* (Fein, 2015, p. 9). It is of particular interest to our study to learn about conflicts of interest and how robo-advisors are generating their portfolio recommendations for individual investors. On robo-advisors being free of conflicts of interest Fein concludes:

> Robo-advisors are affected with a number of conflicts of interest that enable them to engage in self-dealing transactions. Among other things, as noted, in providing services to customers, robo-advisors use affiliated brokers, custodians, clearing firms or other firms from which they receive compensation. They also use their own investment products. (Fein, 2015, p. 15)

Fein also suggests that the robo-advisor is not necessarily acting in the best interest of their clients. Rather, Fein argues that the agreements between clients and robo-advisors seem to lay the responsibility of determining whether the recommendations are in the best interest of the client on the client herself. This is troublesome if the client is not financially literate and per se unfit to make such assessments.

Previous research on financial literacy such as van Rooij et al. (2011) has found that financially illiterate investors are less likely to invest in stocks, less likely to seek professional or qualified advice and are missing out on wealth increases associated with financial literacy. This is in part explained by missing out on the equity premium returns since financially illiterate investors are not willing to take on risks. This tendency among investors are relevant to this thesis since robo-advisors are basing their portfolio recommendations to a significant part on the investors' previous financial knowledge (which could serve as a proxy for financial literacy as it is measured by e.g. the OECD International Network on Financial Education (INFE) in their survey instruments). It is important to point out that while van Rooij et al. (2011) and OECD are estimating financial literacy they are testing the participants while robo-advisors as a rule are merely asking the investors to self-evaluate their financial knowledge. The recent literature on self-awareness regarding one's own level of financial literacy such as Anderson & Robinson (2018) suggests that this is not a very good measure for actual financial literacy for many investors. Anderson & Robinson (2018) found that Swedish investors that were over-estimating their own financial literacy are more likely to face higher fees in their mutual funds and risk underperforming while investors that are correctly assessing their own financial illiteracy are likely to not follow advice and less interested in personal finance in general. This opens for conflicts of interest of robo-advisors and investors that are relevant for this thesis. Especially since we cannot assume that, along Fein's (2015) results, robo-advisors are necessarily taking a clear responsibility for the advice they provide.

1.1.2 Definitions

Robo-advisors

In this paper, we are using the term robo-advisor to refer to the provider of online portfolio recommendation services. These robo-advisors vary somewhat in form but share some key characteristics: they are online, they are giving portfolio recommendations based on a questionnaire (8-9 questions on average in our sample) and are offering a fee-based asset management service after the initial recommendation. The robo-advisors are not entirely defined as the opposite of a traditional, physical financial advisor. Some of the robo-advisory services are provided by traditional advisors and some of them can be complemented with phone-meetings and physical meetings. For the scope of our study we have only looked at the recommendations provided through the online services for robo-advisors regardless of the underlying firm (whether it be independent, a bank or a traditional wealth management firm). Neither have we distinguished robo-advisors from each other based on their level of sophistication. For example, one robo-advisor might be using a few questions in a questionnaire to channel the investor towards one out of three different portfolios, while another robo-advisor is leveraging developed machine learning algorithms to guide the investor among hundreds or even thousands of portfolios. They are both regarded as robo-advisors to the same extent if they are providing services in accordance with our definition.

1.2 Ideal experiment

The ideal experiment to test and explain cross-firm variations would include all imaginable types of data on the robo-advisors such as underlying intentions and thought on how the firms develop their portfolio recommendations. A detailed study on how the business model of each individual robo-advisor and its cost and fee structure could also help explain more of the variations. Once we had access to all these observations we would ideally be able to draw a completely randomized sample from the population. All these independent variable data on every robo-advisor would then be used in order to find correlations with the portfolio recommendations they assign to various investors. These correlations might then in turn tell us something about how robo-advisory firm characteristics are determining the recommendations.

This would provide helpful *ex ante* guidance for investors that are aiming to consume robo-advisory services.

Our own experiment deviates from this ideal experiment on several pivotal points. Some are due to lack of data while others are due to lack of resources. We fail to achieve a randomized controlled experiment because we were limited to include only robo-advisors that provide portfolio recommendations 1) for free and 2) to people only identified by an email address. This limits our dataset to only include about half the total population of robo-advisors and possibly introducing a selection bias. Furthermore, inference based on our sample is hard because we are using data only from the U.S., U.K. and Canada - increasing the risk selection bias problems in our sample even more. Our treatment group is hardly randomized. There are also other approximations and model assumptions that deviate from an ideal experiment (where all independent variable inputs would be perfectly observable with no need for proxies or assumptions).

Because our analysis is based on a model that does not consider all imaginable types of data on the robo-advisors our results are at risk of omitted variable bias. This is a resource problem, because the quality of the accessible data is not necessarily the best for our purposes. For example, if the cost and fee structure would be a relevant variable that has implications for the portfolio recommendations this would not affect our results in the model, but by leaving it out we are over/underestimating the effects of our variables in the model in Formula 3. The fact that the robo-advisors have variations in their exposures to different asset classes does not itself implicate that there are automatically economies of scale, but this is an assumption we are imposing in our model in order to find some approximations for explaining cross-firm variations in portfolio recommendations. Furthermore, in the ideal experiment the asset classes would not only be grouped based on type of asset but also on the riskiness

And, we have made some more rather strict assumptions in our model. We are assuming our generic investors to be coherent and transferable across robo-advisors. While we have tested, and seen with strong statistical significance that this assumption holds (see Table 6.) there is still a possibility of some "borderline cases" where the robo-advisor algorithms are interpreting our generic investors differently and fail to separate them.

Also, the grouping of assets by risk might explain more of the variations than our current grouping by asset class. In our model, we are using asset class as a proxy for risk based on the assumption that equity is riskier than fixed income. This might not always be the case since "fixed income" includes a range of assets from government bonds that are the least risky to high yield bonds whose risks may well exceed that of equity assets. We believe that this assumption is not a significant misspecification in the model. Robo-advisors in our sample are using equity and fixed income in their portfolio recommendations in line with our assumptions (i.e. allocating more equity to risk-tolerant investors). Neither have we seen any robo-advisor informing that they are using any strategy deviating from our assumption. We cannot, however, guarantee that this is never the case. Some robo-advisors might well for example recommend the same level of equity for our generic aggressive and conservative investors, with the difference that the recommended equity assets for the aggressive investor has higher risk (e.g. emerging market equity) compared to the equity assets for the conservative investor (e.g. domestic equity). In this case, we would proxy the robo-advisor as recommending both the aggressive and conservative investor the same equity exposure and thus the same level of risk. A more nuanced measure for risk would be to assess the riskiness of the portfolio recommendation based on the riskiness of each asset class. This would probably be more correct, but constitutes a much more sophisticated type of analysis beyond the scope of this thesis.

2. Data

In this section, we will provide details on how the data was collected and prepared as well as a detailed description of the dataset used for this thesis.

2.1 Data collection process

Our optimal dataset would consist of all possible portfolio recommendations provided by all robo-advisors targeting the U.S., UK and Canadian markets for all individual investors. This type of data is not available and there are no accumulated datasets available for analysis. Therefore, a proprietary data sample has been generated for the purpose of analysis. Here we will explain in detail how the data in this dataset has been extracted.

In short, we gathered a list of robo-advisors and collected data on key characteristics that would be deemed useful in our model. Table 1 shows a list of all the independent variables collected on every robo-advisor.

Robo-advisor characteristics	
Independent variable	*Description*
Country of origin	This variable takes on the value "US", "UK" or "Canada". Indicator variables for country of origin were also used.
Number of questions asked in the questionnaire	This variable is the count of the number of questions asked in the profiling questionnaire. It is including only such questions that were related to the profiling, and excluding questions such as phone number, email address and the like.
Number of portfolios	This variable is the count of all the different portfolios that the robo-advisor is offering. The count is in most cases clearly provided by the firm but in other cases the count was made by randomly generating new portfolios.
Weight towards equity asset classes	This is the weight towards equity asset classes in the robo-advisor's underlying offering. Ranging from 0.0 to 1.0.
Weight towards fixed income asset classes	This is the weight towards fixed income asset classes in the robo-advisor's underlying offering. Ranging from 0.0 to 1.0.
Weight towards other asset classes	This is the weight towards other asset classes in the robo-advisor's underlying offering. Ranging from 0.0 to 1.0.

Table 1. Robo-advisor characteristics. The table shows the independent variables extracted from the robo-advisors that were used in our model.

The dependent variables of interest are the portfolio recommendations provided by these robo-advisors. Table 2 provides a list of the dependent variables and indicator variables used in our model. Each variable will be explained in greater detail further on in this section.

Portfolio recommendations	
Dependent variable	*Description*
Investor style	This variable is based on what investor profile was used to induce the portfolio recommendation. The investor style was either: "conservative," "moderate" or "aggressive". Indicator variables for investor styles were also used.
Recommended weight towards equity asset classes	This is the weight towards equity asset classes in the robo-advisor's portfolio recommendation. Ranging from 0.0 to 1.0.
Recommended weight towards fixed income asset classes	This is the weight towards fixed income asset classes in the robo-advisor's portfolio recommendation. Ranging from 0.0 to 1.0.
Recommended weight towards other asset classes	This is the weight towards other asset classes in the robo-advisor's portfolio recommendation. Ranging from 0.0 to 1.0.

Table 2. Portfolio recommendations. The table shows the dependent variables and indicator variables used in our model.

2.1.1 Robo-advisors

By using market reports for robo-advisors (CBInsights, 2017; Kyle, 2017) and manually scanning the market via the Internet we found a total population of robo-advisors targeting the U.S., UK and Canadian markets of personal investors. This set of 80 robo-advisors was then narrowed down into our sample dataset based on whether they could provide portfolio recommendations without requiring the user to fill in social security numbers or other deanonymizing information. This left us with 41 robo-advisors. Another 6 robo-advisors from this subset were excluded for providing zero-variance outputs, leaving our final sample with 35 robo-advisors. We have to the best of our ability tried to cover the entire accessible market for robo-advisors targeting the U.S., U.K. and Canada and are confident that all these major robo-advisors have been assessed in our data collection process although there are no official count on the total population of robo-advisors on these markets.

There is an issue with potential selection bias in our sample. Picking only those robo-advisors from the U.S., UK and Canada and only those providing portfolio recommendations on specific terms might obstruct inference to the entire population of robo-advisors and even to the subset of U.S., UK and Canadian robo-advisors. We cannot test whether the sample in our data are sharing characteristics other than their low thresholds to giving portfolio recommendations compared to the omitted robo-advisors in this experiment. Therefore, generalizability of our results to the market for robo-advisors within U.S., UK and Canada is reduced.

2.1.1.1 Number of questions asked in the questionnaire and the number of portfolios provided

Tertilt & Scholz (2017) suggest that robo-advisor questionnaires are not doing a proper job of identifying an investor's risk profile. However, the number of questions asked could still influence the recommendations. Suppose that there is a mean portfolio available that all the advisors can recommend. The more questions the advisor is asking the investor, the more detailed recommendations can be provided. Meaning that it is plausible that the number of questions asked in the questionnaire could explain the variations in cross-advisory recommendations.

