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MyPortfolio: The IKEA Effect in Financial Investment Decisions

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Abstract

Creating your own financial portfolio has never been easier than today. While recent literature shows that people overvalue self-built consumer goods ("IKEA effect") we ask the following question: How do investors value and trade a self-built versus a not self-built financial portfolio? Our pre-registered experimental design allows us to rule out any confounding customization, actual ownership, or learning effects. We find that self-building a portfolio significantly increases corresponding attachment. However, neither valuation of the portfolio nor trading decisions are affected. Thus, our precise estimates suggest that there is no economically relevant "IKEA effect" in financial investment decisions. These results indicate that common portfolio self-building opportunities per se do not directly distort financial markets.

Keywords: IKEA Effect, Self-Building Financial Portfolios, Self-directed Investing, Investment Decisions, Psychological Ownership, Belief Formation, Experimental Finance

JEL classification: C91, G11, G41, G50

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1 Introduction

Individual investors might either build a financial portfolio on their own or buy a portfolio that has been built by someone else, e.g., a mutual fund. Recently, self-directed investing has been gaining popularity due to digital innovations such as easily accessible online and mobile brokerages with low fees. For instance, the number of accounts at one of the largest discount brokerage firms, TD Ameritrade, has grown by 60% from 2007 to 2017, and it is estimated that a quarter of all U.S. adults with Internet access are self-directed investors (Forbes, 2018). Especially young first-time investors who prefer to invest on their own, e.g., through the online retail brokerage firm Robinhood, account for a large share of this increase (FINRA, 2019) and this trend has further accelerated since the Covid crisis (Welch, 2021). Moreover, due to the broad availability of exchange traded funds (ETFs), retail investors can build a diversified portfolio on their own more easily nowadays.[1]

However, for the most part, we do not know how this increase in self-directed investments will affect investors and financial markets. Franke et al. (2010) show that the mere awareness of being the creator of a product design leads to higher product valuations by customers. Norton et al. (2012) look at tangible consumer goods and show that individuals have much higher valuations for self-built products. They argue that this so-called IKEA effect[2] (i.e., valuing self-built products more than identical but not self-built products) solely stems from putting one's own labor into a product. Sarstedt et al. (2017) replicate this finding for wristbands and Dohle et al. (2014) as well as Troye and Supphellen (2012) for cooked meals. Crucially, Franke et al. (2010) and Norton et al. (2012) clearly show that the IKEA effect is independent of product customization which might lead to a better preference fit (Franke et al., 2009 and Vrecko and Langer, 2013). Moreover, Norton et al. (2012) show that neither pure effort justification (Festinger, 1957), nor actual (legal) ownership (related to the endowment effect of Thaler, 1980 and Kahneman et al., 1990) explain the IKEA effect. Further, the effect is different from learning about the assembling process (Walasek et al., 2017) and has been linked to the self-concept of people (Marsh et al., 2018) as well as feelings of competence (Mochon et al., 2012). The IKEA effect is also broadly related to the literature on customer participation in the production of goods (Bendapudi and Leone, 2003).

An important proposed driver of the IKEA effect is the subjective feeling of ownership ("psychological ownership").[3] Pierce et al. (2003, p. 93) argue that "the most obvious and perhaps the most powerful means by which an individual invests him/herself into an object is to create it". During the labor process, people project parts of their own personality into this

[1]As an illustration, we show a screenshot of the product homepage of one of the largest ETF providers (Morningstar, 2019), BlackRock, in Panel A of Figure 12 in Appendix A. Customers can use a portfolio builder tool to create their own "iShare" portfolio by specifying the weights of individual asset-class ETFs (Panel B). Alternatively, on the same page, they can buy a comparable pre-built portfolio (Panel C). Thus, investors are faced with the salient decision on whether to self-build their portfolio or not.

[2]This name refers to the Swedish furniture retailer that sells ready-to-assemble goods, usually without major customization options, that require substantial labor-input of the buyer.

