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Investment preferences and risk perception: Financial agents versus clients[☆]

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ABSTRACT

We study four fundamental components of financial agency settings: The perception of commonly used investment profile terminology, agents' customization of portfolios to clients' preferences, the effect of agents' and clients' preferences on investment levels, and the role of compensation schemes. We observe large heterogeneity in the perception of investment profiles, resulting in substantial miscommunication between clients and agents. Financial agents show a high willingness to implement their clients' preferred investment profiles, yet appear to fail because of deviating perceptions. Agents' own investment preferences matter, but take a back seat to clients' preferences in determining investment shares. Different monetary incentive schemes hardly affect behavior. Our results suggest that moral constraints can limit agents' discretion in the agency situation.

1. Introduction

As part of the revised Markets in Financial Instruments Directive (MiFID II), financial advisors in the European Union are obliged to assess their customers' personal attitudes towards taking risks, their risk tolerance, and their risk bearing capacity (Hallahan et al. 2004). Clearly, these are neither easy nor clearly defined tasks and their implementation varies widely ranging from simple customer risk attitude questionnaires to behavioral measures of risk preferences (Grable and Lytton, 1999; Kaufmann et al. 2013; Roszkowski and Grable, 2005). Similarly, investment advisors in the United States are treated as fiduciaries and face duties of care and loyalty, requiring them to "serve the best interest of [their] client and not subordinate [their] client's interest to [their] own" (p. 8, Securities and Exchange Commission, 2019). Independent of jurisdiction, the goals of these regulatory efforts are to align the interests of clients and their agents to prevent the former from fraudulent exploitation by the latter.

Having assessed the risk and investment preferences of their clients, financial agents select products and make investment decisions. Several factors have the potential to affect the decision-making process: The form of investment preference communication from clients to agents might be too unspecific to inform agents well; agents and clients might not share a common perception of risk and the riskiness of financial products;[1] and/or agents might be influenced by exogenous factors such as monetary incentives and company policies. Finally, agents' decisions for their clients might be willingly or unwillingly affected by agents' own preferences.

In a controlled experiment, we systematically assess the role that key components of this interaction play in determining investment behavior of financial agents for their clients. First, we elicit participants' perceptions of investment profile terminology commonly used in financial advice, ranging in wording from *very conservative* to *aggressive growth* (Mutual Fund Dealers Association of

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[1] Bradbury et al. (2015) emphasize the importance of understanding the risks involved in investment decisions and show that these can be improved by simulating experience compared to survey-style risk assessment procedures. Relatedly, Glaser et al. (2019) demonstrate that risk perception concerning financial assets is sensitive to the presentation format.

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Canada, 2014, subsequently MFDA).[2] Then, we let clients communicate their preferred profile to financial agents and observe the degree to which agents subsequently customize investment decisions to clients' preferences in a Gneezy and Potters (1997) task. In a comprehensive 2-by-3 between-subject design, we vary the number of clients each agent faces as well as the agents' compensation scheme. Varying whether each agent invests for just one client (*Single*) or for a total of five clients (*Multiple*) allows us to uncover customization on the aggregate level (between-subjects) and on the individual level (within-subject). It also enables us to test if awareness of heterogeneous preferences among clients affects investment customization by agents. We implement these two conditions with three different compensation schemes: *Fixed, Co-Investment*, and *Limited Liability*. Under *Fixed* compensation, agents always receive the same payment, irrespective of their investment decisions. Under *Co-Investment*, they participate in the outcome of the investment decision, while under *Limited Liability* incentives they only participate if the outcome is positive, eliminating downside risk.

Making risky decisions for others, and more specifically investing for others, has been extensively studied in laboratory experiments. Some authors find agents to take more risks on behalf of their clients than they take for themselves ("risky shift": Chakravarty et al., 2011; Pollmann et al., 2014). Further studies acknowledge a domain dependence with the possibility of losses consistently leading to an increase in risk taking by agents (Polman, 2012; Andersson et al., 2014; Pahlke et al., 2015, 2021). In contrast, others document decreased risk taking for others ("cautious shift": Reynolds et al., 2009; Eriksen and Kvaløy, 2010). Füllbrunn and Luhan (2017) find evidence for a cautious shift, but hold the variety of different designs responsible for the varying results in the literature. More recently, the same authors demonstrate that financial decision making for others is affected by different incentive schemes. With limited liability incentives, they find agents to take excessive risks, while without them a cautious shift is observed (Füllbrunn and Luhan, 2019).

The process of deciding for others involves predicting the other party's preferences. Hsee and Weber (1997) investigate how people predict the risk preferences of others and find evidence for the *Risk-as-Feeling*s hypothesis according to which "people predict others to have similar risk preferences to themselves, but they predict others to be more risk neutral than themselves" (Hsee and Weber, 1997, p. 45; cf. Loewenstein et al., 2001). Roth et al. (2016) replicate the strong effect of own risk attitude in the prediction of others' risk attitudes. Roth and Voskort (2014) find evidence for a false consensus effect in the prediction of others' risk preferences in an experiment with financial professionals. Füllbrunn and Luhan (2017) report agents to invest according to what they believe their principals wish to invest for themselves.

A key component missing from virtually all controlled studies of financial decision making for others is communication. Specifically, a way for clients to inform their agents about their investment preferences.[3] Absent this information, there is hardly any guideline for agents to follow, except for exogenously provided (monetary) incentives and their own preferences. We deliberately give clients the opportunity to communicate their preferred investment profile to their agent, thereby reducing the information asymmetry and providing agents with a guideline for behavior. Notably, we employ terminology for communication used in practice, aimed at allowing non-experts to communicate their preferences without direct reference to actual investment. We believe that this is often an essential aspect of the advice relationship, as otherwise clients could generally implement their preferred portfolio choices themselves or opt for pure brokerage services instead.[4]

We probe recent empirical results by Foerster et al. (2017), who ask whether financial advisors customize portfolios to clients' preferences. Using investment preferences from Know Your Customer (KYC) forms and actual investment portfolio holdings, they find that customization of portfolios to match different clients' needs is very limited. Agents' own risk attitudes are identified to be the strongest predictor for the risky investments on behalf of their clients. Despite the richness of their empirical datasets, the authors lack control compared to studies based on laboratory experiments. Specifically, it remains unclear how matching between agents and clients affects the results. Clients select agents based on a number of different and potentially unobservable characteristics. Similarly, it might be the case that agents simply use their own risk tolerance as their best predictor for clients' risk tolerance if the communication of risk preferences from clients to agents (via KYC forms) is sufficiently unspecific.

Our laboratory experiment sacrifices external validity for experimental control. Two issues are important in this context. First, differences in risk attitudes may be more pronounced between professional financial advisors and their clients than between the student-advisors and student-clients in the lab. If this is the case, lab results may be interpreted as a lower bound on potential mismatch-effects in the field. Second, and pointing in the opposite direction, professional advisors are more experienced in the advice relationship than student-advisors, and may better be able to focus on the clients' needs. If this is the case, we would expect smaller mismatches between client preferences and investments in the field. Our laboratory results confirm the basic finding of Foerster et al. (2017) that both the advisors' and the clients' preferences matter for the investments made on behalf of the clients. However, the effect of advisors' own preferences on investment choices is much less pronounced in our experimental data compared to Foerster et al. (2017)'s field evidence, with the clients' preferences receiving a larger weight than the agents' preferences. Our results are in line with findings by Holzmeister et al. (2019) who find similar patterns for Swedish financial professionals and lay people, as well as Rose's (2021) results for professional advisors..

To the best of our knowledge, we are the first to directly elicit the perceived association of commonly used investment profile terminology with investment shares into risky assets. We find considerable heterogeneity in the perception of investment profiles and are able to trace mismatches between invested amounts and investment preferences back to differences in perceptions between agents and clients. We examine the behavior of agents given their own perception of the investment profiles and find considerable customization of client portfolios to their preferences. Observations from our *Single* and *Multiple* client treatments reveal that tailoring of investments to clients' preferences does not only occur on the aggregate, but also on the individual level. However, agents' own investment preferences also significantly affect their clients' portfolios.

Different compensation schemes, even with unambiguous monetary incentives to disregard clients' preferences, only modestly affect the degree to which agents try to comply with their clients' stated investment preferences. This observation is consistent with the results of Holzmeister et al. (2019) and the evidence provided by Ifcher and Zarghamee (2020). The latter find that agents tend

[2] See Marinelli and Mazzoli (2010) for examples of similar profile terminology being used in the European Union.

[3] A notable exception is Holzmeister et al. (2019) who let clients communicate their risk preference through unlabeled numerical scales ranging from 1 to 4.

[4] Notably, Hackethal et al. (2012) find that advisors from a German brokerage firm tended to be matched with "wealthier, older, more experienced, single, and female investors rather than with poorer, younger and inexperienced ones" (p. 521).

to act as surrogates for their principals. Even with strong financial incentives for the agents to disregard their clients' preferences, the clients' preferences still substantially determine the level of investments in their experiment. The observation that agents' financial motives do not affect their behavior much is corroborated by Rud et al. (2018), who show that financial incentives do not increase misreporting of agents to clients in their study of different market structures. We interpret this as evidence for a moral constraint in agent decision making. However, we also observe that the strength of financial incentives affects the degree to which agents use their discretion to maximize their investments while staying compatible with the clients' wishes. Thus, our results suggest that the impact of such moral constraints may be decreasing in the strength of financial incentives, which may explain the stronger impact of agent preferences in Foerster et al.'s (2017) field data.[5]

Our experiment allows us to ask whether the agent's investment in the risky asset falls into the range of investment levels that the client associates with the investment profile they communicated. We find evidence of a substantial problem of communication between agents and clients: Although agents intend to invest in line with their clients' preferences and their perception of compatible investment levels, they often fail from their clients' perspective. That is, clients end up with investment levels they perceive to be incompatible with their preferences. We attribute this to differences in the perception of the investment profiles.[6]

2. Experimental design

2.1. Methods overview

Over the course of our computerized laboratory experiment, participants pass three stages and take on both the role of a client and a financial agent.[7] The experiment starts with the Profile Perception Stage, in which all participants are asked to map investment profiles onto an investment scale ranging from 0 to 100% of risky asset share. In the Preference Stage, all participants act as clients and state their own investment preferences. Subsequently, all participants become financial agents and take investment decisions knowing the preferences of their clients. For each individual, either the client or the agent role is randomly selected to be payoff relevant at the end of the experiment. As participants go through these stages exactly once and in the specified order, there is no room for agents to cater to clients in expectation of reciprocity. Sessions conclude with a short demographic questionnaire.[8]

[5] Another aspect is the observability of the deviation from the clients' preferences. In the current lab setting, both ex-post observability by the clients, as well as observability by the experimenter, may add to moral consideration. In the field, this deviation will often be less observable.