For this to make sense, however, there should be a correlation between the number of questions asked in the questionnaire and the number of portfolios provided. In line with Tertilt and Scholz (2017) however, we only found a surprisingly small correlation (see Figure 1.a. and Figure 1.b.). Therefore, we expect this to have little explanatory power in our model.

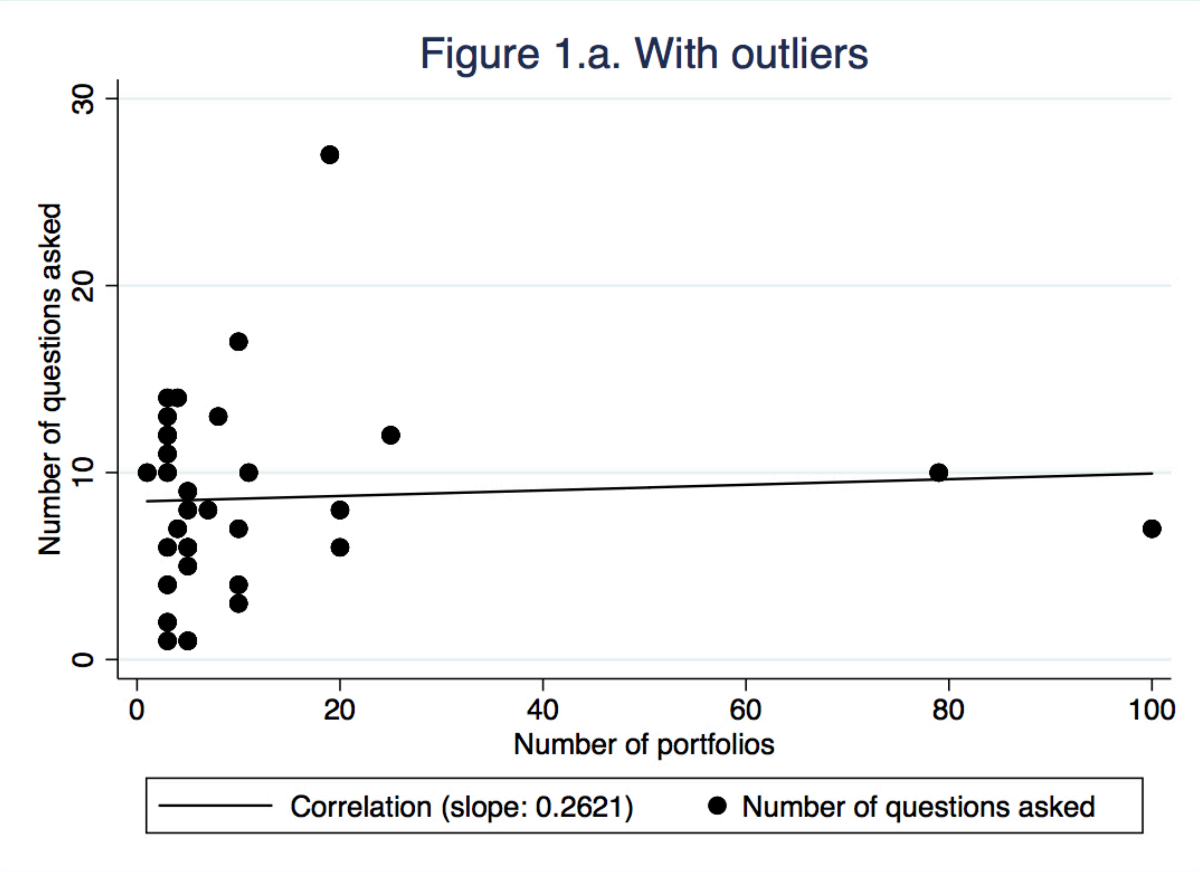

Figure 1.a. With outliers
Number of questions asked
0
10
20
30
0
20
40
60
80
100
Number of portfolios
Correlation (slope: 0.2621)
Number of questions asked

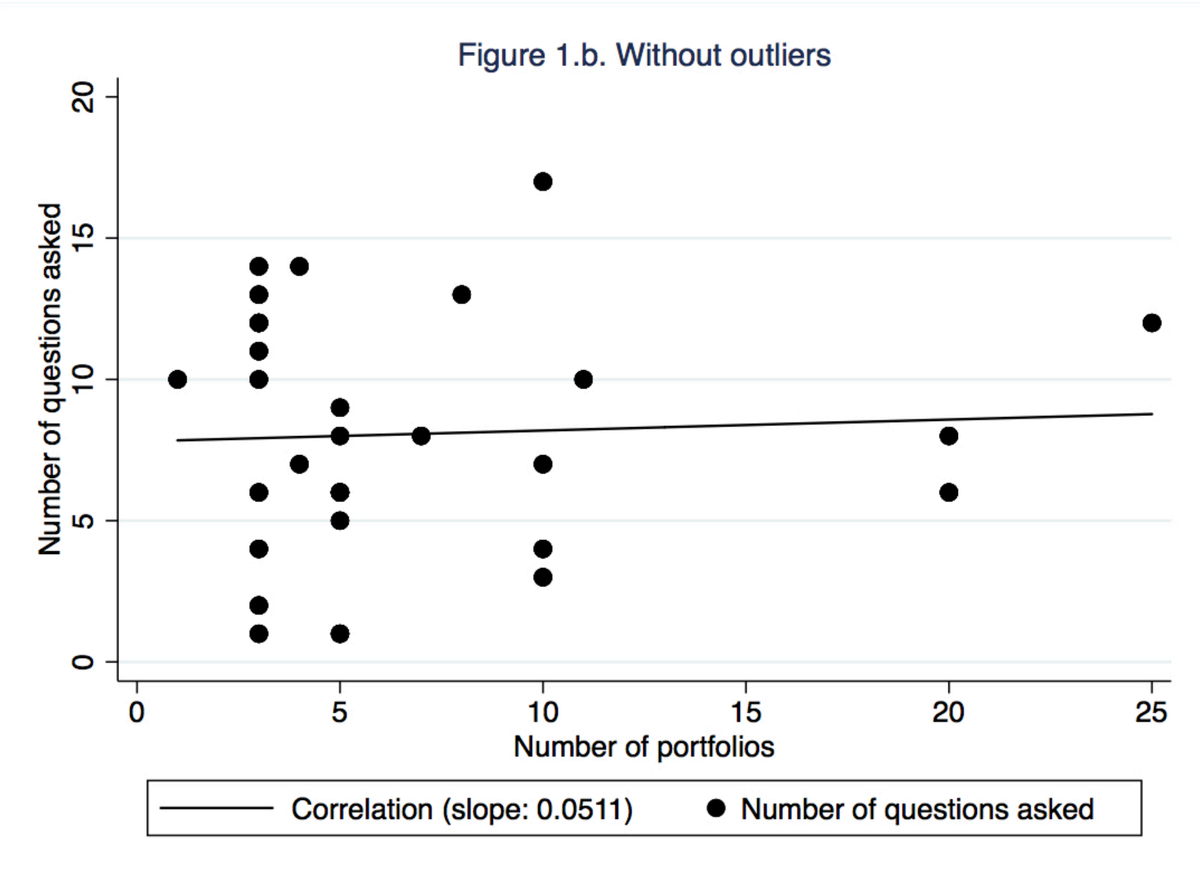

Figure 1.b. Without outliers
Number of questions asked
0
5
10
15
20
0
5
10
15
20
25
Number of portfolios
Correlation (slope: 0.0511)
Number of questions asked

Figure 1.a. & 1.b. The correlation between number of questions asked in the questionnaire by robo-advisors in our sample and the number of portfolios provided by these robo-advisors. We first ran two simple linear regressions on the model $\text{num\_quest}_i = \beta_0 + \beta_1 \cdot \text{num\_portf}_i + \epsilon_i$ to find the regression line and correlations. For Figure 1.a. we did not adjust the sample at all while in Figure 1.b. we dropped outliers (3 observations). We can see that the correlation is slightly smaller (0.0511 compared to 0.0589) when the sample was adjusted for the outlier observations. This indicates that robo-advisors are not tailoring their portfolio offerings by the level of knowledge on investors but use some number of predetermined portfolios.

2.1.1.2 Calculation of weight independent variables for robo-advisors

The independent variables for robo-advisors' weights towards different asset classes in their underlying offering were calculated using the number of assets within each asset class offered by the robo-advisor divided by the total number of assets in the robo-advisor's underlying offering, Formula 1.

The weight *w* of each asset class *i* is calculated as

$$w_{i,j} = \frac{n_{i,j}}{n_{i,j} + n_{i,j}}$$

$$i \in \{\text{equity, fixed income, other}\}$$

where $w_{i,j}$ is the weight of the asset class i for robo-advisor j and where $n_{i,j}$ is the number of asset offerings related to asset class i for robo-advisor j.

Formula 1.

The assets were categorized based on the name of the asset provided by the robo-advisor according to Table 3. Our categories follow the principles of convention by dividing them into equity, fixed income and other asset classes.

The method for listing these asset classes was done *ad hoc* because of the nature of the data. The differences in how the individual robo-advisors disclaimed their investment offerings varied too much to allow for a more precise collection of data. One issue with this approach is that the assets could be grouped in other ways, e.g. on level of risk or beta values. The risk level of various derivatives and gold would make it improbable to place them together if we were to categorize asset classes on level of risk. This because gold has a very low risk (Levitt, 2016). This would also probably not place company bonds and government bonds in the same risk category. The weights found in the dataset can be found in Table 4 categorized by country.

Table 4: Asset class weights by country

Country	Variable	# of Obs.	Mean	Std. Dev.	Min.	Max.
Canada	Exposure equity	18	.52855	.08283064	.4286	.6154
	Exposure fixed income	18	.35868333	.10552364	.2308	.5
	Exposure other	18	.11263333	.05746801	0	.1538
UK	Exposure equity	24	.5273875	.13872811	.3333	.6667
	Exposure fixed income	24	.2879125	.1011179	.1667	.4667
	Exposure other	24	.1847375	.07864693	.0667	.3333
US	Exposure equity	63	.44208571	.16625825	0	.7143
	Exposure fixed income	63	.40651905	.17584834	.1642	1
	Exposure other	63	.15137143	.16537417	0	.6866

Table 4. Asset class weights by country. This table shows the distribution of asset classes by country in our sample. We can see that aggregated U.S. robo-advisors have the highest exposure towards fixed income asset classes while aggregated U.K. robo-advisors have the highest exposure towards other asset classes while aggregated Canadian and U.K. robo-advisors have about the same exposure towards equity asset classes.