[3]Psychological ownership ("attachment"), in contrast to actual (legal) ownership, has been proposed as an important determinant of the endowment effect (Reb and Connolly, 2007). Besides successfully creating an object yourself, other proposed factors that affect attachment are physical proximity (Bushong et al., 2010, Peck and Shu, 2009), time spent with the object (Strahilevitz and Loewenstein, 1998), and whether the object was awarded for your own good performance (Loewenstein and Issacharoff, 1994). For a more detailed overview, please see Ericson and Fuster (2014) and Pierce et al. (2003).

specific product. Since most people have positive associations about themselves ("self-positivity bias", e.g., Taylor and Brown, 1988 and Gawronski et al., 2007), this projection might lead to higher valuations of self-built goods. Hence, labor input can result in psychological ownership, an idea that goes back at least to the work of Locke (1690). Investing the self in an object by creating it might be limited to tangible goods like furniture that require physical work input and that can be touched (Peck and Shu, 2009). However, Franke et al. (2010) obtain similar IKEA effect results as Norton et al. (2012) for intangible T-shirt designs created by using web-based toolkits. Thus, one might expect that the IKEA effect also exists for other intangible goods such as financial portfolios.

The goal of this paper is to examine this specific aspect of self-directed investing, i.e., to understand how the process of self-building a portfolio affects the creator's subsequent valuation and trading. Due to the increasing number of self-directed investors, it is important for all market participants as well as for financial regulators to understand how large these effects might be. In contrast to most decisions about consumer goods, investment decisions are more fundamental and can have major implications for the efficiency of financial markets as well as for the financial well-being of an individual investor, e.g., when thinking about pension savings. On the one hand, the IKEA effect might add to and possibly amplify other biases of retail investors (e.g., due to increased overconfidence Odean, 1998b). On the other hand, if investors are less likely to subsequently sell their self-built portfolios, the IKEA effect might also counterbalance other biases, e.g., harmful excessive trading after the initial buy decision (Odean, 1999) or sentiment-driven selling of owned assets (Da et al., 2015).

According to the IKEA effect, self-building leads to a higher valuation of the resulting financial portfolio. Hence, market participants would systematically have different valuations of the same underlying assets which could lead to temporary mispricing in the presence of limits to arbitrage (Miller, 1977 and Shleifer and Vishny, 1997). Given the remarkable effect size that has been documented for consumer goods (e.g., a 64% valuation increase for simple boxes in Norton et al., 2012), there could be a potentially large impact for financial markets that requires further investigation.

Moreover, the IKEA effect is highly relevant for providers of financial portfolios, e.g., fund companies and retail brokerage firms, that have to decide whether to offer investors self-building tools or completed portfolios. For instance, these providers might think about offering additional guidance to their self-directed clients if self-building leads to subsequent biased decisions. Additionally, the effect can have direct implications for the pricing policies of these companies, e.g., investors might be willing to accept higher fees in order to keep their portfolio with a broker once they have self-built it. Finally, it is also essential for institutional investors, e.g., professional asset managers, who need to evaluate stock market consequences of an increasing share of self-directed retail investor participants.

Our study differs from the existing literature in two major aspects: First, we examine to what extent self-building affects the valuation of financial portfolios in order to quantify its economic importance for financial markets. Hence, we move beyond consumer goods and examine the IKEA effect in the context of financial investment products, i.e., utilitarian goods with an instrumental monetary value. Since self-building is a driver of psychological ownership, not only do we contribute to a better understanding of the drivers and implications of the IKEA effect but also to the broader literature on the endowment effect. Second, the value of a risky financial portfolio depends on investors' expectations about future payoffs and risk. This feature allows us to be the first to examine how exactly self-building impacts belief formation as well as future trading decisions in the context of risky lotteries, which is not possible for pure consumer goods. In doing so, we also contribute to the broad literature that examines psychological factors which determine how investors form beliefs about risk and return as well as their trading decisions (for an overview, see Barberis and Thaler, 2003, and Hirshleifer, 2015).

In order to examine our research questions, i.e., how the process of self-building affects i) valuation and ii) trading behavior, we design a pre-registered online experiment.[4] More precisely, we compare the valuation and trading decisions of an investor who self-built a portfolio and another investor who did not self-build this portfolio. We use an experimental method in order to take careful precautions to separate the IKEA effect from possible confounds, which is hardly possible in an observational study.

First, investors might have higher valuations for self-built portfolios because of the potentially better preference fit due to customization (Vrecko and Langer, 2013). However, literature on the IKEA effect clearly shows that the process of self-building itself changes behavior beyond the effects of customization (Franke et al., 2009 and Norton et al., 2012). Since in this paper we want to precisely focus on the IKEA effect, it is essential to avoid the confounding effect of customization. Importantly, this feature distinguishes our study from the existing literature on the trading behavior of self-directed individual investors (e.g., Barber and Odean, 2000, for an overview see Barber and Odean, 2013).[5] Hence, we provide participants with instructions on how to build a predefined ("standardized") target portfolio so that there is no customization. This is comparable to the approach used by Franke et al. (2010) who provide a target design for a T-shirt that participants have to recreate exactly.