[6] Suppose a client associates "very conservative" with a range of 0–15% investment in the risky asset and communicates "very conservative" as their investment preference to the agent. Suppose further that the agent associates "very conservative" with a range of 0–40% investment in the risky asset. Assume the agent wants to implement the client's preference and chooses an investment of 20% (i.e. the midpoint of the interval the agent associates with "very conservative"). From the agent's own perspective, the agent implements the client's request. However, the investment is not compatible with the "very conservative" profile as perceived by the client (20% > 15%).

[7] The nature of the experiment required the multi-role design to allow feasibility in terms of the number of participants. If taking both perspectives makes agents more sympathetic to the preferences of their clients, our design may provide an upper bound on customization.

[8] All files necessary for replicating the experiment and the results are available at https://osf.io/bm7j6/.

2.2. Tasks

2.2.1. Investment profile perception

In the Profile Perception Stage, we present participants with investment profile names, which are commonly used in the financial industry.[9] Participants learn that there is a risky investment opportunity and the option not to invest. We then ask each participant to map the investment profiles names into ranges of investment amounts in the risky asset on a scale from 0% to 100%. That is, we ask participants to reveal which levels of investment into a risky asset they think of when confronted with each investment profile name. The Profile Perception Stage provides us with an individual measure of how participants perceive the investment profile names in a setup that is patterned on the Gneezy and Potters (1997) task, but stops short of explaining the mechanics of the risky asset in detail.

At this stage in the experiment, participants only know that there will be a risky asset and the option not to invest. We consciously forgo a more detailed description of the asset in order to better resemble the situation in an actual financial advice setting. It is important that risk assessment tasks are free of complex details to foster people's understanding (Mutual Fund Dealers Association of Canada, 2014). Precise details of the financial products are naturally only provided to clients at a later stage of the process, when the actual product selection takes place. In the preceding assessment stages, products are commonly abstracted away from and portfolio composition is presented in a simplified manner. Financial advisors focus, for example, on the broad categories of equity and fixed income assets only (cf. sample investor profiles and asset allocations in Mutual Fund Dealers Association of Canada, 2014).

Fig. 1, Panel A shows the starting point of the mapping procedure as it was presented to the participants on their screens. Starting with the investment profile *very conservative* participants can successively drag and drop each profile box onto the scale. Participants can adjust the size of each box, i.e. adjust lower and upper limits of an investment amount in the risky asset such that it matches their perception of the investment profile. Panel B shows an example of an intermediate step in the elicitation process. In this example, the participant has already mapped two of the profiles to risky investment levels and has adjusted the ranges they cover. Panel C finally shows an example of the completed elicitation process. The participant perceives a risky asset share of roughly 0–10% to match a *very conservative* profile. The *conservative income* profile covers a wide range of risky asset shares from approximately 10% to 50%. A risky asset share of 50–70% maps into a *balanced* profile. Finally, 70% to 80% and 80% to 100% are considered adequate for *growth* and *aggressive growth* profiles, respectively. Note that we enforce consistency, i.e. that investment profiles which imply greater risk appetite than others cannot be mapped into lower risky investment levels. Furthermore, the full range of 0 to 100% had to be covered by the five profiles. Simply dragging them onto the scale was not enough, as they would only cover about 80% of the range by default. Participants had to actively adjust the size of at least one profile to be able to continue. This was implemented to make sure participants had to familiarize themselves with the range adjustment feature.

2.2.2. Investment preferences

In the Preference Stage, we make participants familiar with the details of the Gneezy and Potters (1997) investment task in the agency setting: The client owns an endowment of 10 Euro, of which the agent can allocate any amount to the risky asset. The

[9] The Mutual Fund Dealers Association of Canada (2014) uses these terms as examples for investor profiles in their guideline on the development of investor questionnaires as part of the Know Your Client Process.

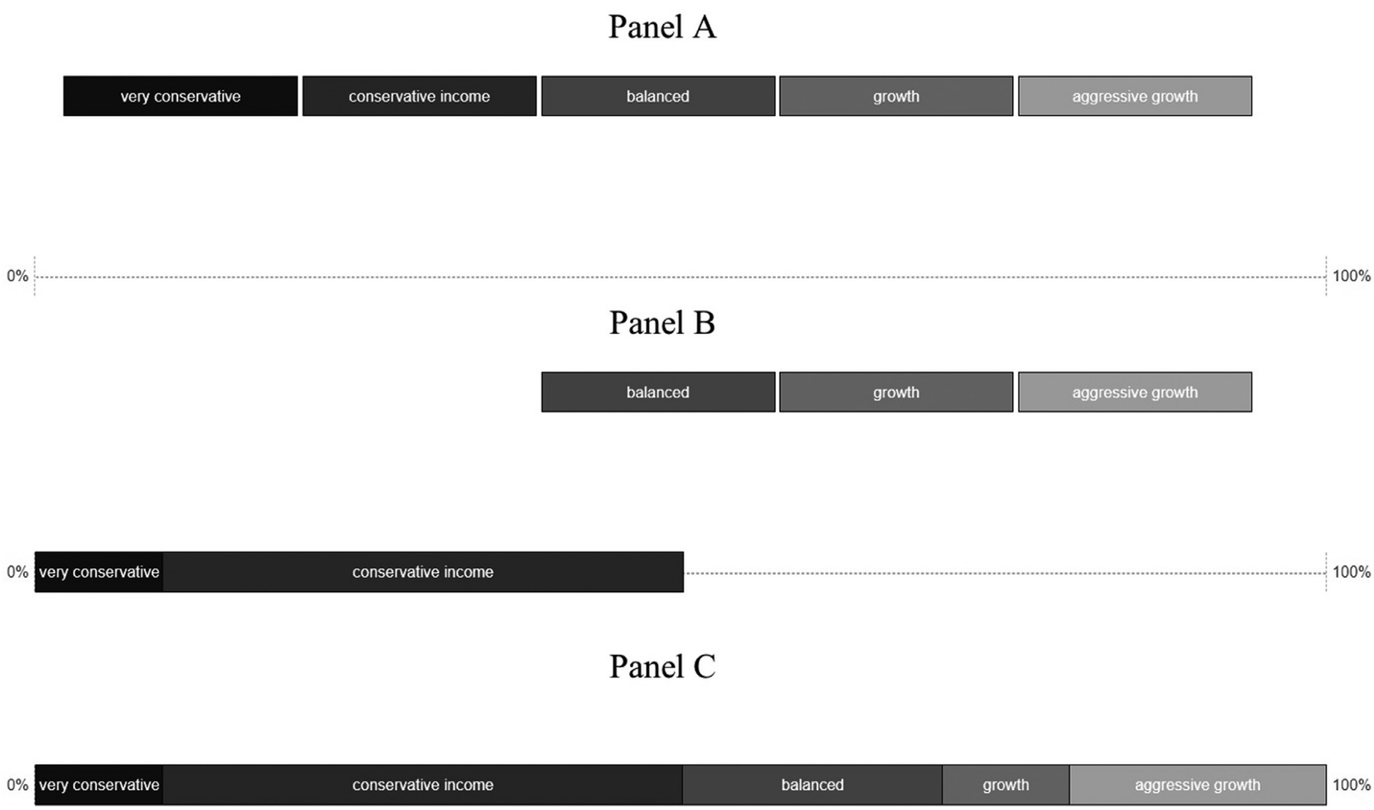

Fig. 1. Investment profile perception elicitation. The figure shows the process of the investment profile perception elicitation. Panel A shows the starting point of the mapping procedure as it was presented to the participants on their screens. Panel B shows an example of an intermediate step in the elicitation process. In this example, the participant has already mapped two of the profiles to risky investment levels and has adjusted the ranges they cover. Panel C finally shows an example of the completed elicitation process. Note that the full range of 0–100% had to be covered by the five profiles. An animated version is available at https://youtu.be/mcTX1QQX2f4.

risky asset resembles a lottery and has a return of +250% with probability $p = 1/3$ and a return of −100% with a probability of $1 - p = 2/3$.[10] The agent decides to invest an amount $x \in [0, 10]$ in the risky asset. Clients keep any share of the endowment that is not invested in the risky asset for sure (return 0%). We employ the Gneezy and Potters (1997) task, because of three reasons. First, it is easy to understand for participants and avoids the additional complexity of arguably more realistic tasks involving historical real-world data. Second, it models down the complex investment decision as a one-dimensional choice of an investment into a risky asset. As such, it is conceptually close to the investment profiles, which are ordered along the implied riskiness of the investments they aim to describe. Third, the task links our experiment to previous studies on financial decision-making for others which have employed similar settings (cf. Pollmann et al., 2014; Füllbrunn and Luhan, 2017).

In this stage, all participants take on the role of a client and state their investment preference by selecting one of the investment profiles they already encountered in the Profile Perception Stage. The selected profile (not the complete mapping) is then communicated to the agent in the Investment Stage. That is, participants directly communicate their investment preference to their agent in a tightly-controlled, one-way fashion. Participants are reminded that the preferred profile is communicated with the intention that the agent uses the information when making the investment decision. While this rather explicit demand for compliance with the clients' preferences might seem unconventional for a typical laboratory experiment, it is a very natural aspect in the context of financial agency. Clearly, all of the communication between clients and agents is aimed at informing and guiding the agents' subsequent actions in real-life situations. This is especially true if communication takes the form of an investment preference assessment initiated by the agent.

We deliberately chose not to have clients and agents chat about the preferred investment, but opted for the one-directional, single statement mode of communication. Such a mode is common for risk preference communication in many practical settings, as preferences are presumed a fixed and predetermined trait, not the results of a collaborative effort between agent and client. We consciously decided to have participants state their investment preference in terms of an investment profile rather than an explicit investment share. In relevant contexts, clients are presumable not able to communicate more than the preference profile: we aim to model the situation faced by typical clients of retail financial advice, i.e. individuals who do not have extensive financial knowledge.

2.2.3. Investment decisions

In the Investment Stage, all participants become financial agents and make the investment decision for their clients. In this stage, agents are informed about the investment profile selected by their clients in the Preference Stage. Agents are not bound by their clients' investment profile preference, but can freely choose any feasible investment in the risky asset. When deciding how much to invest on their clients' behalf, agents are informed for each client about their preferred investment profile (but not the client's

[10] Participants were given the probabilities and the returns (in percentages) associated with the two outcomes of the lottery. To make sure participants understood the returns correctly, we also showed the fully reduced formulas to calculate the resulting payoffs for the two outcomes. We did not explicitly tell participants that the expected return was positive at 16.67%.