The theory suggests that any firm will try and maximize their profits, and one way of doing this is by reducing transaction costs (Olsson, 2005). This is, of course, the case for robo-advisors as well as any other firm. Specializing in investing in one asset class could help a robo-advisor increase profits in numerous ways such as reducing courtage fees, economies-of-scale in analysis and management expertise. The intuition is that a hypothetical robo-advisor would not recommend portfolio weights towards a product, e.g. gold, if the robo-advisor did not provide any services that invested in gold. The weights of asset classes in the robo-advisor’s underlying offering is therefore in this data being treated as a proxy for its specialization. The hypothesis is that economies-of-scale from specialization could explain the variations in cross-advisory portfolio recommendations.

2.1.1.3 Country of origin

The country of origin of the robo-advisor was determined by the country they were registered in. Country of origin of the firm is an interesting control variable since previous research suggests that there are country differences in investor attitudes towards certain asset classes (IMF, 2011) meaning that one possible explanation to cross-firm portfolio recommendations could be that they are originated from different countries. Apart from investor attitudes there could also be regulatory differences across countries affecting the recommendations (Guiso and Sodini, 2012). These factors would be controlled for with this variable.

Table 5. Distribution across countries

Country	Freq.	Percent	Cum.
Canada	6	17.14	17.14
UK	8	22.86	40.00
US	21	60.00	100.00
Total	35	100.00	

Table 5. The sample's country of origin distribution.

The number of US robo-advisors in our study is representing more than half the sample data (see Table 5.) This is not surprising given that the size of the US market for these services is in line with Tertilt & Scholz (2017) that suggests that the US market for robo-advisors is the most developed in the world.

Figure 2. Scatter plot of recommended portfolio allocations by equity-to-fixed income ratio by investor style and country of origin

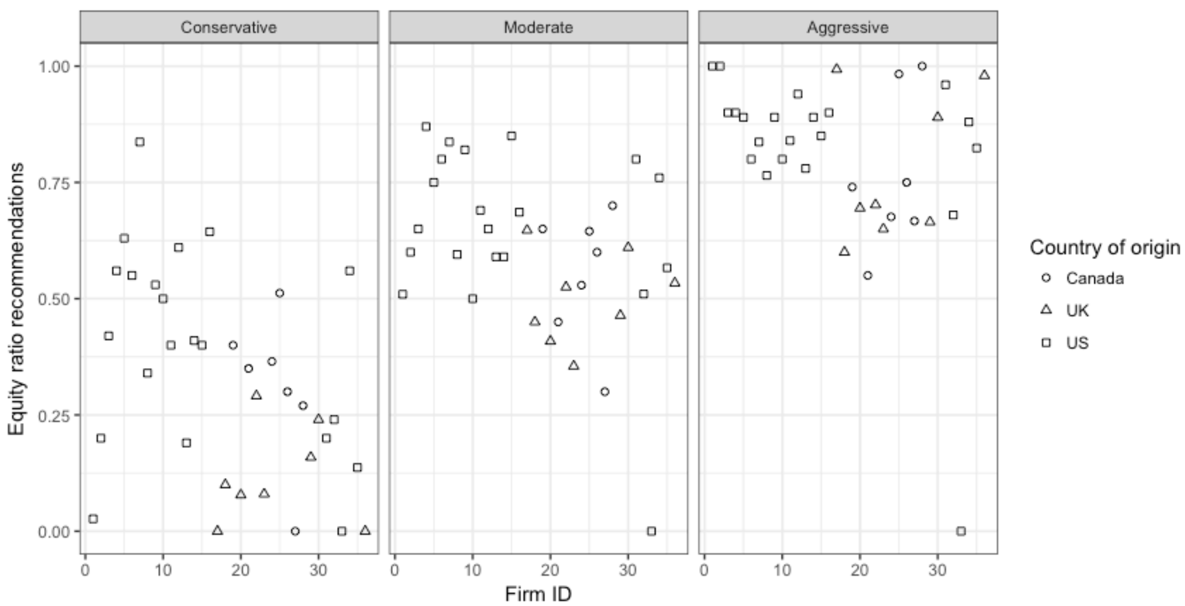

Figure 2. Scatter plot of recommended portfolio allocations by equity-to-fixed income ratio by investor style and country of origin. In section one ("Aggressive") we see that the spread is rather small compared to the sections two ("Moderate") and three ("Conservative"). The "Conservative" section has the largest spread.

Looking at Figure 2 we see that there is a tendency towards U.K. (Δ) and Canadian (○) clusters for conservative and moderate investors in our sample while U.S. (dm^3) observations are much more scattered. The small samples from the UK and Canadian populations are however making it hard to infer too much about this hypothetical country effect by just looking at the data.

2.1.2 Dependent variables: portfolio recommendations

In this part of our data we will describe the process of gathering output data, namely the portfolio recommendations from each robo-advisor. Most importantly, we describe the creation of our generic investor profiles that were exploited in extracting the portfolio recommendations.

2.1.2.1 Generic investors

To compare advice provided by individual robo-advisors we created three generic investor profiles that would differ from each other in terms of age, previous experience with investments and, most importantly, risk-appetite. Namely, "Conservative," "Moderate" and "Aggressive". The differences between these profile characteristics are deemed to have significant effect on the portfolio recommendations in terms of asset allocation in the literature on modern portfolio theory such as Merton (1969) and Moreschi (2005). Our goal with these generic investors was to extract portfolio recommendations that would differ from each generic investor and still be comparable between advisers. Initially, we successfully managed to extract 123 recommended portfolios, 41 adhering to each generic investor, 3 from each robo-advisor. In the end, only 105 of these were used because of zero-variance recommendations across investor types for six robo-advisors in our sample.

Previous research and the discussion on financial literacy suggest that it might be relevant to examine what type of advice uninformed investors are receiving since they are assumed to lack the ability to assess the quality of their recommendations. Our generic investor profiles are a way of assessing what type of recommendations differently informed and risk-averse investors are facing to nuance the data and contribute to the discussion on financial literacy.

Each of these portfolio recommendations $p_{j,g}$ has three weights w_i where $i \in \{\text{equity, fixed income, other}\}$,

$g \in \{\text{"Conservative"}, \text{"Moderate"}, \text{"Aggressive"}\}$ and where $\sum w_i = 1$.

The generic investor profiles have been assembled by using identical and in some cases similar answers to risk-profile questionnaires across robo-advisers. The generic risk profile is therefore the sum of all the answers to these questions. The answers we provided are therefore consistent across the advisers, making it possible to compare the portfolio recommendations between them for each investor. Even though the questionnaires differ by both the scope and scale of questions asked, our profiles are both realistic and coherent (See Appendix A). The coherency of these generic investors has also been in line with the language used by the robo-advisors (Kaya, 2017). The industry is using similar generic investor types when they create portfolios, and while there is no correct benchmark or true underlying asset allocation recommendation for these portfolios we can still see clear patterns in the data with regards to investor style.

An ANOVA test (see Table 6) gave us support that the robo-advisors are able to accurately separate the investor types and on average give them different portfolio recommendations from one another with high levels of significance ($p < 0.001$ for all investor styles).

Table 6: ANOVA Test result table

	No FE b/se	FE b/se	No FE robust b/se	FE robust b/se
Conservative	-0.509***	-0.509***	-0.509***	-0.509***
	(0.05)	(0.03)	(0.05)	(0.03)
Moderate	-0.214***	-0.214***	-0.214***	-0.214***
	(0.05)	(0.03)	(0.04)	(0.02)
Intercept	0.865***	0.241***	0.865***	0.241***
	(0.03)	(0.02)	(0.03)	(0.02)
R^2	0.551	0.786	0.551	0.786

* p<0.05, ** p<0.01, *** p<0.001

Table 6. Notes: ANOVA test result table. Notes: Column 1 is an OLS regression on the model $y_i = \beta_0 + \beta_1 \cdot \text{Conservative}_i + \beta_2 \cdot \text{Moderate}_i + \epsilon_i$ where z_i is the Equity ratio, Conservative_i and Moderate_i are investor style dummies. ϵ_i is the error term. Because of degrees of freedom limitations our Aggressive investor style dummy variable cannot be included in the model but should be interpreted as the β_0 (Intercept). The third column runs the same model but with y_i being adjusted for robo-advisory fixed effects. The equity ratio z_i is calculated as $z_i = y_i - \bar{y}$ for each firm across the three types of investors. The second and fourth columns are robustness checks. This table shows that the variations in portfolio recommendations across generic investor styles are highly statistically significant, meaning that we are sure our sample of robo-advisors are treating the investors differently on average. Otherwise we would either have constructed very unintelligible investors or the robo-advisors would not make advice based on the investor (which we need to assume that any advisor must). The robustness checks do not change the results. However, fixed effects are boosting the R^2 from 0.551 to 0.786 suggesting that some part of the variations can be explained by within variations for the robo-advisors in our sample.

This means that our generic investor profiles are doing a good job at creating portfolio recommendations that are relevant to our analysis. Namely recommendations that are significantly correlated to each type of investor. While this hints towards that investor style is explaining a large part of cross-firm recommendations this is not really explaining why some robo-advisors are giving one generic investor one portfolio recommendation while another robo-advisor might give the very same investor a completely different portfolio recommendation. The proof of investor style having a significant effect on the recommendations is merely showing that our categories are relevant. The assumption that investor style is affecting portfolio recommendation is fundamental to the purpose of this study.

2.1.2.2 Descriptives of portfolio recommendations

In the following we will provide the reader with descriptives on the portfolio recommendations (the dependent variables).

The result from the data extraction phase has provided us with an interesting dataset that might shed some light on the variation in the recommendations across firms and across generic investor types. The initial analysis of data descriptives reveals that there are larger standard deviations for conservative investors (see Table 7 and Figure 3).

Table 7: Descriptives table for portfolio recommendations across asset classes and investor style

Investor Style	Variable	Mean	Std. Dev.	Min.	Max.
Aggressive	Rec. equity	.80184444	.18532568	0	1
	Rec. fixed income	.13181667	.17357587	0	1
	Rec. other	.06659167	.0866944	0	.35
Conservative	Rec. equity	.32026667	.21754802	0	.837
	Rec. fixed income	.54338889	.21963829	0	1
	Rec. other	.13634167	.2183214	0	1
Moderate	Rec. equity	.59698333	.17385758	0	.87
	Rec. fixed income	.33591944	.17628185	0	1
	Rec. other	.0674	.07313808	0	.275

Table 7. Descriptives table for portfolio recommendations across asset classes and investor style. We see that the conservative investor is facing much higher standard deviations for all asset classes compared to moderate and aggressive investors.