Second, participants spend a considerable amount of time self-building the portfolio. During this process they might gain a better understanding of the assets used as well as the properties of the portfolio. In addition, they might value all portfolios higher afterwards because they recognize that building a portfolio is actually harder than originally expected or because of mood effects (Schwarz and Clore, 1983). Our design addresses this concern by having *every* participant self-build a portfolio. We ensure that participants obtain the same information and spend the same amount of time for building a portfolio. In order to identify the treatment effect, we use two different target portfolios. We randomize which portfolio has to be self-built by a participant to account for portfolio-specific effects. Crucially, after building their portfolio, participants have to do a valuation and trading task for their self-built portfolio as well as for the other target portfolio. Thus, we have a within-subject comparison between the self-built portfolio as well as the other target portfolio to identify the IKEA-effect. Both target portfolios consist of the same assets and only vary with respect to the weights of the individual

[4] See `https://aspredicted.org/blind.php?x=33mq5y` for the pre-registration. Ethics approval (#444SUfaz) was obtained by the German Association for Experimental Economic Research (GfeW).

[5] For instance, Merkle and Ungeheuer (2021) show that investors who self-select their securities underestimate the relationship between their portfolio and the stock market (systematic risk) more strongly. In particular, our approach is different to a recent experimental study by Ashtiani et al. (2021) who find that involving investors in the selection process of portfolios reduces panic selling behavior.

assets so that the two target portfolios have different risk and return characteristics. Moreover, we provide participants with the same information regarding the self-built and not self-built portfolio. Hence, all participants obtain the same information set.

Third, we endow participants with the self-built as well as the not self-built portfolio to disentangle the treatment effect from any actual (legal) ownership effects.

Participants have to self-build a financial portfolio by selecting and choosing the weights of multiple assets so that the resulting portfolio matches the risk and return characteristics of the provided target portfolio. Before we analyze the main results, we examine how participants perceived this self-building process in order to validate our treatment. Based on prior work, process effort, enjoyment (Franke and Schreier, 2010), pride (Mochon et al., 2012) and feelings of accomplishment (Franke et al., 2010) are important value drivers of self-built products. On average, participants in our experiment evaluate the task as rather complex but enjoyable. They claim that they had to put rather much effort into the construction of the portfolio and agreed to feel proud about having accomplished building their portfolio. Hence, our treatment has the same desirable combination of properties as suggested in the previous literature.

As our first main result, we document that participants are significantly more attached towards their self-built portfolio as opposed to the not self-built portfolio. Surprisingly, however, we find no significant difference in valuations for self-built versus not self-built portfolios, both considering the mean and the whole distribution of valuations. Importantly, the estimate for the difference is very close to zero (0.14%) and the effect size is economically negligible (Cohen's d = 0.0). This finding is robust to a variety of specifications (for instance, adding various control variables and participant-specific random effects, excluding extreme valuations, or dropping participants who take an extremely short or long time to complete the tasks). Consistently, we also find no significant differences in participants' beliefs about the portfolios' risk and return characteristics. We further document that there are no systematic differences in the ways how portfolio-specific information is processed by analyzing mouse tracking data. In addition, we do not find heterogeneous treatment effects with respect to various dimensions, e.g., demographics or post-experimental measures.

We go on to analyze how the self-building process influences subsequent beliefs and trading decisions when new signals arrive. In financial markets, investors are regularly exposed to new information and signals about their investments. Does self-building affect how participants react to *new* price signals which put them in the capital gain or loss domain? Not only could such an effect have wealth implications for self-building investors, but the resulting differences in opinion about signals could also contribute to market volatility and the excessive trading volume that is empirically observed in asset markets (e.g., Hong and Stein, 2007 and Carlé et al., 2019).

One of the most robust empirical findings about individual trading behavior is the disposition effect which refers to the tendency to sell positions that have increased in value too early and keep positions that have decreased in value for too long (Shefrin and Statman, 1985). Recently, Chang et al. (2016) argue that investors might avoid realizing losses because they dislike admitting their own mistakes. Indeed, they find that increasing investors' cognitive dissonance results in a larger disposition effect. Moreover, Andersen et al. (2020) show that higher optimism of investors leads to a stronger disposition effect. Following this argumentation, we expect that the disposition effect is stronger for a self-built portfolio because investors have a stronger association between this portfolio and themselves. Since trading according to the disposition effect is empirically associated with worse performance (Odean, 1998a), it is important to explicitly examine this potential consequence which might be wealth-destroying for investors. However, we do not find a significant difference in the probability to sell a self-built versus a not self-built portfolio at *any* given paper gain or loss, i.e., there is also no effect on the disposition effect.