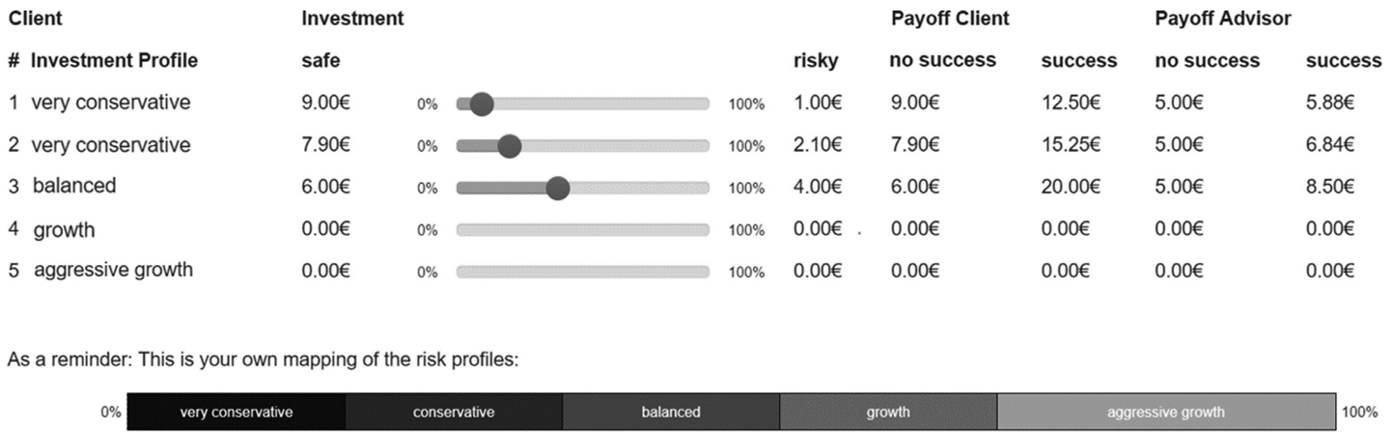

Fig. 2. Agents' decision screens. The figure shows the lower half of the agents' decision screen in the *Multiple* treatments. The first column shows the investment profile communicated by each of the five clients. The next three columns show investments in the risky assets as well as the decision slider, which is used to allocate the endowment between the two. In this example, the decision maker has already set investments for the first three clients, but has not started to select investments for the last two (no default slider position). The next two columns show the payoffs the clients receive in the investment success / no success cases. The final two columns show the corresponding payoffs to the agent, taking their limited liability into account. All values in the table update instantly with slider movements. Below the decision table, a reminder of the agent's own mapping of the investment profiles to investment shares in the risky asset is shown. An animated version is available at https://youtu.be/s7IS2FRWY1o.

complete mapping of all profiles).[11] Agents make their investment decisions by moving sliders to set the risky investment for their clients. Next to the sliders, agents see the clients' resulting minimum and maximum payoffs as well as their own resulting minimum and maximum agent payoffs.[12] The payoff displays update with every move of a slider for instant feedback on the effects of different investment levels. Agents always take the investment decisions for all of their clients on the same screen before proceeding to the next stage. This allows them to easily differentiate investments between different profile preferences, if they intend to do so. Fig. 2 shows an example of the decision screen. For reference, they are also reminded of their own mapping of investment profiles into investment levels in the risky asset. This aims to reduce noise in the allocation: if agents aim to implement client preferences but are ignorant about potential differences in mappings, we would observe investments consistent with their own schedules. Not showing their own mapping would add some noise if profiles are not exactly remembered, adding noise in the identification of whether agents follow clients' preferences (see Section 3.2.3).

At this point, agents and clients are also aware of a non-monetary accountability mechanism: After learning about the investment decision of their agent and their final payoff, clients are asked to send a short message to their agent expressing their (dis)satisfaction with the investment decision. The pre-defined messages read "I am [very satisfied/satisfied/dissatisfied/very dissatisfied] with your decision". We implement this weak accountability mechanism to allude to the personal relationship between financial agents and their clients typically present in real-world settings. It gives agents a reason to consider their clients' preferences and has the potential to create tension between agents' intrinsic motivations and external, monetary incentives. We discuss the effects of accountability in Section 5.

The experimental design presented in this section aims to assess how agents make use of information on clients' risky investment preferences. The information is only of general nature, that is, not specific to the task and not referring to exact investment amounts. We believe that this is a typical feature of agent-client communication in many contexts outside the lab. However, our setup has some implications that we need to keep in mind when interpreting the results. It is conceivable that agents arrive at somewhat different assessments about how to interpret a certain risky share in the investment task after learning about the underlying lottery compared to the general assessment they reported before. If they believe that this is also true for their clients, they may distort their investment, and it is unclear whether this is to the clients' disadvantage. On the other hand, the implied vagueness also allows agents to justify distortion of the investment in a way that is consistent with their own preferences and financial interests.

2.3. Treatments

2.3.1. Treatment overview

Using a 2-by-3 between-subject design, we systematically vary the number of clients on whose behalf agents have to take the investment decision as well as the payment scheme for agents. In the *Single* treatments, agents take the investment decision for exactly one client whereas in the *Multiple* treatments, agents take the decision for a total of five clients simultaneously. Agents can set the investment for each of their five clients individually. In the *Fixed* payment scheme, agents get a fixed payment of 5 Euro for their investment decision. Under *Limited Liability*, agents get the same fixed payment plus an additional 35% share of the positive return of the investment decision. That is, they do not face any downside risk. Finally, in the *Co-Investment* condition, agents get the fixed payment and a 25% share of their client's portfolio after the investment decision and its outcome have materialized. Importantly, agents know their financial incentives before deciding on the clients' investment (Gneezy et al., 2020).

2.3.2. Number of clients

In the *Single* treatments, the computer matches two participants within a session. We are particularly interested in situations in which a client's and an agent's preferred investment strategies differ. Therefore, we assign them such that we observe the highest possible variability of investment preferences within pairs. After all investment decisions have been made, one of the two participants in a pair is randomly selected to be the payoff-relevant agent, the other one becomes the client. Note that the instructions neutrally

[11] The investment profiles were presented in ascending order from lowest implied risk preference to highest. Given the wealth of information on the decision screen, we aimed to reduce the potential for confusion which a less natural, random order of client preferences would have created.

[12] The agents' payoffs depend on the compensation treatments, which are explained in Section 3.3 below.

tell participants that clients and agents are matched. We do not reveal the mechanism, but also do not claim randomness. Revealing the mechanism might have prompted participants to try and strategically choose the profile to communicate to the agent based on some belief about the distribution of preferences and perceptions among session participants. We deliberately choose not to reveal the matching protocol to prevent triggering these kinds of deliberations.

In the *Multiple* treatments, participants are allocated into groups of six. We introduce this treatment in order to increase the probability of agents observing heterogeneous investment preferences of their clients and hence being able to observe the extent of customization for individual agents. We assign groups to maximize the variability of preferred investment profiles.[13] Every participant takes the investment decision as an agent for every one of the five other participants in the group. Note that groups and group membership are opaque. Agents simply take decisions for five clients. Finally, we randomly select three participants of each group to be the payoff-relevant agents and randomly match each one of them with one of the remaining three participants, who become clients. That is, each agent is paid for their decision for single randomly selected client. We choose three agents from each group in order to keep the probability of being an agent constant across treatments. Thus, participants in both the *Single* and *Multiple* conditions face a 50% probability of being paid according to their decisions as financial agents. We succeeded in exposing agents to a reasonable degree of heterogeneity with 96.3% of our participants seeing at least three different investment profiles.

2.3.3. Payment schemes

We further systematically vary three payment schemes put in place for the financial agents. Under all payment schemes, clients are paid according to the investment determined by their agent and the outcome of the investment task. In the *Fixed* payment scheme, agents get a fixed payment of 5 Euro, independent of their clients' investment outcome. This condition serves as a baseline absent any monetary incentives for the agent to either consider or disregard the clients' preferences. At the same time, agents also do not benefit monetarily from implementing their own investment preferences as their outcome in terms of payoffs are unaffected.

Under the *Limited Liability* compensation scheme, agents receive a fixed payment of 5 Euro plus a share of 35% on the positive return of their corresponding clients. That is, agents do not face any downside risk, because their compensation is bounded below by the fixed payment, which is independent from investment success. However, they do have clear and substantial incentives to increase their own expected payoff by taking more risk, creating a situation of limited liability. Specifically, by investing 100% of their clients' money compared to not investing anything, they stand to gain 8.75€ (+175%) if the good lottery outcome occurs.

The *Co-Investment* compensation scheme lies in between the two extremes and partially aligns interests of agents and clients. Under this compensation scheme, agents receive a fixed payment of 5 Euro plus a share of 25% on the payoff of their corresponding clients. When investing 100% of their client's money rather than nothing, agents in this treatment stand to gain 6.25€ (+125%) or lose 2.5€ (−33%) depending on the lottery outcome. In contrast to the *Limited Liability* treatment, agents face a downside risk because they can also lose by choosing riskier investments. Still, agents' expected earnings increase as they invest more in the risky asset. That is, agents face a similar payoff structure as their clients but in an attenuated form: The variance in payoffs is lower compared to

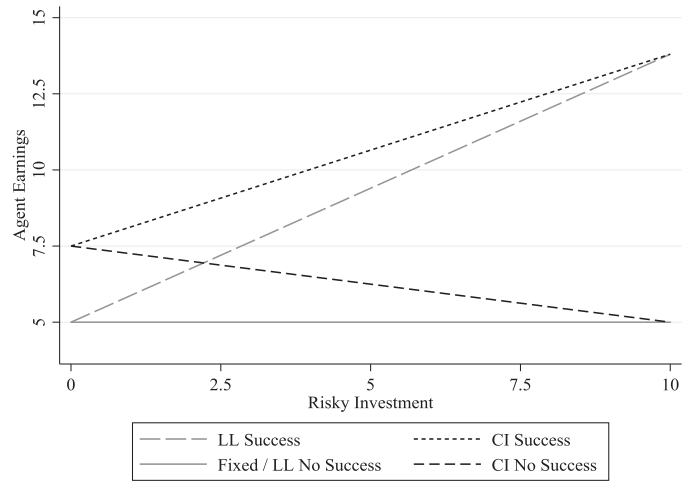

Fig. 3. Agents' compensation schemes. The figure shows the three payment schemes put in place for the financial agents. In the *Fixed* payment scheme agents get a fixed payment of 5 Euro. Under the *Limited Liability (LL)* compensation scheme, agents receive a fixed payment of 5 Euro plus a share of 35% on the positive return of their corresponding clients while under the *Co-Investment (CI)* compensation scheme, agents receive a fixed payment of 5 Euro plus a share of 25% on the payoff of their corresponding clients.

their clients' and in the worst case they end up with a payoff of 5 Euro whereas their clients can receive a zero-payoff. We chose not to implement perfectly aligned incentives with agents and clients receiving identical payoffs from the investment, because it would effectively transform the agency situation into a situation in which agents can simply decide for their own account without ever having to consider the effect on their clients. Partial dependence of own payoffs on clients' outcomes creates a tension between the two actors and additionally allows us to keep agents' expected payoffs comparable (if not equal) between compensation schemes.