Figure 3. Boxplot of descriptives for portfolio recommendations across asset classes and investor style

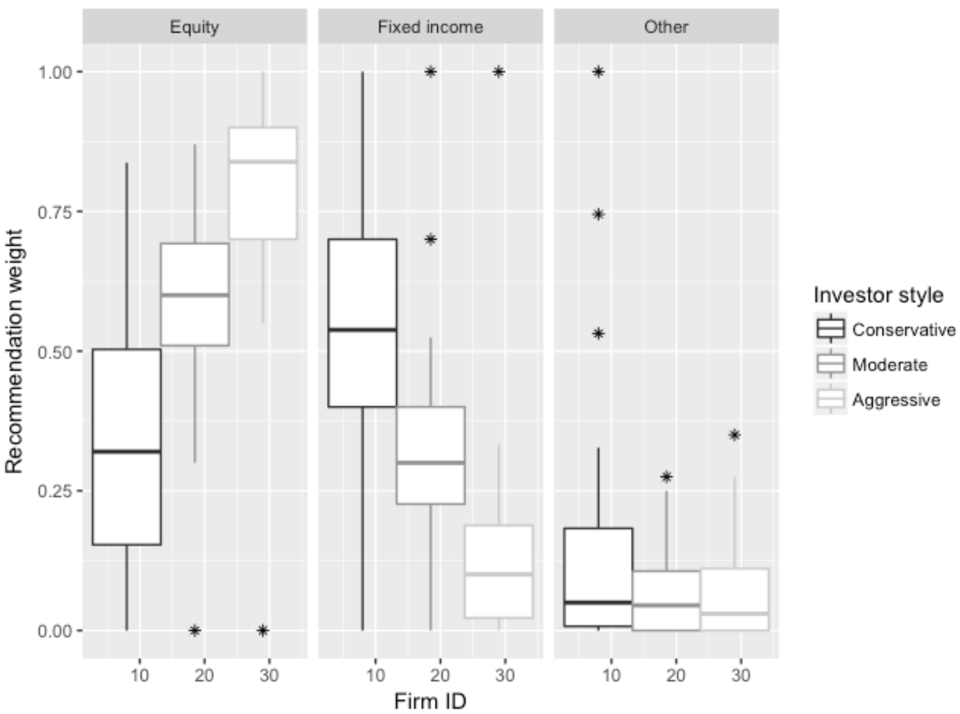

Figure 3. Boxplot of descriptives for portfolio recommendations across asset classes and investor style. Notice the longer range of the boxes and between the "whiskers" on the conservative investor's boxes for fixed income and equity asset classes. Stars mark the outliers in our sample.

This is especially true for portfolio recommendations towards equity and fixed income weights after adjusting the data for outliers (Std. Dev. of 0.22 for conservative investors compared to 0.17 and 0.18 for aggressive and moderate investors respectively for fixed income and Std. Dev. of 0.22 compared to 0.19 and 0.17 for equity, perhaps best illustrated in Figure 4 and 5.)

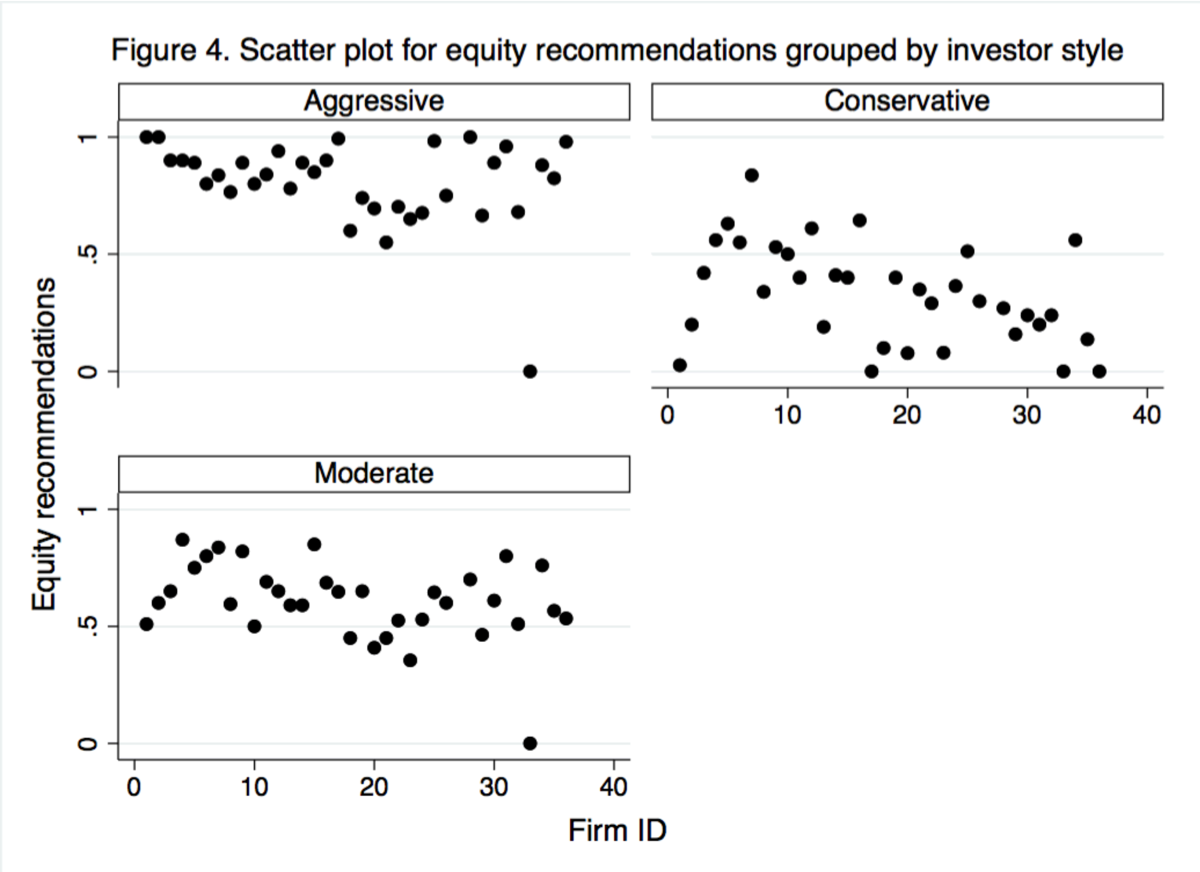

Figure 4. Scatter plot of equity recommendations across robo-advisors grouped by investor style.

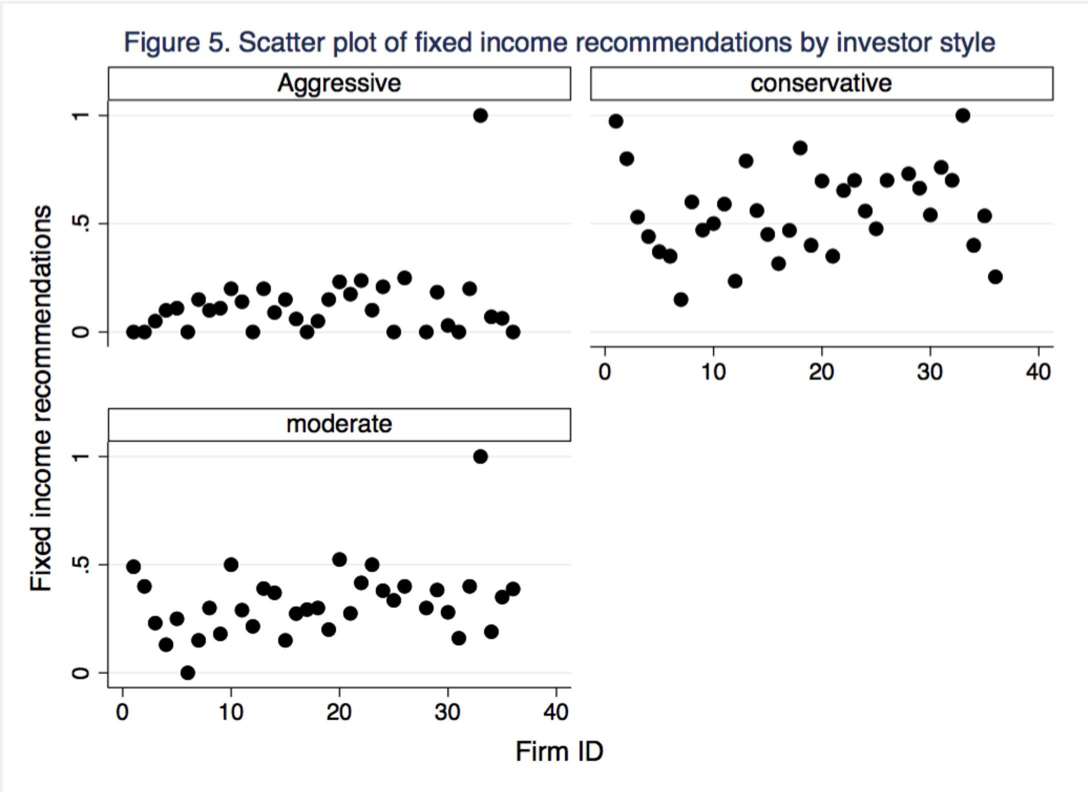

Figure 5. Scatter plot of fixed income recommendations across robo-advisors grouped by investor style.

While the recommended weights for other asset classes were quite stable when adjusted for outliers firms with id's: 18, 28, 37 (see Figure 6.).

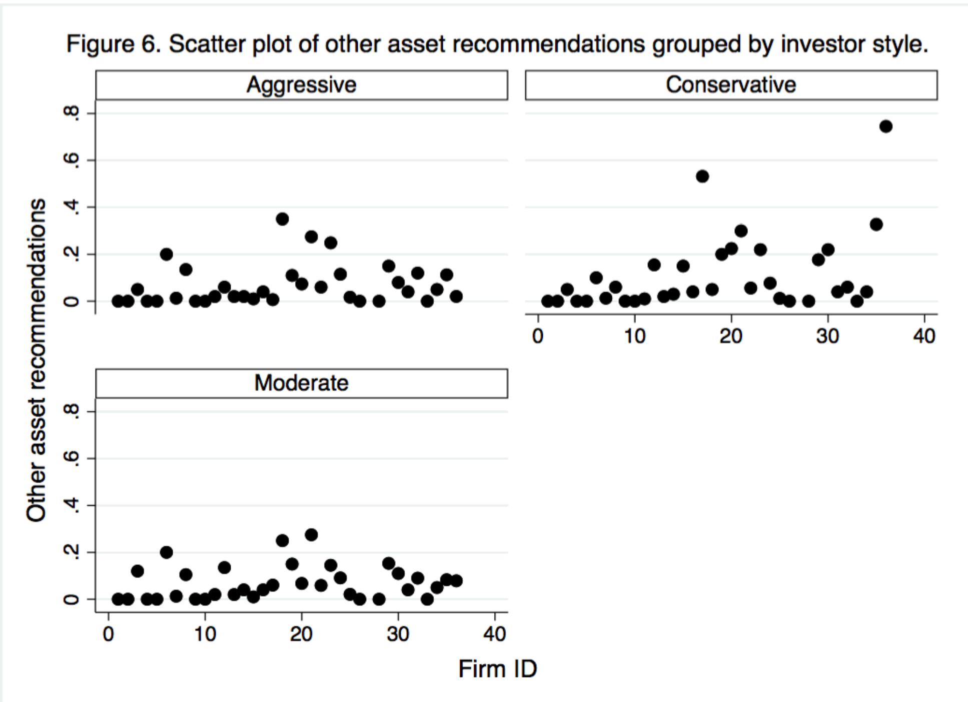

Figure 6. Scatter plot of other asset recommendations across robo-advisors grouped by investor style.