Nevertheless, self-building might still affect investors' beliefs after receiving new signals. Hartzmark et al. (2021) show that ownership of a good causes overreaction, i.e., too optimistic (pessimistic) beliefs after receiving new positive (negative) signals, potentially because ownership channels higher attention towards related information. Motivated by this finding, we test whether this reasoning also applies to self-building. Alternatively, self-building might also lead to overoptimistic beliefs after positive as well as negative signals, e.g., due to a self-positivity bias. However, we find that participants do not have systematically different beliefs for their self-built versus not self-built portfolio after evaluating new signals. Finally, we document that the null effect in beliefs and trading decisions is not heterogeneous across several demographic dimensions. Overall, these findings are in line with the results from the valuation task.

How reliable are our documented null effects? Most importantly, the high precision of our estimates suggests that any potential effect size that we are unable to detect would be economically irrelevant. The upper limit of the 95% confidence interval yields a 0.54% higher valuation of self-built portfolios which still corresponds to an economically negligible effect size. Hence, the documented null effects are not caused by a lack of statistical power, mitigating the concern of false misses (Harvey and Liu, 2020). Finally, by applying a method suggested by Harvey (2017), we can further reject (p-value ≤ 0.001) an economically meaningful but still small effect even if we assume a very strong prior in favor of finding a meaningful effect. Furthermore, we document that participants in our experiment are comparable to real US investors with respect to financial literacy and educational background, and that the null effects also hold for participants who actually self-invest in financial markets. For these reasons, we feel confident that our findings are representative for self-directed investors in real life.

Finally, we discuss potential reasons for why no economically meaningful IKEA effect for financial portfolios seems to exist, although its existence has been documented for various other goods. For this purpose, we identify specific characteristics of a financial portfolio as an intangible instrumental good and relate them to potential channels of the IKEA effect. Hence, our results also contribute to a better understanding of the drivers of the IKEA effect by showing its absence for an important type of economic good.

Overall, we conclude that self-building does not directly bias beliefs about expected return and risk. Moreover, there is also no standalone value-increasing component that stems from psychological ownership only. As a result, we find that the process of self-building a portfolio by itself does not affect the valuations or trading decisions of its creator. This finding suggests that previous results for physical and intangible consumer goods cannot directly be transferred to risky financial assets which are intangible instrumental goods.

All in all, our results indicate that the self-building process of common self-directed investment opportunities per se does not directly affect individual investors' behavior. Self-building seems to increase investors' subjective attachment to the portfolio without biasing valuations and trading decisions. Hence, they might be a suitable tool to let investors customize, stimulate learning effects, and increase the low stock market participation rate of individual investors (Mankiw and Zeldes, 1991) without directly affecting financial markets in a negative way, e.g., by inducing temporary mispricing. Nevertheless, the possibility to self-build might still impact financial markets at the extensive margin, for instance, by attracting a new group of financial investors who differ from current investors with respect to certain relevant characteristics (e.g., risk-taking, cognitive abilities, or how prone they are to behavioral biases).

Moreover, there might be other important problems that arise from self-directed investing besides the self-building process ("IKEA effect") itself, e.g., differences in (trading) costs or re-balancing and market timing decisions. Further, most self-building opportunities are accompanied by an increased degree of customization. In this case, self-directed investors might be influenced by other behavioral biases (e.g., sentiment, see Baker and Wurgler, 2006, choosing attention-grabbing assets, see Barber and Odean, 2008, neglecting correlations, see Kroll et al., 1988 or overconfidence about own stock pickings, see Odean, 1998b and Statman et al., 2006) that lead to non-optimal outcomes. While examining these questions is fruitful for future research that assesses the overall impact of self-directed investing, this paper shows that these potential effects do not seem to come from the self-building process itself, i.e., a psychological IKEA effect.