Note that we do not use the principal-agent setting as means to study effort-provision or shirking. As such, our incentive schemes are not targeted at affecting the effort agents spend on the investment decision. Instead, we are interested in seeing how different incentive schemes affect the riskiness of investments taken for clients by the agents. Our *Co-Investment* and *Limited Liability* schemes are designed to pull agents' investments towards benefitting themselves. The *Fixed* one, in contrast, should not have this effect.

To simplify the experiment, agents' compensations are always paid by the experimenter and do not come out of clients' portfolios. This is known to participants in the experiment. Fig. 3 shows the agents' earnings as a function of the investment in the risky asset for our payment schemes.

2.4. Procedures

The experiment was conducted at the AWI-Lab, the experimental laboratory at Heidelberg University in Germany in 2018. Sessions were organized with the software hroot (Bock et al., 2014) and the experiment was programmed using oTree (Chen et al., 2016). Participants entered the laboratory and were randomly placed at one of the 20 separated computers. All instructions were displayed on-screen and questions were answered in private. We ensure understanding of the instructions by letting participants advance through the instruction section only after answering a set of comprehension questions correctly. The experiment concluded with a short demographic questionnaire. Participants received cash payments in private and were dismissed from the laboratory. A total of 434 student participants took part

[13] See Appendix B for details on the group matching procedure and an example for two groups.

in the experiment (56.2% female, 30.2% economics students, average age: 23.0). In total, we ran 26 sessions (6×3 for the main treatments, and 2×4 for additional control conditions discussed below) with 324 participants in the main treatments and 110 participants in the controls. Each session lasted about 45 min and participants earned an average amount of 11.94 (s. d: 7.50) Euro including a show up fee of 4 Euro.

3. Results

3.1. Results overview

Our main intention is to investigate what drives risky investment shares in an agency setting. To do so, we divide the analysis into two parts. We focus on agents' behavior first and investigate whether they follow their clients' profiles or rather base their decision on their own risk preference. For this analysis, our measure of agents' and clients' preferences is the general investment profile they selected before knowing the exact specification of the risky asset. Next, we take on the perspective of clients and investigate whether they "get what they want." Here, the considerations we discussed in Section 2.2.3 apply. As an intermediate step, we examine how the perception of the investment profiles affects the decisions taken.

3.2. Agents' behavior

3.2.1. Investments in the risky asset

Fig. 4 shows the average investment in the risky asset for different combinations of the clients' and agents' preferred investment profiles.[14] In line with Foerster et al. (2017; cf. their Fig. 5) and Holzmeister et al. (2019), we find that agents' own preferences influence the investments they make on behalf of their clients. Within each profile preferred by clients, we find that the average investments in the risky asset increase with the preferred profile of the agent. A first visual inspection reveals that both the risk preference of the client as well as the risk preference of the agent seem to play a role when taking risky decisions on behalf of others.

As a second step, we are interested in whether agents aim to implement their clients' preferred investment profile. Recall that agents only know their own mapping of investment profiles into investment shares and the preferred profile (but not exact mapping) of their clients. Thus, the best an agent can do to act in accordance with their client's preference is making an investment that they believe to be compatible with the client's preferred profile. While we do not explicitly elicit agents' beliefs about the profile mappings of their clients, it seems reasonable that agents' own mappings correspond to these beliefs quite closely (cf. False Consensus Effect, e.g., Roth and Voskort, 2014; Roth et al., 2016).[15] If we take the preferences clients' communicate in the first stage at face value, we find that in 49.3% of the decisions over all treatments, agents select investment levels which fall within the ranges of investments which are compatible with their clients' wishes. This is despite the fact that none of our payment schemes provides monetary incentives to follow the clients' wishes. In contrary, the *Limited Liability* conditions even unambiguously incentivizes agents to take risks above and beyond their clients' preferences for own monetary gain.

Table 1
Risky investment shares by treatment condition.

	Compensation		
	Fixed	Limited Liability	Co-Investment
Single	47.8%	50.9%	50.7%
	(20.2%)	(22.5%)	(22.3%)
Multiple	46.9%	56.5%	50.1%
	(26.8%)	(28.6%)	(25.5%)

Mean investment shares with standard deviations in parenthesis. For treatment *Single* the number of observations is 54 for each compensation treatment. For *Multiple* it is 270, because we observe five investments decisions (not independent) for each participant.

Table 1 provides an overview of mean risky investment shares separated by treatment conditions. In order to investigate agents' investment behavior more formally and test for treatment differences, we use Tobit[16] regressions to estimate the investment share in the risky asset. In specification (1), we regress the risky share on the agents' and the clients' preferred investment profiles, included as individual indicator variables. In specification (2), we add treatment indicators and their interactions, as well as controls for age, gender, and being an economics student. Table 2 reports the results.

Comparing each agent preference category to the "very conservative" baseline reveals that only a preference for "aggressive growth" leads agents to invest significantly more in the risky asset for their clients. Agents with this greatest appetite for risk invest approximately 16% more. In contrast, every single client preference indicator is highly significant, expressing differences to the baseline category. More importantly, all pairwise comparisons of the estimation coefficients are also highly significant, indicating that each client preference has a distinct effect on agents' investments (F-tests for both models, all $p < 0.001$). Client investment preferences indicating greater appetite for risk translate into higher investment levels by agents. Clients with a "conservative income", "balanced", "growth", or "aggressive growth" preference receive investments that are 17.2%, 32.9%, 48.5%, and 61.9% higher, respectively, than clients indicating a "very conservative" preference.[17]

The effect of clients' preferences on the amount invested into the risky asset is larger than the effect of agents' preferences both in terms of statistical as well as economic significance.[18]

In the *Single* conditions, agents' investments are not significantly affected by the *Co-Investment* and *Limited Liability* compensation schemes, relative to the *Fixed* baseline. Under *Fixed* compensation, agents' investments are slightly, but significantly lower when deciding for *Multiple* rather than a single client. *Co-Investment* and *Limited Liability* compensation completely offset this reduction and even yield significantly higher average investments compared to the *Single/Fixed* baseline.[19] However, the effects of the two compensation schemes do not differ in the multiple client setting (F-test: $p = 0.80$). We conclude that agents' in-

[14] We report the number of observations for each group in Appendix A, Table A1.

[15] In fact, agents might be aware that their own mapping might not be universal. This might lead them to a conscious investment decision based on what they believe their client's mapping to be, rather than their own mapping. However, given that we quite saliently remind agents of their own mapping on the decision page, we consider this possibility to be unlikely to affect our results much. In addition, and as highlighted in section 2.2.3, the perception of the riskiness of the asset might have changed after learning about its specifics in the investment stage.

[16] OLS regressions yield qualitatively similar results, but the Tobit regressions better account for the censoring at 0% and 100% investment shares.

[17] Running regression (2) for the Single and Multiple conditions separately results in qualitatively similar results for the effects of agents' and clients' preferences.

[18] The effects of the lower four agent preferences are not significantly different from zero. Only "aggressive growth" leads to 16.3% (model 2: 17.1%) higher investments. We make pairwise tests of the coefficients of clients' preferences against this benchmark: Model 1: 17.21 vs. 16.33 $p = 0.92$; 32.92 vs 16.33 $p = 0.05$; 48.51 vs. 16.33 $p < 0.001$; 61.89 vs 16.33 $p < 0.001$. Model 2: 19.07 vs. 17.1 $p = 0.81$; 32.78 vs 17.10 $p = 0.06$; 50.02 vs 17.1 $p < 0.001$; 64.39 vs. 17.1 $p < 0.001$.

[19] F-tests, Co-Investment: $p < 0.05$; Limited Liability: $p < 0.05$.