The conservative investors are, however, still facing substantially higher variations in their recommended other asset classes weights compared to moderate and aggressive investors, as we can see in Table 7.

2.1.3 Data preparation

Since most of the variation across generic investors (as shown in part 2.1.2.2) are coming from equity and fixed income weights, while the weights for other asset classes group is relatively constant we introduced a ratio variable:

$$\text{Ratio}_{equity} = \frac{\text{Equity}}{\text{Fixed Income} + \text{Equity}}$$

Where

Equity= the recommended percentage of equity in a portfolio of only equity and fixed income.

Fixed Income = the recommended percentage of fixed income in a portfolio of only equity and fixed income.

Formula 2.

We are using this ratio of measuring the weight of equity in relation to the sum of fixed income assets and equity assets in the entire portfolio in order to avoid the division by zero problem in mathematics. This ratio is now only impossible to calculate for portfolios that carry a 1.0 weight in other asset classes.

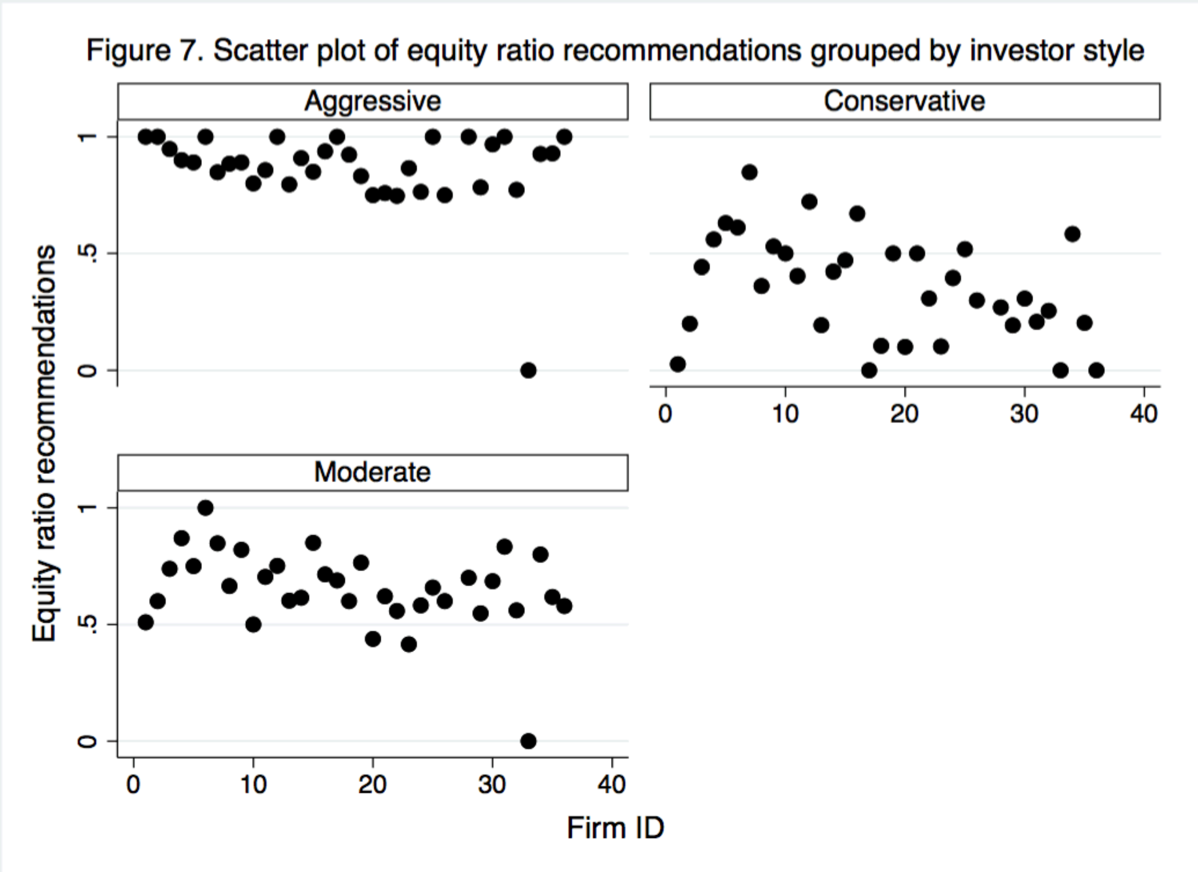

Figure 7. Scatter plot of equity ratio recommendations across robo-advisors grouped by investor style.

The use of the equity ratio does not change the fact that standard deviation is still substantially higher for the conservative investor (see Figure 7 and Table 8). We have thus constructed the dependent variable that will be used in our model for analysis.

3. Method

In this part, we will briefly describe the background and context of the targeted robo-advisory market. After, we will present our method for explaining the cross-advisory variations in portfolio recommendations. We will thereafter compare our method to the ideal experiment and list the implications of the method's deviations from the ideal scenario.

3.1 Background

We can see a paradigm shift in the pension system facing challenges with retirement savings in the last decades. We have shifted from a time where pensions were provided from the companies through defined-benefit retirement plans (meaning that the savings was related to the income and how many years you had worked), to a time with defined-contribution savings plans (meaning that the employees themselves must choose how to allocate the money and hence the savings will depend on the employees' decisions). In other words, the responsibility of pensions is now on the hands of the individual workers and not the companies (Lusardi and Mitchell, 2013).

Furthermore, investing could be said to be complex for a lot of people and over the years the availability and types of investments has grown within the financial market. Besides the need to understand the markets, the difficulty further lies within disputes such as self-awareness about risk taking as well as tax implications of different types of investments (Fisch et al., 2017). Many investors have a limited knowledge in financial literacy (Lusardi et al., 2012), partly due to constrained financial experience but also due to an increased risk aversion in relation to getting older. This limitation of knowledge in financial literacy is contributing to an increased exposure to deprived financial decisions (Fisch et al, 2017). It can also be perceived as there is a need for advice among a substantial part of the population taking part in the financial markets. And for many decades investors have been given financial advice from advisors in the field where they have provided investment strategies as well as asset and portfolio management (Fisch et al., 2017).

So why have robo advisers become more and more popular during the past decade? Throughout history, particularly during the last decades, technology has disrupted different industries and contributed to both scalability and productivity. So, why would the financial market be an exception? (Sorrentino, 2017). Only during the last couple of years, the technological environment has changed dramatically. Today people interact with each other 24/7, all around the globe and a lot of consumers are now comfortable getting financial advice from advisors that don't necessarily have to be physical present. At the same time, in both emerging and mature markets, the number of consumers that potentially need financial advice is increasing rapidly, making it hard for institutions such as banks and asset management firms to grow in the same pace in order to meet the demand (McKinsey & Company, 2015). Furthermore, the development of digital solutions and technologies are reaching new heights and technologies such as artificial intelligence and machine learning are making it possible for services as robo advisors to develop even further (Guedim, 2017). Through interactions with our phones, the customer experience has also become very important when deciding if and where to move assets. We can also see that in many markets, regulators pay more attention to management fees charged from the advisors as well as making sure that the financial advice keeps a good standard, thus improving the transparency in the market (McKinsey & Company, 2015).

Also, in the recent years, exchange traded funds (ETFs) have become very popular as an investment alternative. The usage of ETFs has also led to the opportunity to build transparent and diversified portfolios for a relative low cost which in turn suits the robo advisory industry well (KPMG, 2016).

3.2. Hypothesis development

As has been suggested in the presentation of the study's dataset we have used several hypothetical explanations for the cross-firm variations in portfolio recommendations. These hypothetical explanations can be formulated in summary as follows.

Cross-firm variations in portfolio recommendations can be explained by

- type of investor,
- country differences,
- number of questions asked in the questionnaire,
- number of portfolios and
- weights toward the three different asset classes; equity, fixed income and others.

Each of these hypotheses are plausible in its own right given the research on the field, covered earlier in this report. By using the quantitative measurements in the dataset, we can by statistical methods of ordinary least squares (OLS) regression and robust regression test our model. The model is presented in Formula 3.

$$y_{ij} = \beta_0 + \beta_1 \cdot \text{Country}_i + \beta_2 \cdot \text{Conservative}_j + \beta_3 \cdot \text{Moderate}_j + \beta_4 \cdot \text{Number of questions}_i + \beta_5 \cdot \text{Number of portfolios}_i + \beta_6 \cdot \text{Exposure to equity}_i + \beta_7 \cdot \text{Exposure to fixed income}_i + \epsilon_i$$

Where:

$y_{ij} =$ the ratio of equity to the equity and fixed income portfolio for investor j by robo-advisor i,

$\text{Country}_i =$ the county of origin indicator variables,

$\text{Investor style}_j =$ the investor style indicator variables and $j \in \{\text{"Conservative"}, \text{"Moderate"}, \text{"Aggressive"}\}$,

$\text{Number of questions}_i =$ the number of questions asked in the questionnaire,

$\text{Number of portfolios}_i =$ the number of portfolios in the robo-advisor i's offering.

Formula 3.

Since our analysis is sensitive to outliers given the relatively small number of total observations we have decided to both run an OLS and then further test the results with robust regressions. Robust regression works by giving observations with high residual values a small weight in the explanations and therefore complements our OLS nicely even after we've dropped the most obvious outliers (Wooldridge, 2016).

We will also run the Formula 3 model controlling for firm fixed effect on each investor style in isolation to try the residual hypothesis of the existence of an investment philosophy bias on the firm level which could explain cross-firm variations. We call this a residual hypothesis as it is elusive and not directly captured by any of our independent variables, but indirectly captured by what we cannot explain. In order to see if the fixed effect can explain any of the residuals of our Formula 3 model we control for within fixed effects in our regression.

4. Analysis and findings

In this section, we will present the results from our statistical methods on the dataset as well as an analysis of these results in relation to our research question and the related literature.

4.1 Results

We have been aiming to try and explain the variations in cross-firm portfolio recommendations and now it's time to present the results of our regressions.