2 Experimental Design

2.1 General Setup and Treatment

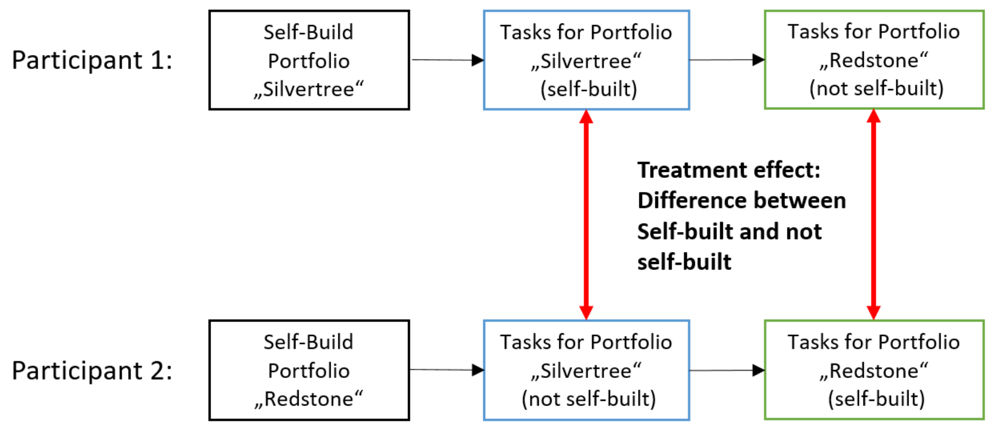
At the beginning of the online experiment, participants self-build a financial portfolio. To rule out the confounding effect of customization, participants have to build a pre-specified target portfolio. More precisely, they have to combine different assets so that the resulting portfolio exactly matches the return and risk characteristics of the target portfolio. Since there is a unique solution, there is no customization by design. This setting is similar to the one used by Franke et al. (2010) who provide a target design for a T-shirt that participants have to reproduce. Obviously, self-building often goes along with the opportunity to customize. However, Norton et al. (2012) and Franke et al. (2010) clearly show that a pure IKEA effect (i.e., an effect of self-building) exists in a setting without any customization opportunity. This finding is also consistent with the idea that people "see their reflection [...] and feel their own effort" (Pierce et al., 2003) in self-built goods, which leads to psychological ownership. Therefore, we have no reason to believe that the IKEA effect only exists conditional on customization. Moreover, participants in our experiment indicate that they have a high feeling of accomplishment after building their portfolio. Hence, they do not seem to perceive customization as a dominant part of the self-building process. In fact, by ruling out customization we can clearly examine how the self-building process, i.e., putting in own labor, affects valuations and trading decisions itself.

Moreover, building a portfolio might be associated with general learning effects (e.g., about correlations, see Laudenbach et al., 2021) or changes in beliefs about financial portfolios in general. In addition, participants spend substantial time and energy for the self-building process.

Finally, a mere exposure effect (Zajonc, 1968) as well as general mood effects (Schwarz and Clore, 1983) might exist after the successful completion of the portfolio. To rule out all these confounding factors, we let *every* participant self-build a portfolio.

In order to identify the treatment effect, we use two different target portfolios named "SilverTree" and "RedStone". In order to help participants recognize the two different portfolios, we use these generic but realistic names and also use corresponding graphical logos when referring to the portfolios (see Appendix E). We randomize which of the two portfolios a participant has to self-build. Crucially, participants have to do tasks for their self-built portfolio (for example SilverTree) as well as the other portfolio (in this example, RedStone). Thus, participants make all relevant decisions for both portfolios, while only one of them has been self-built before. Hence, each individual both serves as treatment and control, depending on the portfolio considered. Since participants do tasks for both portfolios but have only self-built one of them, any systematic difference in the observed outcomes for the same portfolio can be attributed to the self-building process itself (treatment effect). We carefully ensure that all participants have the same objective information set about the characteristics of the two target portfolios (for additional details, please refer to the following subchapters). Based on an example of two participants, We illustrate the identification of the treatment effect in Figure 1.

Figure 1: Design - Identification of the Treatment Effect



In this figure, we provide an exemplary illustration of the identification of the treatment effect based on two participants. For an illustration of the experimental design with all randomizations, please see Figure 7.

Participants do two tasks for each of the two target portfolios, namely a valuation and a trading task. The valuation task is designed to test the baseline IKEA effect, i.e., whether participants have a higher valuation for their self-built portfolio. The trading task is designed to examine whether participants' trading and forecasting behavior after receiving new signals is different for self-built and not self-built portfolios.

In the following subchapters, we describe the target portfolios, the portfolio-building process as well as the tasks (valuation and trading) in more detail.

2.2 Self-Building a Portfolio

2.2.1 Target Portfolios

Both target portfolios consist of the same five asset classes and there are three assets within each asset class (for details, see Appendix E) that are also the same for each target portfolio. To increase external validity, we use real-life return data obtained from Bloomberg for these two portfolios. More precisely, we use monthly returns from 2002 to 2019 which yields a total of 216 return realizations each.