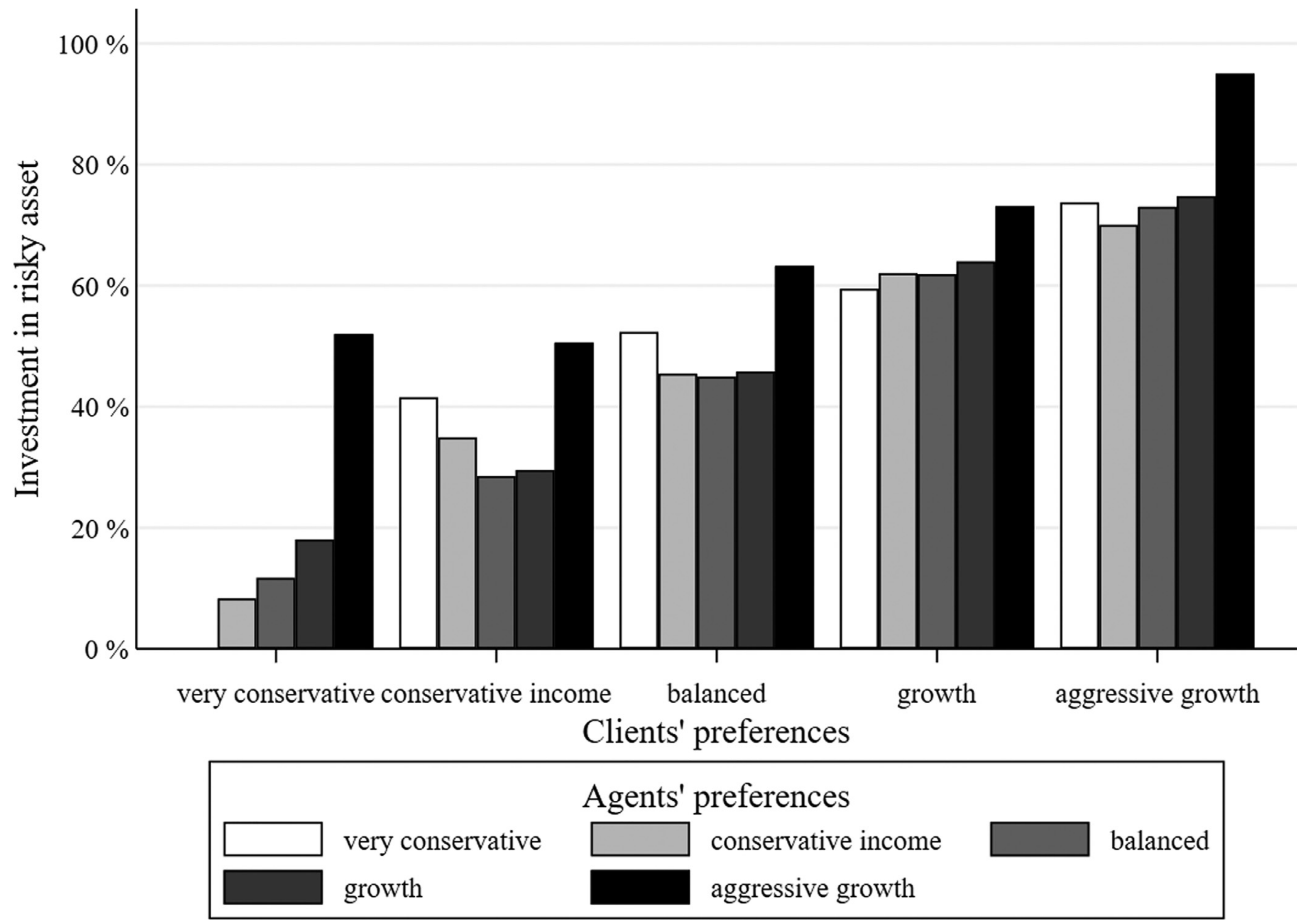

Fig. 4. Investment in the risky asset by clients' and agents' profiles. This figure shows the average investment shares in the risky asset for each client and agent preference combination, pooling observations from all treatments. Data is first grouped by the clients' communicated preferences (horizontal axis categories). In each of these groups, we show average investments from agents separated by their own investment preferences.

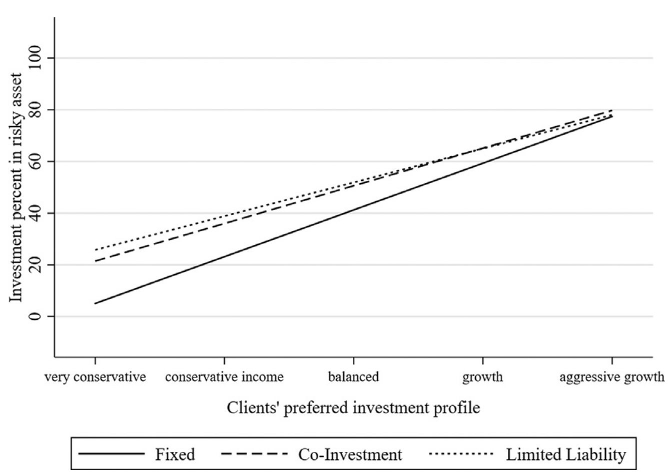

Fig. 5. Risky investments by compensation scheme. The graph shows aggregated investments for each preferred investment profile in the *Multiple* client conditions. We plot separately fitted values for each compensation scheme.

vestment decisions are to large parts driven by the consideration of their clients' preferences. Only the most extreme of agent preferences has an effect on investments and remains comparatively small. The different compensation schemes only have limited, unsystematic effects.

3.2.2. Portfolio customization and monetary incentives

While we observe that about half of our agents do not invest in line with their clients' preferences, they might still have the intent to do so, but fail in implementing their intent. The *Multiple* treatment makes the heterogeneity of different investment profiles among an agent's clients salient. The agents in this condition are aware that clients have different tastes. By measuring how strongly individual agents differentiate between clients with different investment profile preferences, we can uncover the agents' intentions to follow their clients' preferences. The more they take their clients into account, the stronger they should differentiate investments between profiles. The less importance they put on clients' preferences, the more similar should be the invested amounts for all clients. Furthermore, we are interested in whether the compensation schemes affect the extent of differentiation between clients with different investment preferences.

Due to the monetary incentives under the *Limited Liability* compensation, we expect agents to invest more and differentiate less between different investment preferences as compared to the *Fixed* treatment. Fig. 5 shows the differentiation of agents' investments for their clients for our three compensation schemes (Figs. A1 to A3 in Appendix A shows the differentiation of each individual

Table 2
Regression analysis - investments in the risky asset.

	Investment in risky asset (1)	Investment in risky asset (2)
Limited Liability		−0.48
		(3.77)
Co-Investment		−1.45
		(3.76)
Multiple		−6.54*
		(2.84)
Limited Liability × Multiple		10.99*
		(5.13)
Co-Investment × Multiple		12.44*
		(5.07)
Agent preference indicators		
Conservative income	−4.09	−1.49
	(5.55)	(5.31)
Balanced	−4.68	−5.19
	(5.28)	(5.05)
Growth	−3.03	−2.82
	(5.37)	(5.31)
Aggressive growth	16.33*	17.10*
	(8.11)	(7.89)
Client preference indicators		
Conservative income	17.21***	19.07***
	(3.20)	(3.14)
Balanced	32.92***	32.78***
	(2.58)	(2.54)
Growth	48.51***	50.02***
	(2.72)	(2.70)
Aggressive growth	61.89***	64.39***
	(3.81)	(3.92)
Constant	16.88**	−1.73*
	(5.55)	(11.13)
Controls	No	Yes
Observations	972	972

We report Tobit regression coefficient estimates with standard errors in parentheses. The standard errors are clustered on the individual level. The dependent variable is the investment share in the risky asset in percent. The base category for the preference indicators is "very conservative", for *Multiple* it is *Single*, and for the compensation schemes it is *Fixed*. Controls include age, gender, and studying economics. 19 observations are censored at 0; 73 at 100. ***/**/* indicate significance at 0.1% / 1% / 5%.

agent for each compensation treatments). The degree of differentiation is highest under the *Fixed* compensation and lowest under the *Limited Liability* compensation. The correlations between riskier investment preferences and actual investments for clients are all positive and significantly different from zero (*Fixed*: $\rho = 0.79$, $p < 0.01$; *Co-Investment*: $\rho = 0.61$, $p < 0.01$; *Limited Liability*: $\rho = 0.49$, $p < 0.01$; spearman correlation coefficients). The correlation between the clients' profiles and the investment in the risky asset is strongest under *Fixed* compensation and significantly larger than in the presence of incentives under *Limited Liability* (0.79 vs. 0.49, $p < 0.01$) and *Co-Investment* compensation (0.79 vs. 0.61, $p = 0.055$). That is, we find high levels of customization of investments for clients. Even under the strongest of financial incentives, agents do not disregard their clients' preferences.

3.2.3. Agents' discretion

Despite the fact that agents in our experiment tailor investments to clients' preferences, they might still react to incentives in a less obvious way. Recall that agents only learn about the preferred investment profile of their clients. The profiles cover a range of admissible investment levels. Agents can follow their clients' requests and still use their discretion to their own monetary advantage by choosing investments at the upper end of the requested investment intervals. In the *Co-Investment* and *Limited Liability* treatments, this behavior would allow them to both cater to their clients' requests and maximize their own earnings potential.

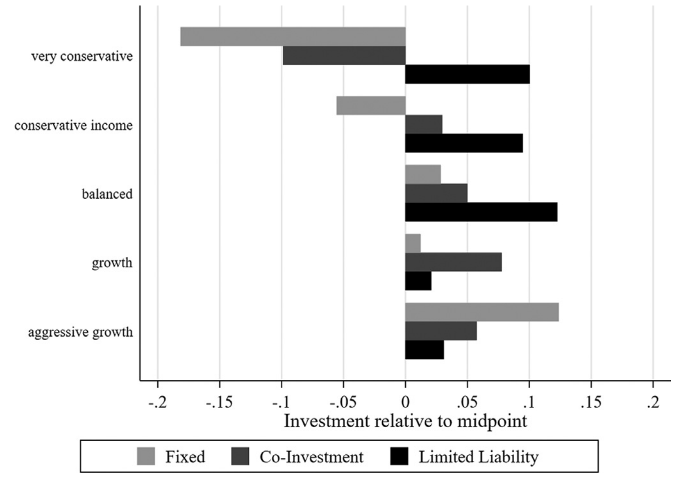

Fig. 6. Agents' discretion. The graph shows agents' investments relative to the requested investment profile for agents who invested in line with their client's preference.

To analyze whether this behavior occurs in our experiment, we first determine the midpoint of the investment interval that was requested by the client, taking the agent's perception of the investment profile as a basis. We do this for each of the agents who made an investment decision that is compatible with their client's request. Then we compare the agents' actual investments to the midpoint of these intervals. Fig. 6 shows the results for each compensation treatment and for each of the five investment profiles. A value of zero corresponds to the midpoint of the interval, while values of -0.5 and 0.5 would correspond to the lower and upper boundaries of the requested interval.

There are visible differences in how agents use their discretion between the three treatment conditions. In the *Fixed* treatment agents seem to use their discretion to conform to the clients' requests as much as possible.[20] For conservative requests they tend to make investments closer to the lower boundary of the interval, while for more risky requests they go beyond the midpoint of the requested interval. In the *Co-Investment* treatment we observe a slight shift to the right, with only one of the five requests leading to investments below the midpoint of the requested interval. The *Limited Liability* treatment finally reveals that agents invest in the upper half of the requested interval for all of the five possible investment requests. Relative investments are significantly higher (i.e. closer to the upper boundary) in the *Limited Liability* condition compared to the *Fixed* condition (F: 0.008 vs. LL: 0.070, $p < 0.05$, two-sided t-test). Differences between the *Fixed* and the *Co-Investment* as well as the *Co-Investment* and the *Limited Liability* conditions are not statistically significantly different (F: 0.008 vs. CI: 0.039, $p = 0.34$; CI: 0.039 vs. LL: 0.070, $p = 0.34$; both two-sided t-tests). While the effect is strongest for very conservative requests, it is somewhat smaller for investment profiles which imply a higher risk appetite. Clearly, agents in our experiment react to their own financial incentives, yet they seem to be bound by a moral obligation to their clients.[21] The trade-off between own interests and ethical self-image as an advisor replicates patterns found in recommendation games by Gneezy et al. (2020). That

[20] This effect has been hypothesized by Hackethal et al. (2019), who also suggest that client involvement in the process of financial advice may be detrimental to clients' financial outcomes.