Table 9: Ordinary Least Squares (OLS) regression.

$$y_{ij} = \beta_1 \cdot Country_i + \beta_2 \cdot Conservative_i + \beta_3 \cdot Moderate_i + \beta_4 \cdot Aggressive_i + \beta_5 \cdot \text{Number of questions}_i + \beta_6 \cdot \text{Number of portfolios}_i + \beta_7 \cdot \text{Exposure to equity}_i + \beta_8 \cdot \text{Exposure to fixed income}_i + \epsilon_i$$

	M1	M2	M3	M4
	b/se	b/se	b/se	b/se
Conservative	-0.509***	-0.509***	-0.509***	-0.509***
	(0.05)	(0.04)	(0.04)	(0.04)
Moderate	-0.214***	-0.214***	-0.214***	-0.214***
	(0.05)	(0.04)	(0.04)	(0.04)
U.S.		0.016	0.042	0.044
		(0.05)	(0.05)	(0.05)
U.K.		-0.112	-0.149**	-0.152**
		(0.06)	(0.05)	(0.05)
Exposure to equity			0.004	-0.016
			(0.14)	(0.14)
Exposure to fixed income			-0.526***	-0.583***
			(0.14)	(0.14)
Number of questions				0.004
				(0.00)
Number of portfolios				0.001
				(0.00)
Constant	0.865***	0.881***	1.067***	1.051***
	(0.03)	(0.05)	(0.12)	(0.12)
R^2	0.551	0.586	0.665	0.674

* p<0.05, ** p<0.01, *** p<0,001

Table 9. Table of results from our Ordinary Least Squares (OLS) regressions. The OLS is based on the model

$$y_{ij} = \beta_1 \cdot Country_i + \beta_2 \cdot Conservative_i + \beta_3 \cdot Moderate_i + \beta_4 \cdot Aggressive_i + \beta_5 \cdot \text{Number of questions}_i + \beta_6 \cdot \text{Number of portfolios}_i + \beta_7 \cdot \text{Exposure to equity}_i + \beta_8 \cdot \text{Exposure to fixed income}_i + \epsilon_i$$

In the first column, we are controlling for investor style by using the Moderate_i and Conservative_i dummies. The Aggressive_i dummy could not be used because of degrees of freedom limitations leading to perfect multicollinearity. Instead, the Aggressive_i is the Intercept in column 1. In column 2 we also control for country of origination using the country dummy variables. Here as well, we have excluded Canada to avoid perfect multicollinearity. In column 3 we are introducing the independent variables for the robo-advisor *i*'s exposure to equity and fixed income respectively in their underlying offering. Lastly, in column 4, we include the variables for number of questions asked and number of portfolios in the robo-advisor *i*'s offering.

From the OLS regression we found that robo-advisors with higher exposure to fixed income in their underlying offerings are on average making lower equity allocation recommendations. This is in line with the economies of scale hypothesis. There also seem to be a significant country effect for UK robo-advisors in line with the hypothesis that the country of origination might explain some of the variation across firms. These results hold also for a robust regression (see Table 10) even though the strongness in the effect from exposure to fixed income to be less strongly significant.

When running our models for each investor style (see Table 11) we get similar results. They are less significant although, of course, the number of observation has also shrunken down to 35 making it much harder to find statistical evidence for any hypothesis. For the aggressive and moderate investors, we are able to explain more of the variations with statistical significance. The fixed effect control (column 4 in Table 11) is increasing the explanatory power for conservative investor recommendations from $R^2 = 0.350$ to $R^2 = 0.527$ while it lowers the explanatory power for moderate and aggressive investor recommendations.

We cannot however explain any of the variation within the conservative generic investor subset of the data. This means that our model does not perform a very good job at explaining why conservative investors are getting such high variations, while we find some significant effect for the other investors for the same number of observations.

4.2 Analysis

Our results above are supporting the hypothesis that economies of scale from having an expertise in fixed income products is having an effect on a robo-advisor's portfolio recommendation. The higher the underlying exposure towards fixed income, the higher the recommendation towards fixed income assets. This effect is harder to reject if we exclude the conservative investors from the sample (p-values of < 0.001).

The fact that conservative investors are receiving such a large variation in recommendations across the advisors one of the key finding in this thesis. But we are unable to find any observable characteristics in the constitution of the robo-advisors that can account for this high variation. This might be the result of our small sample size, but we cannot find any trends that would suggest that the variation is coming from country effects (where our sample sizes are the smallest). Instead, we are looking at the literature on financial literacy and the fact that the generic conservative investor in our experiment is sharing the characteristics of a financially illiterate investor. This means that the preferences of the conservative investor are not being treated as actual preferences but rather as lack of knowledge of investments. As such, they are not taken into consideration to the same extent as the preferences of the generic moderate and aggressive investor respectively. The preferences of conservative investors are likely to be at odds with what the theory on portfolio investments and personal finance suggests which makes it harder for robo-advisors to be responsive to these. For this reason, conservative investors are receiving recommendations more based on the robo-advisory firm's investment philosophy rather than on the actual preferences. We can illustrate this by using two theoretical business models for robo-advisors,

- The investment philosophy bias model
- The customer preferences model

In these models, we assume that there are no economies of scale benefits for the robo-advisor but that portfolio recommendations are only based on investment philosophy bias and customer preferences in each respective model.

The investment philosophy bias model process of portfolio recommendation	*The customer preferences model process of portfolio recommendation*
The robo-advisor has a set of portfolios, p_1 , p_2 , p_3 … p_n based on the robo-advisor's investment philosophy. In the questionnaire phase of the portfolio recommendation, the robo-advisor algorithm is guiding each investor towards any of the n predefined	The robo-advisor is asking questions. As the algorithm learns more about the investor, it tailors a portfolio that is based on the preferences of its customer and portfolio theory. In the end, the recommended portfolio will be generated in line with the

portfolios. If the different robo-advisors' investment philosophies are consistent across firms, then the standard deviations for each generic investor's portfolio recommendations will be small. This means that robo-advisors in our sample are more consistent in their investment philosophies when it comes to recommendations for aggressive and moderate but less so for conservative investors.	investor's preference rather than on any investment philosophy bias impact from the robo-advisor. This type of process was very rare in our sample, which is also in line with the advisor's number of portfolios.

33 out of 35 robo-advisors in our sample had quite a low number of portfolios (*n* ranging from 3-25), meaning they were operating under model 1 rather than model 2. Since we cannot find any explanation in the independent variables of the robo-advisors to explain why conservative investors were facing high cross-firm variations in portfolio recommendations we believe that firms operating under model 1 is a plausible explanation. This is also in line with Fein's (2015) criticism of robo-advisors not actually providing personal advice but rather matching the investor " an investment strategy based on asset allocation formulas recommended for investors with similar preferences" (Fein, 2015, p. 12). This means that the recommended portfolios for conservative investors or investors with similar preferences vary a great deal across robo-advisors.

Our fixed effect adjustments in the model boosted the R^2 of our model with nearly 20% for conservative investors (see Table 11) something that also supports investment philosophy bias hypothesis. The fixed effect from each individual robo-advisor is a good proxy for investment philosophy bias. However, this does not explain why the variations are so much higher for conservative investors in comparison to other investor styles.

The low level of tailoring portfolios is in line with the economies-of-scale hypothesis. If the robo-advisor has fewer portfolios to handle, *ceteris paribus*, they will have increasing economies-of-scale as the assets under management increase. This is, however, assumed to be part of the business model for robo-advisors and explains the nature of the service offered rather than the cross-firm variations.

Also in favor of this hypothesis is that our approximating assumption suggests that conservative investors are also financially illiterate. This means that it is harder for conservative investors to determine and assess whether a certain portfolio recommendation is in line with their preferences or not, which is also a possible conclusion do be drawn from previous research (Anderson & Robinson, 2018). The same conservative investors are also less likely to make cross-firm comparisons. Note that this thesis does not suggest that conservative investors are receiving better or worse advice compared to moderate and aggressive ones. The literature suggests that financially illiterate and conservative investors are generally taking too little risk and are therefore missing out on the equity premium. We have not been looking at robo-advisors' cost and fee structures, so there is nothing in our sample discussing the possibility that conservative investors are victims to fraudulent behavior on behalf of these firms. However, given Fein's (2015) research that shows how clients in relation to robo-advisors are themselves responsible by agreement for determining the quality of the investment advice they are provided, it would be alarming if conservative investors are provided such different recommendations with full responsibility but little or no knowledge or tools to assess these recommendations. In this study, we have not analyzed the user agreements of the robo-advisors in our sample and therefore we cannot confirm or reject this scenario.

5. Conclusions

In this part, we draw conclusions from our experiment and make suggestions for further research on the topic of cross-firm variations within the market of robo-advisors.

5.1 Conclusion

Our study has been able to show that while there are large consistencies in what type of portfolio recommendations robo-advisors are giving to investors with moderate and aggressive investment styles, investors with conservative investment styles are facing largely inconsistent recommendations. Some of the variations between robo-advisors can be explained by the firm's exposure to fixed income assets in their underlying offering; the higher the exposure towards fixed income assets the higher recommendation towards this class of assets. This is in line with our economies of scale hypothesis.

Our results also point towards that robo-advisors originating from the United Kingdoms are on average recommending 15.2% lower equity exposure in their portfolios compared to the whole sample with some statistical significance ($p < 0.05$). This is in line with the hypothesis that countries have some fixed effects, because the firms adapt to their domestic market customers and their preferences. We interpret this to suggest the prevalence of certain essential beliefs or preferences in the UK market that is not as prevalent in the other markets for robo-advisors.

We cannot explain why conservative investors are facing such inconsistent recommendations but suggest that it might be due to inconsistencies in investment philosophy bias across robo-advisors. Nearly all robo-advisors in our sample are making recommendations by guiding investors towards *ex ante* allocated portfolios. And according to our hypothesis and analysis we conclude that there is support that the portfolios that robo-advisors are guiding the conservative investors towards are looking very differently across advisors because of variations in investment philosophy. Apparently, robo-advisors' investment philosophies are more consistent when it comes to moderate and aggressive investors.

Another plausible explanation is that since conservative investors could also be classified as financially illiterate, and therefore unlikely to make cross-firm comparisons on their own, make it easier for robo-advisors to "get away" with any advice. They are thus less likely to make inconvenient adjustments to meet the customer preferences of conservative investors.

5.2 Suggestions for further research

There are several suggestions for further research in this interesting and important field. First, using riskiness of asset types as a measurement of riskiness of portfolio rather than asset classes will improve the accuracy of the results in this study as discussed in our Methods. It is a limitation in this paper to assume that the robo-advisors are using asset classes to adjust their risk exposure while there is a possibility that they also adjust for risk within their asset classes. We urge future research to re-run our experiment with other measurements for portfolio recommendations to further explore the issues addressed in this thesis.

Also, by qualitatively asking the designers of the robo-advisors future researchers might be able to find out more on how the preferences of conservative investors are being treated. Some research questions could be: Are these preferences being treated as a proxy for financial illiteracy rather than actual preferences? What are the social and ethical dimensions of treating the most vulnerable investor group in such a way? Is it defensible to nudge financially illiterate investors towards more equity?

Another interesting topic would be to calculate and compare the economic consequences of following the recommendations of different robo-advisors: how skilled are these advisors? What are the cost to the customer of getting advice from fixed income specialized robo-advisors, or UK firms, for example?

6. References

6.1 Papers published in periodicals

- Anderson and Robinson. March 20, 2018. Who Feels the Nudge? Knowledge, Self-Awareness and Retirement Savings Decisions. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3021962.
- Baker and Dellaert. February 16, 2018. Regulating Robo Advice Across the Financial Services Industry. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2932189. Page 724.
- Bhattacharya et al. April 2012. Is Unbiased Financial Advice to Retail Investors Sufficient? Answers from a Large Field Study. Available at JStor: https://www.jstor.org/stable/41407854?seq=1#page_scan_tab_contents.
- Chalmers, J. and Reuter, J. September 15, 2015. "Is Conflicted Investment Advice Better than No Advice?" Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1785833.
- Dimmock and Kouwenberg. June 2010. Loss-Aversion and Household Portfolio Choice. Journal of Empirical Finance. Available at ScienceDirect: https://www.sciencedirect.com/science/article/pii/S0927539809000930.
- Fein. November 14, 2015. Robo-Advisors: A Closer Look. Available at SSRN: https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=2658701 or http://dx.doi.org/10.2139/ssrn.2658701.
- Fisch et al. July 11, 2015. The Knowledge Gap in Workplace Retirement Investing and the Role of Professional Advisors. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2629464.