The only difference between portfolio SilverTree and RedStone is the weighting of the asset classes so that the overall portfolio characteristics differ. We specify the weights of the different asset classes in such a way that portfolio RedStone has a higher mean return but is also more risky than portfolio SilverTree. More precisely, portfolio RedStone has a monthly mean return of 0.86% and the volatility (standard deviation) is 4.08%. Portfolio SilverTree has a monthly mean return of 0.66% and the volatility is 2.45%.

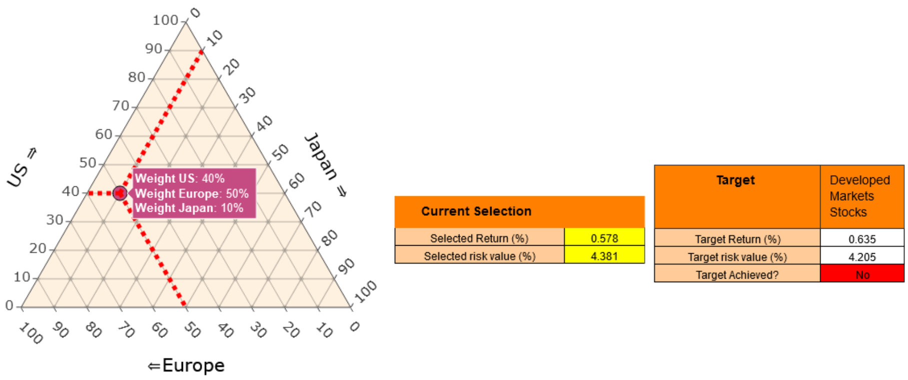
We saliently provide information (the composition of the portfolio as well as return and risk) about the self-built and not self-built portfolio directly before participants begin with the tasks for the respective portfolio (details provided in Appendix E). Hence, there is no difference in the *portfolio-specific* information set between participants who self-built a portfolio and those who did not. Note that we purposefully focus participants on the two most relevant aspects of a portfolio – the return and the risk as is standard in most finance experiments. However, we obviously lose some external validity by abstracting from other potentially relevant dimensions like additional firm-specific aspects (e.g., ESG-measures), investor-related aspects (e.g., the possibility to share investment results) or the purpose of the investment. We abstract from these other factors to cleanly identify our results as otherwise, we would not know whether and how these other dimensions interact with the decision-making process of participants. Otherwise, in case of a null effect, we would not be able to identify whether this finding is driven by these additional dimensions. Thus, we focus participants on the return and the risk. However, we still preserve external validity as the portfolios we present to participants are composed of real assets and the underlying return distributions are from historical real world data. Moreover, participants are provided with comprehensive definitions and explanations about the asset classes during the self-building process (see E.6). Another reason for mainly focusing on return and risk is that the task is already rather complicated and entails a lot of information. Amongst our participants, the median answer to the question on how complex participants considered the task to be was “rather complex” (4 within a range from 1-5) and the median answer to the question of how much effort participants had to put into the construction of the portfolio is “rather much” (4 within a range from 1-5). Thus, to shield participants from cognitive overload (see, for instance, Agnew and Szykman, 2005), which might, for instance, lead to frustration, we abstain from presenting further dimensions.

2.2.2 The Portfolio-building Process

Before participants start building their portfolio, we provide them with a short introduction on the underlying financial concepts (details provided in Appendix E). Afterwards, participants determine the weights of the assets within each of the five asset classes. Finally, they have to choose the weights of the asset classes in their portfolio in order to exactly match the provided return and risk characteristics of the target portfolio.

Within asset class allocation task: By choosing the weights of the three assets, participants change the mean return and risk value of the current sub-portfolio. Participants are provided with a mean return and risk target for each individual sub-portfolio as well as for the overall portfolio (in the last step). Moreover, we tell participants the correct weight of one of the assets, prohibit any short positions and only allow for discrete weights (with incremental change $\Delta = 10\%$). Furthermore, we provide a hint to participants (i.e., we tell them the correct weight of the second asset) if they are not able to find the correct solution after 20 clicks. This procedure ensures that also financially unsophisticated participants can solve the task. Nevertheless, some statistical knowledge helps to solve the task faster, which ensures that the labor-input is perceived as meaningful. Further, we choose the target portfolio characteristics in such a way that there is a unique solution. Because of these restrictions, participants can easily adjust the weights of the three assets by using a mouse-controlled "triangular slider". Figure 2 illustrates this within asset class allocation task. Overall, this type of task is comparable to the real-life example of a portfolio building tool shown in Figure 12 in Appendix A.