[21] Similar behavior is known from the literature on cheating: Individuals are more likely to cheat a little bit, rather than a lot (Fischbacher and Föllmi-Heusi, 2013; Halevy et al., 2014). Note that the moral obligation may be induced by observability both by the client and the experimenter.

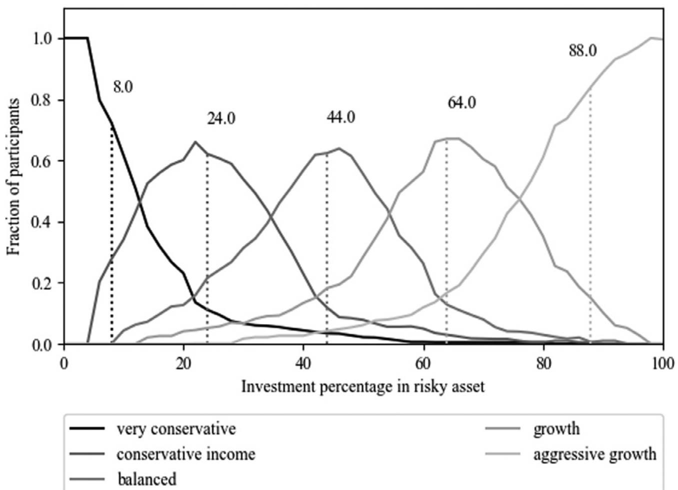

Fig. 7. Perception of investment profiles. For each possible investment share in the risky asset, the graph shows the fraction of participants who mapped the respective investment profile to the investment share. The individual distributions are labeled with their medians.

is, while the issues of mismatch between advisor and client risk preferences and experience in assessing and implementing clients' preferences will influence the strength of the different motives in the lab and the field, the qualitative pattern observed in the field seems to be well captured in the laboratory experimental setting.

3.3. Clients' perspective

The question of how people perceive risks has attracted much research effort. Diacon (2004) compares the perceptions of individual consumers and expert financial advisors and finds strong differences in the perception of financial risks between both groups. Slovic (1987) reports that perceptions vary between experts and lay people for physical or engineering risks and financial risks. However, this result has recently been contested by Holzmeister et al. (2020), who do not find substantial differences between financial professionals and lay people in what drives risk perception. Note, that in our experiments, all participants provide their perceptions before they even know that they will take on different roles later on. Combined with our rather homogeneous standard student sample and random treatment assignment, we can only observe heterogeneity in the perception of investment profiles but cannot study systematic differences between agent and client roles.

Fig. 7 shows the distributions of perceptions of the different investment profiles in our sample. The figure highlights a sizeable overlap of the profiles. For instance, investments in the risky asset between 30 and 60% of the endowment are perceived to match any of the available investment profiles by some participants. Consequently, there is a high degree of heterogeneity in the perception of the different investment profiles and it is far from obvious what they mean to people subjectively. Holzmeister et al. (2019), who use a numerical scale to communicate investment preferences, make a similar observation: The investment levels observed for each risk level requested by clients are very dispersed, indicating that even with numerical scales communication of investment preferences is far from trivial and perceptions may still differ widely. Thus, the investment profiles commonly used in financial advice appear to be very noisy in their perception, even when only considering a rather homogenous student sample.

From a client's perspective, the best benchmark for the decision their agent takes on their behalf is whether they perceive the invested amount to fall into the range the client associates with the requested profile.[22] Across all treatments, this is the case for 43.8% of all clients. Table 3 breaks it down by treatment condition. Each cell shows the percentage of clients that get an investment which is compatible with their requested profile. For the *Multiple* treatments, clients seem to get what they prefer more often compared to the *Single* treatments, however none of the pairwise differences are statistically significant.

Table 3
Share of clients with investments compatible with their preference.

	Compensation		
	Fixed	Co-Investment	Limited Liability
Single	42.6%	42.6%	40.7%
Multiple	54.4%	45.6%	45.9%

The table reports the share of clients that receive and investment that falls into the range of compatible investment shared implied by the requested profile (based on their own mapping of profiles into investment shares).

Recall that agents only know their clients' preferences, but do not know their individual mappings. Thus, if investments are not perceived to be compatible with the clients' preferences, there are multiple potential reasons: (1) Agents might share the same perception of the profile but deliberately choose not to follow the clients' requests; or (2) agents have a different perception of the requested profile (without realizing it), but try to implement their clients' request based on their own (deviating) perception. The latter agents intend to implement clients' requests, but clients might still end up with an investment they perceive to be incompatible with their request. We now restrict our analysis to agents who, to the best of their knowledge, choose an investment that is compatible with the requested profile based on their own mapping. That is, we change the reference from the clients' mappings to the agents' mapping. For only 61.6% of investments by these agents, clients perceive the investment to be compatible with their preferred investment profile. In 38.4% of the decisions in which agents try to implement their clients' preferred investment profiles, they fail to comply from their clients' point of view. With 19.2% of clients perceiving the decision being lower than preferred and 19.2% perceiving the decision as being higher than preferred, there does not seem to be any systematic deviation, but simply a mismatch between the perceptions of how the investment profiles translated into investments in the risky asset.

Finally, we look at the satisfaction messages that clients send to their agents after learning how much was invested on their behalf, whether the investment was successful, and the payoff they receive as a result. In the context of investment decisions for others, it is of particular interest if agents' incentives affect clients' satisfaction with their decision. On a scale from -2 to $+2$ (corresponding to messages *very dissatisfied* to *very satisfied*), average satisfaction scores tend to be positive under all compensation schemes (*Fixed*: 0.80, *Co-Investment*: 0.33, *Limited Liability*: 0.37). While satisfaction seems to be highest with *Fixed* compensation, none of the pair-wise comparisons actually indicates statistical significance in the differences (Mann-Whitney-U tests, all $p > 0.1$). In our experiment, the different incentive schemes do not affect clients' satis-

[22] One might argue that a better benchmark would be to compare the agents' investment performance to the counterfactual outcome of the same client taking the investment decision for themselves. However, these cases are never observable, as clients who are able to make the informed investment decision themselves would not rely on an agent, and clients who seek an agent do it as not to invest themselves. The performance comparison would also be based on outcomes, which are jointly determined by agents' decisions and a chance component. As such there is a chance to fall prey to outcome bias, a phenomenon by which irrelevant outcome information is used to assess the quality of a decision (cf. König-Kersting et al., 2021).

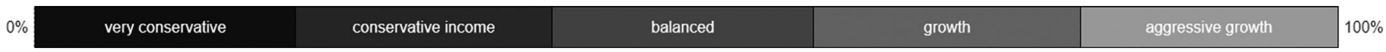

Fig. 8. Preference perception stage in the Certainty treatment. In the *Certainty* treatment, we establish a common understanding of the investment strategies by fixing each interval to a size of 20%.

faction with their agents' decision. The interested reader is pointed to König-Kersting et al. (2021) for a detailed analysis of the effects of agents following their clients' wishes and the effects of the random investment outcome on clients' satisfaction.

4. Robustness

4.1. Profile perception

In our main treatments, 49.3% of agents seem to take the communicated investment profile at face value and intend to implement their clients' preferences, i.e., choose investment shares that should – from their own perspective – be compatible with their clients' requests. Even under clear monetary incentives to take larger risks, agents strongly consider their clients' preferred investment profiles. We find evidence of a fundamental problem of communication in financial advice when relying on the use of investment profile terminology. There is a large degree of heterogeneity in the perception of these profiles, which opens up the door for unintended mismatches between agents' decisions and clients' preferences.

In advice practice, communication between clients and agents can be more extensive than the legally required exchange of financial information and communication of risk and investment preferences. Two-way communication between agents and their clients can shape the perception of risk and allow agents to get a better understanding of their clients' true preferences. While it is not our goal to study how perceptions of risk change and potentially converge between those involved, we are aware that a shared understanding of the risks involved and a common the language to communicate them may benefit both sides. The question arises whether the observed translation error can be reduced by better defining the investment profiles and fostering a common understanding between agents and their clients.

We conducted two additional control treatments. The first aims at examining how the uncertainty surrounding the understanding of the investment profiles affects the decisions. Thus, in the *Certainty* treatment, we modify the profile perception stage, while all other stages stay unchanged. In contrast to our main treatments, we do not elicit participants' perception of each investment strategy. We rather establish a common understanding of these terms. This is done by showing participants the five investment profiles and explicitly defining how they are supposed to map into different investment levels.[23] Each investment profile now covers a fixed range of 20% as shown in Fig. 8. Fixing the perception of the profiles removes the possibility of observing unintended mismatches for agents who aim to implement the desired profile: If an agent implements their client's preferred profile, the client will perceive the agent's behavior to be in line with his investment request by design. If there is a mismatch, it must be because of agents deliberately choosing investments that are incompatible with clients' preferences. The remaining experiment stays unchanged: Clients pick their preferred investment profile, which is communicated to their agent. Agents make the investment decisions. For the *Certainty* treatment, we only run the *Single* variant of our design and set *Limited Liability* incentives.[24]

To gauge the impact of the differences in perception of the investment profiles, we compare how often clients receive the investment they ask for from an agent who aims to implement their client's preference in the *Certainty* versus the *Single/Limited Liability* conditions. For this analysis, we only look at well-meaning agents who select an investment level that falls within the range of investment shares that the agent deems compatible with the requested profile. We then check if the selected investment level also falls within the range of the requested profile from the client's perspective. We find that in *Single/Limited Liability* this is the case for 46.2% of the clients. In *Certainty*, the respective number is – by design – 100%, because any mismatches due to differences in the perception of the profiles are eliminated. The difference is statistically significant (test of proportions, $p < 0.01$).

However, the *Certainty* treatment also shows that the absence of uncertainty about the clients' perception of the investment profiles increases the effect of compensation incentives on agents' behavior. Investments in *Certainty* are higher than in the main *Single/Limited Liability* treatment after controlling for agents' and clients' preferences.[25] The share of agents who invest more than preferred by their clients is significantly larger than the share of agents who invest less than preferred in the *Certainty* treatment (test of proportions, 0.44 vs. 0.13, $p < 0.01$). This is not the case for the *Single/Limited Liability* treatment under uncertainty (test of proportions, 0.30 vs. 0.22, $p = 0.38$).