- Fisch et al. August 2017. The Economics of Complex Decision Making: The Emergence of the Robo Adviser.
- Guiso and Sodini. April, 2012. Household Finance: An Emerging Field. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2066307.
- Lusardi and Mitchell. April 13, 2014. The Economic Importance of Financial Literacy: Theory and Evidence. Available at: SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2243635.
- Lusardi et al. February 2012. Financial Sophistication in the Older Population. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2010395.
- Merton. 1969. Lifetime Portfolio Selection under Uncertainty: The Continuous-Time Case. Available at EconPapers: https://econpapers.repec.org/article/tprrestat/v_3a51_3ay_3a1969_3ai_3a3_3ap_3a247-57.htm.
- Moreschi, R. W. February 2005. "An Analysis Of The Ability Of Individuals To Predict Their Own Risk Tolerance". Journal of Business & Economics Research.
- Rickard Olsson. October, 2005. Portfolio management under transaction costs: Model development and Swedish evidence.
- Robert C. Merton. Aug, 1969. Lifetime Portfolio Selection under Uncertainty: The Continuous-Time Case Source: The Review of Economics and Statistics, Vol. 51, No. 3. Pp. 247-257. Published by: The MIT Press Stable. URL: http://www.jstor.org/stable/1926560.
- Tertilt and Scholz. June 13, 2017. To Advise, or Not to Advise — How Robo-Advisors Evaluate the Risk Preferences of Private Investors. Available at SSRN: https://ssrn.com/abstract=2913178 or http://dx.doi.org/10.2139/ssrn.2913178
- Van Roij et al. 2011. Financial literacy and stock market participation. Available at Sciencedirect: https://www.sciencedirect.com/science/article/pii/S0304405X11000717?via%3Dihub.

6.2 Working Papers

- Berndt et al. June 15, 2017. Competition in the Financial Advisory Market: Robo versus Traditional Advisors.
- Burke et al. February 2015. Impacts of Conflicts of Interest in the Financial Services Industry.

6.3 Monographs

- International Monetary Fund. Monetary and Capital Markets Department. September 21, 2011. Global Financial Stability Report, Grappling with Crisis Legacies. Chapter 2, pp 59-60. URL: https://www.imf.org/en/Publications/GFSR/Issues/2016/12/31/Global-Financial-Stability-Report-September-2011-Grappling-with-Crisis-Legacies-24745.
- Mandell L, 2008. Financial Literacy of High School Students. In: Xiao J.J. (eds) Handbook of Consumer Finance Research. Springer, New York, NY.
- Wooldridge. 2016. Introductory Econometrics: A Modern Approach, 6th Edition. Page 302.

6.4 Articles

- CBInsights. April 21, 2017. A Wealth Tech World: Mapping Robo-Advisors Around the Globe. URL: https://www.cbinsights.com/research/robo-advisor-global-fintech-map/.
- Guedim. October 5, 2017. 27 Robo Advisers That are Reshaping Personal Finance. URL: https://edgylabs.com/27-robo-advisers-that-are-reshaping-personal-finance.
- Kaya. August 10, 2017. Robo-advice - a true innovation in asset management (White Paper). From Deutsche Bank. URL: https://www.dbresearch.com/PROD/RPS_EN-PROD/PROD0000000000449125/Robo-advice_%C2%96_a_true_innovation_in_asset_managemen.pdf.
- Kyle. December 31, 2017. The Complete Guide to Canada´s Robo Advisors. URL: https://youngandthrifty.ca/complete-guide-to-canadas-robo-advisors/.
- Levitt. March 29, 2016. High- vs. Low-Beta ETFs to Help Your Diversification. URL: http://etfdb.com/portfolio-management/high-vs-low-beta-etfs-to-help-your-diversification/.
- Robo Advising, Catching up and getting ahead (White paper). From KPMG. URL: https://home.kpmg.com/content/dam/kpmg/pdf/2016/07/Robo-Advising-Catching-Up-And-Getting-Ahead.pdf.
- Sorrentino. July 28, 2017. Are Robo-Advisors the Wave of the Future? (White paper). From Global Financial Private Capital. URL: http://www.synergygroupinc.com/i/TOTW-3.pdf.
- The Virtual Financial Advisor: Delivering Personalized Advice in the Digital Age (White paper). From McKinsey&Company. URL: https://www.mckinsey.com/~/media/McKinsey/Industries/Financial%20Services/Our

%20Insights/The%20virtual%20financial%20advisor/The-virtual-financial-advisor.ashx.

- Transparency Market Research. 2017. Robo-Advisors Market - Global Industry Analysis, Size, Share, Growth, Trends, and Forecast 2017 - 2025. URL: https://www.transparencymarketresearch.com/robo-advisors-market.html.

7. Appendices

7.1 Tables and figures

Table 3. Asset classes. This table shows the asset classes used as well as their sub-asset classes by name.

Asset classes		
Equity	Fixed Income	Other
Domestic equity	Company bonds	REIT (Real-estate investment trust)
International equity	Government bonds	Cash / Savings account
Emerging market equity		Gold
Canadian equity		Commodities
U.S. equity		Real estate
Japanese equity		Income strategy
		Derivatives
		Currency
		Inflation hedge/protection
		Money market

Table 3. Asset classes. This table shows the asset classes used as well as their sub-asset classes by name.

Table 8. Descriptives table for the equity ratio variable (Formula 2) by investor style.

Investor style	Variable	Mean	Std. Dev.	Min.	Max.
Conservative	Equity ratio	.35557429	.22258461	0	.8479
Moderate	Equity ratio	.65105714	.17177551	0	1
Aggressive	Equity ratio	.86501714	.17477834	0	1

Table 10: Robust Regression

	M1 b/se	M2 b/se	M3 b/se	M4 b/se
Conservative	-0.509***	-0.509***	-0.509***	-0.509***
	(0.05)	(0.05)	(0.04)	(0.04)
Moderate	-0.214***	-0.214***	-0.214***	-0.214***
	(0.04)	(0.04)	(0.03)	(0.03)
U.S.		0.016	0.042	0.044
		(0.04)	(0.04)	(0.04)
U.K.		-0.112**	-0.149***	-0.152**
		(0.04)	(0.04)	(0.05)
Exposure to equity			0.004	-0.016
			(0.13)	(0.12)
Exposure to fixed income			-0.526**	-0.583**
			(0.19)	(0.21)
Number of questions				0.004
				(0.00)
Number of portfolios				0.001
				(0.00)
Constant	0.865***	0.881***	1.067***	1.051***
	(0.03)	(0.04)	(0.11)	(0.12)
R^2	0.551	0.586	0.665	0.674

* p<0.05, ** p<0.01, *** p<0,001

Table 10. Table of results from our Robust regression. The robust regression is based on the model

$$y_{ij} = \beta_1 \cdot Country_i + \beta_2 \cdot Conservative_i + \beta_3 \cdot Moderate_i + \beta_4 \cdot Aggressive_i + \beta_5 \cdot \text{Number of questions}_i + \beta_6 \cdot \text{Number of portfolios}_i + \beta_7 \cdot \text{Exposure to equity}_i + \beta_8 \cdot \text{Exposure to fixed income}_i + \epsilon_i$$

In the first column, we are controlling for investor style by using the Moderate_i and Conservative_i dummies. The Aggressive_i dummy could not be used because of degrees of freedom limitations leading to perfect multicollinearity. Instead, the Aggressive_i is the Intercept in column 1. In column 2 we also control for country of origination using the country dummy variables. Here as well, we have excluded Canada to avoid perfect multicollinearity. In column 3 we are introducing the independent variables for the robo-advisor *i*'s exposure to equity and fixed income respectively in their underlying offering. Lastly, in column 4, we include the variables for number of questions asked and number of portfolios in the robo-advisor *i*'s offering. This robustness check deviates very little from the OLS regression, indicating that outliers in our small sample does not affect the overall results.

	Conservative				Moderate				Aggressive			
	Model 1	Model 2	Model 3	Fixed Effects	Model 1	Model 2	Model 3	Fixed Effects	Model 1	Model 2	Model 3	Fixed Effects
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
U.S.	0.007	0.003	0.027	-0.016	0.029	0.058	0.058	0.014	0.013	0.065	0.046	0.002
	(0.09)	(0.09)	(0.10)	(0.05)	(0.08)	(0.07)	(0.07)	(0.03)	(0.08)	(0.06)	(0.06)	(0.04)
U.K.	-0.274*	-0.295*	-0.279*	-0.127*	-0.090	-0.136	-0.140	0.012	0.029	-0.016	-0.037	0.115*
	(0.10)	(0.11)	(0.11)	(0.06)	(0.09)	(0.08)	(0.08)	(0.03)	(0.10)	(0.07)	(0.07)	(0.05)
Exposure to equity		-0.212	-0.171	-0.155		-0.028	-0.048	-0.032		0.251	0.171	0.187
		(0.28)	(0.29)	(0.15)		(0.20)	(0.21)	(0.09)		(0.19)	(0.17)	(0.13)
Exposure to fixed ~e		-0.285	-0.243	0.339*		-0.650**	-0.702**	-0.119		-0.643**	-0.804***	-0.221
		(0.28)	(0.29)	(0.15)		(0.20)	(0.21)	(0.09)		(0.18)	(0.18)	(0.13)
Number of question~d			0.007	0.003			0.003	-0.001			0.003	-0.002
			(0.01)	(0.00)			(0.00)	(0.00)			(0.00)	(0.00)
Number of portfolios			-0.001	-0.002*			0.001	-0.000			0.003*	0.002*
			(0.00)	(0.00)			(0.00)	(0.00)			(0.00)	(0.00)
Constant	0.414***	0.628*	0.529*	-0.280*	0.654***	0.902***	0.894***	0.084	0.851***	0.948***	1.006***	0.196
	(0.08)	(0.23)	(0.25)	(0.13)	(0.07)	(0.17)	(0.18)	(0.08)	(0.07)	(0.16)	(0.15)	(0.11)
R^2	0.287	0.312	0.350	0.527	0.082	0.395	0.413	0.100	0.003	0.501	0.610	0.543

Table 11.

The regressions are using four different models for each investor type ($\text{Conservative} = 1, \text{Moderate} = 1, \text{Aggressive} = 1$ respectively).