Figure 2: Within Asset Class Allocation Task – Example Screenshot



In this figure, we depict a screenshot of the within asset class allocation task (in this example, for asset class "developed markets stocks"). On the left-hand side of the screen, participants can adjust the weights of the three assets within this asset class by using a mouse-controlled "triangular slider". On the right-hand side, participants can see the resulting portfolio characteristics of their current selection as well as the characteristics of the target portfolio. In this screenshot, the participant has not yet achieved the final composition of the asset class.

Between asset class allocation task: After completing the within-asset class allocations, participants have to choose the weights of the asset classes in their final portfolio. We illustrate this task in Figure 3. Since there are five asset classes in total, determining all weights simultaneously is almost infeasible. For this reason, we do this task sequentially. Participants begin to determine the weights of the first two asset classes to achieve a return and risk sub-target. Afterwards, their weights are fixed and participants add the next asset class to the current portfolio. This process is repeated until the final portfolio is achieved. Participants can only complete the task if they manage to exactly construct the target portfolio. Not only does this feature ensure that there is no customization, but also that participants complete the task successfully which is, according to the findings of Norton et al. (2012), a necessary condition for the existence of the IKEA effect. Afterwards, participants continue with the valuation and trading tasks for both their self-built and the other portfolio.

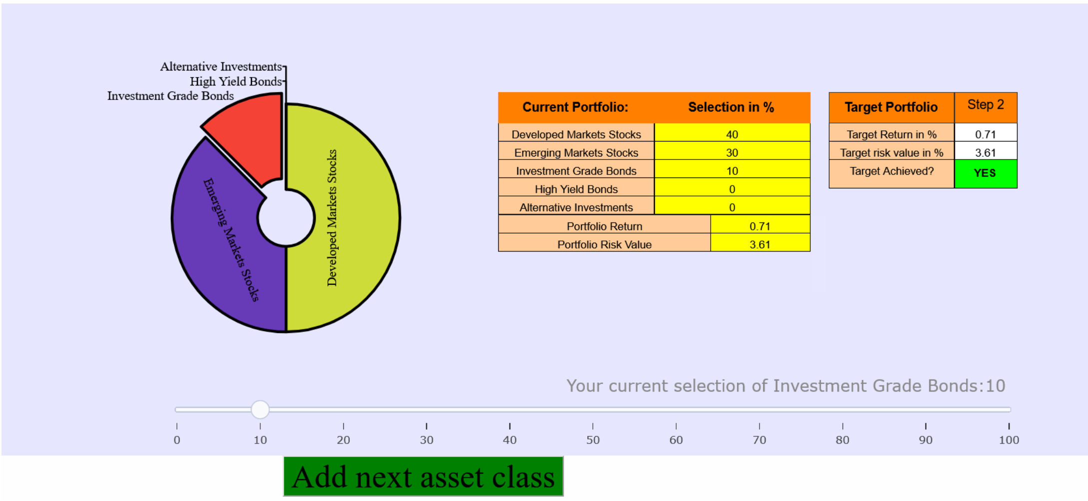
One concern the critical reader may have is that our two portfolios might be rather similar in terms of returns and volatility. However, this similarity of the parameters is basically a function of a clean design. To ensure that there are no confounding learning or familiarity effects (related to a mere exposure effect, see Zajonc, 1968) we have to keep the assets as well as their weights within each of the five asset classes constant. Importantly, we have to rule out that participants are more informed about their self-built portfolio than about the other, not self-built portfolio. Hence, it is crucial that participants fully understand the differences and similarities between the two portfolios when we introduce the not self-built portfolio to them. For this reason, when introducing the not self-built portfolio, we tell participants that the assets and weights of the assets within an asset class are exactly the same as in their self-built portfolio and that only the final weights between asset classes are different. If we change the weights of the assets within an asset class that would make communicating these differences to participants much more difficult. As a consequence, we could not clearly identify a potential IKEA effect since there is a confounding factor of differences in understandability/information sets between the self-built and not self-built portfolio. Thus, all we can vary, without posing a threat to the identification, is the weight of the five asset classes in the portfolio (i.e., the between asset class allocation task).