4.2. Accountability

The consistently high degree to which agents follow their clients' preferences in our experiment is quite remarkable, yet in line with observations by Holzmeister et al. (2019), Ifcher and Zarghamee (2020), and Rud et al. (2018). Different incentive schemes do not have much of an effect on investment levels. We hypothesize that the accountability aspect, which is common to all of our main treatments, could be the driving force behind this result. Recall that in all treatment conditions, accountability can stem from multiple sources: First, clients tell agents how to invest for them. Second, clients can always hold their agents directly accountable for their decision by sending messages of satisfaction or dissatisfaction with the investment decisions after the fact.[26] Finally, the clear and consistent framing of the experiment as a situation of financial decision-making might instill a heightened feeling of responsibility in agents for their clients' well-being.

[23] We make sure participants engage with the scale and understand it correctly by asking additional comprehension questions in this treatment. Specifically, we ask them to select the profile which corresponds to a specific investment level and we have participants enter the boundaries of the interval that fits one of the profiles.

[24] While the *Single* variant keeps the required number of participants manageable, we use *Limited Liability* incentives rather than the baseline *Fixed* incentives, because in the main treatments they yielded the highest number of deviations from clients' requests. If a common perception of investment profiles reduces the mismatches between clients and agents, it is most likely to show in this condition.

[25] We regress the investment share in the risky asset on a *Certainty* treatment indicator and agents' and clients' preferred investment profile indicators. The Tobit coefficient estimate for the *Certainty* indicator is 14.3, $p < 0.01$.

[26] For a detailed analysis of these messages, refer to König-Kersting et al. (2021).

After all, financial decisions are often considered a matter of mutual trust. Thus, in a second control condition, *No Accountability*, we remove these aspects. The instructions are neutrally framed,[27] there is no elicitation and no explicit communication of investment preferences, and clients can no longer express their satisfaction or dissatisfaction with the agents' decisions. What remains is the pure investment game on behalf of another participant. We again run the *Single/Limited Liability* variant only. At the end of the session, the principal learns their final payoff and how much the agent invested on their behalf.[28] Crucially, there is no opportunity for the principal to hold the agent accountable. There is no feedback mechanism and no additional round of the investment game.

Despite removing the accountability aspects, we do not find a significant increase in the risky investment shares (Kolmogorov-Smirnov test for the equality of distributions: $p = 0.87$; means: *Single/Limited Liability*: 5.09 vs. *No Accountability*: 5.56, Mann-Whitney-U $p = 0.64$). It seems that agents have a feeling of responsibility for their clients, even in the absence of accountability-enhancing design aspects.

5. Conclusion

We study four key aspects of financial agency in highly controlled laboratory experiments: Perception of investment profiles, the degree of portfolio customization, the effects of agents' preferences on clients' portfolios, and the role of compensation schemes. We observe the perception of investment profile terminology, as used in the financial industry, to be very heterogeneous, which results in considerable miscommunication between clients and their financial agents. Notably, establishing a shared understanding of investment profile terminology is not enough to significantly increase the share of clients that receive an investment that is in line with their preferences.

In general, we observe a pronounced willingness of agents to customize portfolios to their clients' preferences. Even in light of monetary incentives to disregard their clients' wishes, agents still differentiate considerably. We find evidence for a larger tendency of agents to use their discretion in choosing investment levels to their monetary advantage under limited liability incentives compared to other incentive schemes. Removing accountability aspects from the financial agency setting does not result in a significant reduction of portfolio customization in our setting. We conjecture that agents feel a moral obligation to make prudent investments for their clients in decision-making for others setting, especially as behavior is still observable by the experimenter. Such obligation is traded off against own interests, which may become very salient and strong in the field, and especially as observability of a deviation from the clients' best interests may be less observable in the field.

Foerster et al. (2017) report that agent characteristics have a strong influence on portfolio allocations for clients. According to their analysis, agent characteristics appear to be even more powerful in shaping portfolios than clients' preferences. We find support for the fact that agents' own preferences matter for investment choices for clients, but in a controlled laboratory setting with a much more abstract setting, student participants, and excluding self-selection in the advisor-client match. In our setting, however, we find decisions for clients to be predominantly driven by client preferences and estimate agents' influences to be weaker.

One reason for this difference could be selection. Linnainmaa et al. (2021) show that financial advisors often invest for their own account similar to how they invest for their clients. Yet, they also highlight marked differences in investment behavior between different advisors. In addition, some financial institutions have been found to select their employees based on behavioral criteria associated with misconduct (Egan et al. 2019). In a recent experiment involving professional financial advisors and members of the general population, Rose (2021) finds that clients prefer to be matched with advisors with similar risk preferences rather than demographics. In addition, she reports that advisors' investments for their clients are affected by the risk bearing capacity of the client and the agent. In line with our results, the clients' preferences have the bigger impact. Thus, the apparent effects of agents' preferences may be overstated in previous studies based on archival data and the strong effects observed by Foerster et al. (2017) can be expected to be dampened in our laboratory setting, which does not allow for self-selection between agents and clients.

Closely connected to selection is the aspect of reputation. In the current study, we abstract from any kind of reputation building by agents by focusing on one-shot interactions without an opportunity for clients to choose their agents. It could be a worthwhile undertaking to study how reputation effects influence agents' investments for their clients. This might be especially fruitful if it is combined with an element of competition among agents to retain their clients over the course of multiple periods. For example, reputation has been shown to reduce the likelihood of misreporting by credit rating agencies (Rabanal and Rud, 2018) and reduce the prevalence of risk-shifting (Hernandez-Lagos et al. 2017).

Overall, we see the evidence from multiple studies on portfolio customization converge quite nicely. Studies based on real-world observational data as well as experimental studies in the field and in the laboratory identify fundamentally the same aspects to shape agents' decisions for their clients: Their own preferences, their clients' preferences, and the compensation schemes. Moral constraints appear to keep the different effects in balance. These results have practical implications for settings of financial agency: In spite of the common perception that financial agents act purely self-interestedly, we find agents to be in general willing to implement their clients' preferences. This still holds under compensation schemes which provide strong financial incentives for agents to take large risks. However, our findings also point to a fundamental problem in the communication of investment preferences. Misunderstandings between agents and clients are abundant and thus might strengthen the common perception that financial decisions taken by agents deviate from their clients' interests.

While it stands to argue that some of the miscommunication may be resolved by more extensive face-to-face communication between professional financial agents and their clients, the market for (semi-)automated financial decision making is growing. These technology-driven applications require effective, intuitive, and reliable elicitation of risk and investment preferences that does not rely on extensive back-and-forth communication. Our results suggest that the current standard of assessing clients' investment preferences through a relatively simple set of verbal investment profile descriptions may not be adequate in these contexts.

Declaration of Competing Interest

None.

[27] For example, we use "decision maker" and "recipient" instead of "agent" and "client".

[28] From the final payoff, the principal can always infer the chosen investment. For convenience, we provide both pieces of information.

Appendix A. Additional figures

Table A1
Number of observations.

	Client's preferences				
	very conservative	conservative income	balanced	growth	aggressive growth
Observations	24	80	120	116	38
Agents' preferences					
very conservative	0	9	28	26	4
conservative income	9	12	64	70	25
balanced	28	64	66	111	51
growth	26	70	111	52	31
aggressive growth	4	25	51	31	4

All treatments except "no accountability". Total $N = 378$. Top panel shows how many participants have requested each investment profile from their agents. Bottom panel shows how many investment decisions we observe for each requested profile, separated by the agents' own requested profiles. The observations do not sum up to 378 because in the *Multiple* treatment each agent made investment decisions for five clients. In total we observe 972 investment decisions.

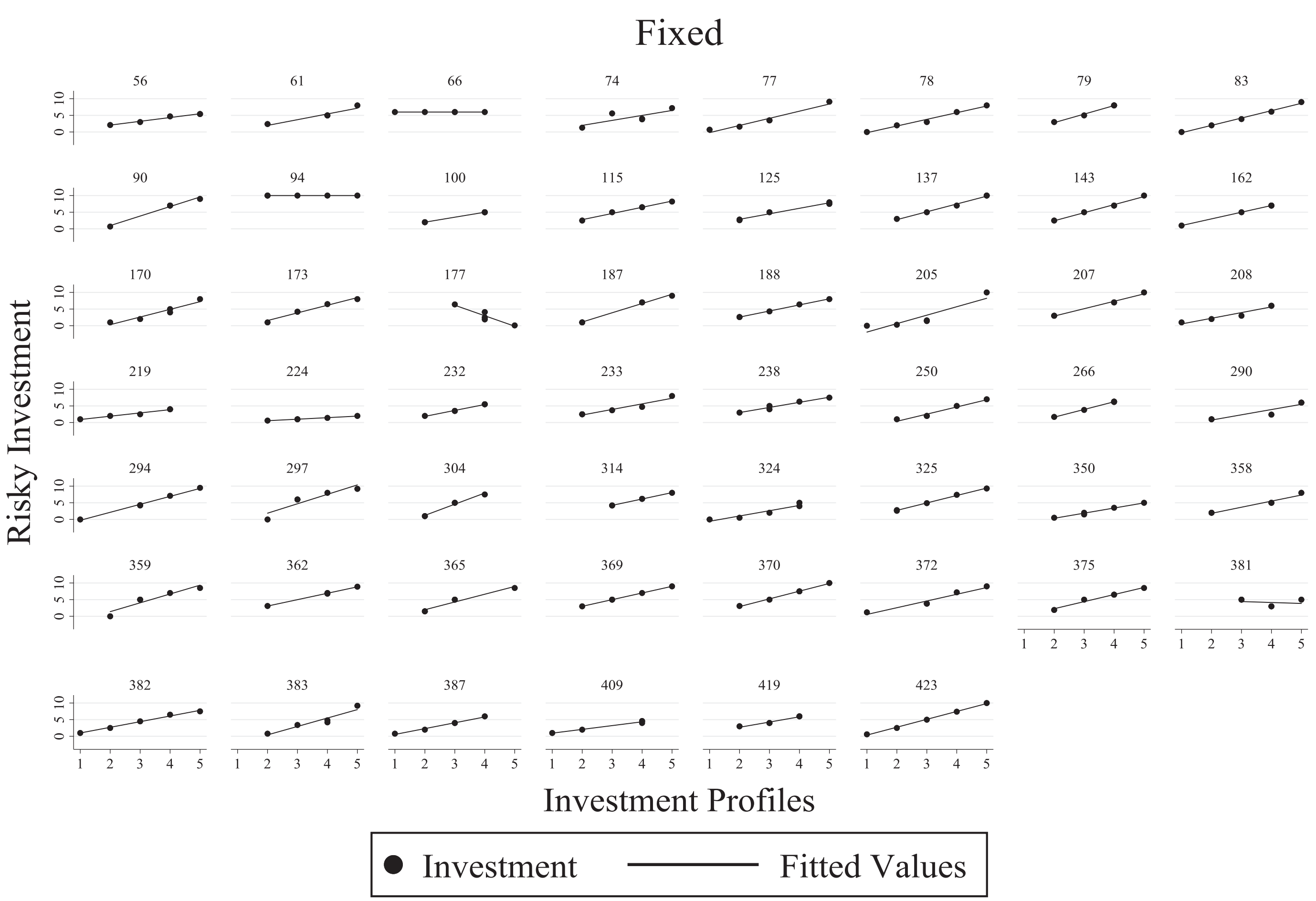

Fig. A1. Risky investment in Fixed treatment by agent. The graph shows for each participant in the *Fixed/Multiple* treatment the investment given the communicated profiles (1 = very conservative, 5 = aggressive growth) of their clients as well as the fitted values.