Model 1: $y_i = \text{Intercept} + \beta_1 \cdot \text{Country\_UK}_i + \beta_2 \cdot \text{Country\_US}_i + \epsilon_i$

Model2:

$$y_i = \text{Intercept} + \beta_1 \cdot \text{Country\_UK}_i + \beta_2 \cdot \text{Country\_US}_i + \beta_3 \cdot \text{Exp\_equity}_i + \beta_4 \cdot \text{Exp\_fixed}_i + \epsilon_i$$

Model 3:

$$y_i = \text{Intercept} + \beta_1 \cdot \text{Country\_UK}_i + \beta_2 \cdot \text{Country\_US}_i + \beta_3 \cdot \text{Exp\_equity}_i + \beta_4 \cdot \text{Exp\_fixed}_i + \beta_5 \cdot \text{Num\_quest}_i + \beta_6 \cdot \text{Num\_portf}_i + \epsilon_i$$

Fixed Effect control column:

$$z_i = \text{Intercept} + \beta_1 \cdot \text{Country\_UK}_i + \beta_2 \cdot \text{Country\_US}_i + \beta_3 \cdot \text{Exp\_equity}_i + \beta_4 \cdot \text{Exp\_fixed}_i + \beta_5 \cdot \text{Num\_quest}_i + \beta_6 \cdot \text{Num\_portf}_i + \epsilon_i$$

Where

y_i = Equity ratio recommendation of the total equity plus fixed income asset portfolio

Country_UK_i = Country of origin is United Kingdom

Country_US_i = Country of origin is United States

Exp_equity_i = The exposure towards equity in the underlying offering

Exp_fixed_i = The exposure towards fixed income in the underlying offering

Num_quest_i = The number of questions asked in the questionnaire

Num_portf_i = The number of portfolios offered

ϵ_i = The error term

z_i = The demeaned equity ratio recommendation of the total equity plus fixed income asset portfolio, calculated as $z_i = y_i - \bar{y}$.

7.2 Appendix A. Generic investor questionnaire answers

Questions \ Investor Type	Conservative	Moderate	Aggressive
Age (birth date)	50 (1968-01-01)	40 (1978-01-01)	30 (1988-01-01)
Gender	male	male	male
Annual Income	$50,000 (USD, CAD) / €45,708	$50,000 (USD, CAD) / €45,708	$50,000 (USD, CAD) / €45,708
How much to invest now	$5,000 (USD, CAD)) / €4,570	$5,000 (USD, CAD)) / €4,570	$5,000 (USD, CAD)) / €4,570
Single/Partnership	Single	Single	Single
Monthly Savings	10% of monthly income ($420, $5,040 yearly)	10% of monthly income ($420, $5,040 yearly)	10% of monthly income ($420, $5,040 yearly)
Age of Retirement (years until retirement)	67 (17 years)	67 (27 years)	67 (37 years)
Risk-tolerance	Low (lowest possible risk)	Moderate (always in the middle)	High (highest possible risk)
Years in retirement	17	17	17
Investment goal/reason	Retirement	Retirement	Retirement
Previous Investment Experience	No/None/Beginner or novice	Yes/Some/Moderately experienced/Some stocks, funds or ETFs	Yes/Good/A sophisticated investor
Desired Retirement Amount (monthly)	$3333 ($40,000 yearly) (2,19%)	$713 (7,86%)	$1,340 (14,61%)
"When you hear "risk" related to your finances, what is the first thought that comes to mind?"	"I worry that I could be left with nothing."/Loss	"I understand that it's an inherent part of the investing process."/Uncertainty	"I think of the thrill of investing."/Thrill
Have you ever experienced a 20% or more decline in the value of your investments in one year?	No	No	Yes
If you were ever to experience a 20% decline or more in the value of your investments in one year, what would you do?	Sell everything./Change to more conservative investments or withdraw my money.	Sell some./Observe the market and consider changing to more conservative investments if the market doesn't begin to recover soon.	Buy more./Add to my investment to capitalize on the downturn.
The global stock market is often volatile. If your entire investment portfolio lost 10% of its value in a month during a market decline, what would you do?	Sell all of your investments	Sell some	Buy more
How would you describe your approach to making important financial decisions?	I try to avoid making decisions.	I reluctantly make decisions.	I confidently make decisions and don't look back.
Comfort zone of fluctuations (range)?	-10% +15% or -11% +20%, or -5% + 10%	-25% +35%, or -25% +25%	-45% +60%, or -36% +32%, or -20% +30%,

Which statement best reflects your willingness to experience market risk in return for potential growth of your portfolio?	I want to preserve my wealth, even if it means not keeping pace with inflation.	I want to grow my portfolio at a steady pace over time and am comfortable with some market swings.	I want to maximize growth, with increased risk in exchange for the potential of greater gains.
If you had a large, unexpected expense arise, are you able to cover it without touching this account?	No, I'd need to use the money in this account.	I may need to use some of the money, but not all.	Yes, I have savings other than this account I can easily access.
What are you looking for in a financial advisor?	I'd like someone to completely manage my investments, so that I don't have to	I'd like to create a diversified investment portfolio	I'd like to match or beat the performance of the markets
Children/Dependees?	No	No	No
When deciding how to invest your money, which do you care about more?	Minimizing losses	Both equally	Maximizing gains
How do you feel about this statement: "Historically, the benefits of investing have been worth the risks and I believe this will continue in the future."	I believe this to be true only some of the time	I somewhat agree: I believe this to be true most of the time.	I strongly agree: The benefits of investing are worth the risks.
How comfortable are you with fluctuations in the value of the investments in this account?	Less comfortable: I value stability and preservation of capital over the potential for higher returns.	Somewhat comfortable: I prefer a balanced approach.	Very comfortable: I'm willing to accept substantial fluctuations in hopes of higher returns.
During any one-year period, what would you do if there were a meaningful decline in the value of the investments in this account?	I would consider converting some or all of the investments in this account to cash; downturns in the market make me uncomfortable.	I would stay the course; I'm comfortable with occasional downturns in the market.	I would invest more; I see downturns in the market as opportunities.
Is there a chance you might need the money invested in this account to cover large, unexpected expenses?	Yes, it is likely I will need the money invested in this account to cover unexpected expenses.	I may need some of the money invested in this account to cover unexpected expenses.	No, I won't need the money invested in this account for unexpected expenses.
Tell us if you agree with this statement: "Based on my financial situation, I can weather market downturns and absorb losses without jeopardizing my goal for this account."	I disagree: I have fewer assets and less flexibility with the goal of this account.	I somewhat agree: I may have other assets or flexibility with the goal for this account.	I agree: I have other assets and flexibility with the goal for this account.
Which portfolio would make you most comfortable?	Gain 3% a year, with minimal risk	Gain 10% a year, with medium risk	Gain 14% a year, with high risk
You are betting on a coin flip: which bet would you take?	If heads: win $10. If tails: lose $0.	If heads: win $50. If tails: lose $20.	If heads: win $100. If tails: lose $50.
Will you depend on this portfolio for a portion of your monthly income?	no	no	no
Do you want your portfolio to be entirely comprised of socially responsible companies?	no	no	no
Which of the following best describes the securities you have held in your portfolio?	not sure	not sure	not sure
How do you normally determine what to buy/sell in your portfolio?	I have never bought or sold securities before	I only rebalance my portfolio periodically	I rely on my gut
What percentage of your current income will you need in retirement?	80% of income	80% of income	80% of income

Generally, I prefer investments with little or no fluctuation in value, and I'm willing to accept the lower return associated with these investments.	Strongly agree	Somewhat agree	Strongly disagree
During market declines, I tend to sell portions of my riskier assets and invest the money in safer assets.	Strongly agree	Somewhat agree	Strongly disagree
How stable are your current and future income sources? My current and future income sources (for example, salary, Social Security, pension) are:	Very unstable	Stable	Very stable
How many months of income do you have in savings? (savings divided by monthly earnings)	1,2	1,2	1,2
Do you expect to make withdrawals (other than RMDs) before the end of your investment time horizon (either a one-time withdrawal or consistent, periodic withdrawals of more than 50% of your portfolio value)?	No	No	No
educational level	bachelor	bachelor	bachelor
work field	finance (mid-level)	finance (mid-level)	finance (mid-level)
Which of the following most closely describes your investment objectives?	I want to maintain my wealth and protect against inflation. For this, I am willing to bear single-digit fluctuations in the performance of my portfolio.	I want to build my wealth moderately and expect returns above regular interest rates. For this I am willing to accept fluctuations in my portfolio value of around 10-20%.	I want to build my wealth considerably, i.e. multiply my investment over the long run. For this I am willing to accept greater fluctuations (over 20%) in the value of my investment.
What is the amount of your regular monthly outgoings?	75% of monthly income	75% of monthly income	75% of monthly income
For how long does your emergency cash reserve cover your monthly expenditure?	3 months	4 months	5 months
How much cash might you need in the next 12 months?	10% or more	5%	None
How much cash might you need in the next 5 years?	30% or more	10%	None
THE REALITY OF THE MARKET IS THAT IT GOES UP AND DOWN, AT WHAT LEVEL OF SHORT TERM LOSS DO YOU BEGIN TO FEEL VERY UNCOMFORTABLE?	10% loss	15% loss	No short term drop makes me uncomfortable.
Which of the following words do you most associate with investing money?	loss	uncertainty	excitement
In the past, have you come to regret important financial decisions?	always	sometimes	never
I prefer the certain returns of a deposit account to risky investments	strongly agree	no strong opinion	strongly disagree
Over the next few years, do you expect your future earnings or income to:	stay about the same	stay about the same	stay about the same
How secure are your current and future earnings or other income (e.g. salary, pension, interest)?	Fairly secure	Fairly secure	Fairly secure
How important to your household budgets would any income from this investment be?	make a useful contribution	make a useful contribution	make a useful contribution
The amount you are proposing to invest, ignoring any value in your own house, represents:	relatively small portion of my savings	relatively small portion of my savings	relatively small portion of my savings
How would your best friend describe you as a risk taker?	A real risk avoider.	Willing to take risks after completing adequate research.	A real gambler.

If you had to invest $50,000, which of the following investment choices would you find most appealing?	60% low, 30% medium, 10% high risk investments	30% low, 40% medium, 30% high risk investments	10% low, 40% medium, 50% high risk investments
You are on a TV game show and can choose one of the following, which one would you take?	$1,000 in cash	50% chance at winning $5,000.	5% chance at winning $100,000
You have an opportunity to invest in a startup venture that has a 20% chance of success. If successful you could make 50 to 100 times your investment. If unsuccessful your entire investment would be gone. How much would you invest?	Nothing.	Three months' salary	Six months' salary
Do you agree with the following statement? "Even if I could get high returns I would prefer not to invest my money in something that might decline in value"	Strongly agree.	Disagree.	Strongly disagree.
Where are you on your financial journey?	Building my wealth	Building my wealth	Building my wealth
What best describes your investing goal?	Avoiding losses while accepting lower returns.	Seeking greater returns while taking on moderate risk.	Maximizing returns while accepting potential large account value fluctuations.
What would you do if your portfolio decreased 20% during a market decline, but you didn't need the money for 10 years?	Move to less risky investments immediately.	Do nothing.	Do nothing.