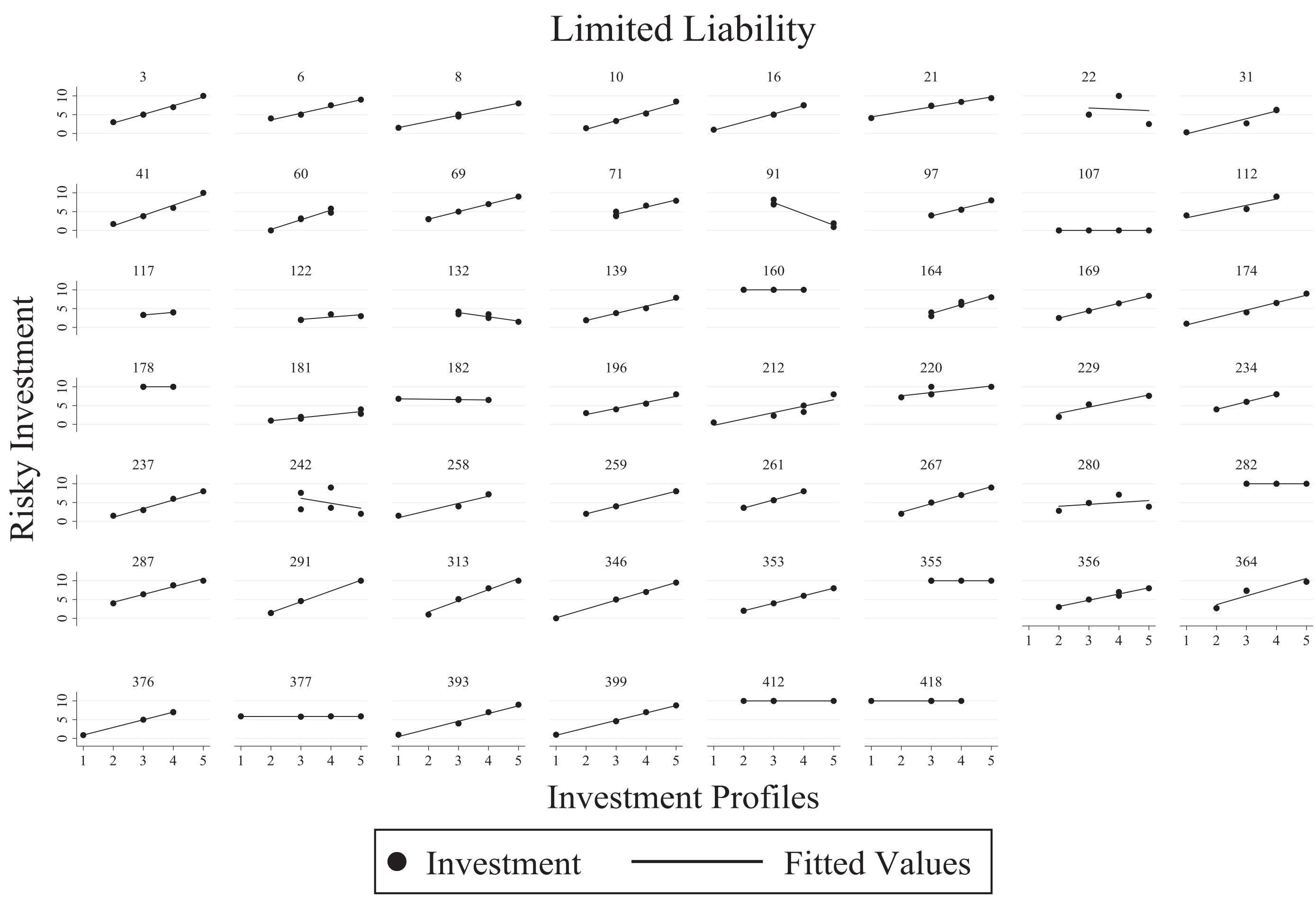

Fig. A2. Risky investment in the Limited Liability treatment by agent. The graph shows for each participant in the *Limited Liability/Multiple* treatment the investment given the communicated profiles (1 = very conservative, 5 = aggressive growth) of their clients as well as the fitted values.

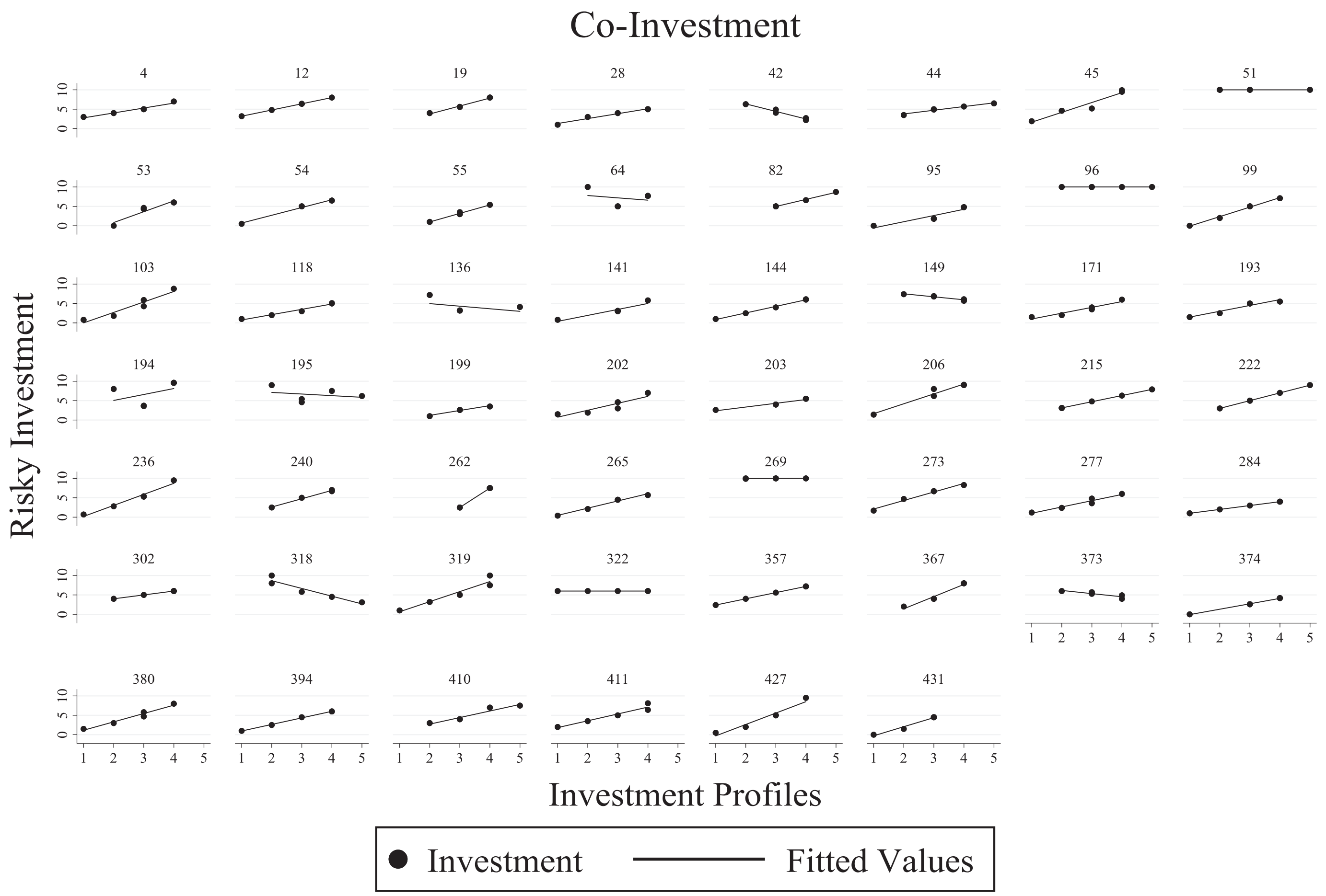

Fig. A3. Risky investment in the Co-Investment treatment by agent. The graph shows for each participant in the *Co-Investment/Multiple* treatment the investment given the communicated profiles (1 = very conservative, 5 = aggressive growth) of their clients as well as the fitted values.

Appendix B. Group matching procedure

Assume we have $m = 12$ participants to be distributed into $n = 2$ groups. Let *(id: profile)* describe a participant with identifier $id \in [1, \ldots, m]$ and investment preference $profile \in [a, b, c, d, e]$. Let earlier letters of the alphabet denote profiles that imply lower risk appetite than higher letters.

1. Make a list of participants and their profiles:

$$P = [(1: a), (2: b), (3: c), (4: d), (5: e), (6: a), (7: b), (8: c), (9: d), (10: e), (11: a), (12: b)]$$

2. Sort the list by profiles, from lowest risk appetite to highest:

$$P_s = [(1: a), (6: a), (11: a), (2: b), (7: b), (12: b), (3: c), (8: c), (4: d), (9: d), (5: e), (10: e)]$$

3. Form n groups. Let $k \in [1, \ldots, n]$ denote each group's identifier. Each group consists of every n-th participant in the list, starting from participant k. That is: Group $k = 1$ consists of every second participant in the sorted list, starting from the first participant. Group $k = 2$ consists of every second participant in the sorted list, starting from the second participant.

$$G_1 = [(1: a), (11: a), (7: b), (3: c), (4: d), (5: e)]$$

$$G_2 = [(6: a), (2: b), (12: b), (8: c), (9: d), (10: e)]$$

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