We further had to ensure that each asset class is present in both portfolios for two reasons: First, this is essential as otherwise participants might again learn different aspects about the portfolio as some asset classes would be irrelevant. Second, participants spend a considerable amount of time and effort in finding the correct weights of the assets within an asset class. Hence, they might be frustrated if the weight of that asset class in the final portfolio is too low or even non-existing. That, in turn, might reduce the size of the IKEA effect because participants perceive their work input as not meaningful. For these reasons, we had to fix each asset class at least at 10% (as we had a grid with steps of 10% to make the task not excessively demanding but still challenging).

Thus, based on our historical real-life return data, the minimum-return-portfolio in our setting would have a return of 0.614% (i.e., a portfolio having most mass at investment grade bonds) and the maximum-return-portfolio would have a return of 1.075% (i.e., a portfolio having most mass at emerging market stocks). Therefore, the overall maximum variation in returns between two portfolios we could achieve is 0.461. Hence, even in the most extreme cases the returns are rather close. Also note that the five asset classes that we use are already relatively diverse and should cover a broad range of risk categories that would also be readily available for a self-directed retail investor in real-life.

Moreover, we already leverage a large portion of the possible variation in returns in our setting. Portfolio SilverTree, which has a monthly mean return of 0.66%, is very close to the minimum return portfolio and portfolio RedStone, which has a monthly mean return of 0.86%, is rather close to the maximum return portfolio. The main reason for not using the two extremes is to avoid the impression on the participants' side that the portfolios in our experiment are dominated by one asset class (which would be the case for the two extremes as both put 60% of the weight on just on asset class). Since we explicitly inform participants about the benefits of broad diversification, this choice ensures that participants view the portfolios as meaningful. Last, since the self-building task is about precisely determining the weights of each class and combining different assets, participants might perceive their labor input as pointless if certain assets have an insignificant weight.

Figure 3: Between Asset Classes Allocation Task – Example Screenshot



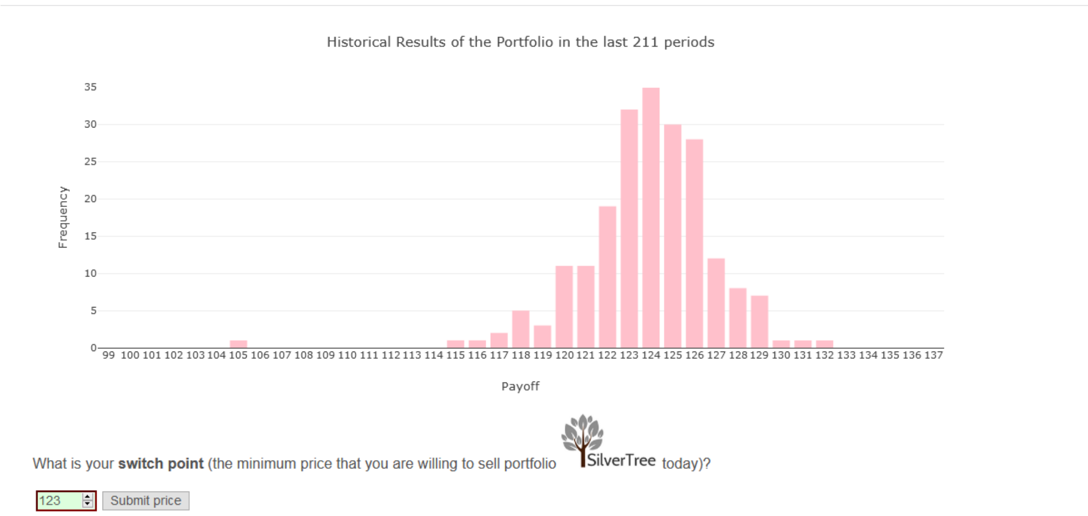
In this figure, we depict a screenshot of the between asset class allocation task. Participants sequentially fix the weights of the five asset classes in their portfolio. At the bottom of the screen, participants can use a slider to determine the weight of the current asset class that has to be added to the existing portfolio. On the right-hand side of the screen, participants can see the current sub-target characteristics they have to achieve. After participants fix the weight of the currently to-be-added asset class correctly, they move on by adding the next class and are provided with a new sub-target. This procedure is repeated until participants have combined all asset classes correctly and achieved their final portfolio. In this screenshot, the participant has already fixed the weights of asset classes "developed markets stocks" and "emerging markets stocks". Further, the participant has correctly selected the weight of the currently to-be-added asset class "investment grade bonds". The next step is to fix the weight of asset class "high yield bonds" in order to move on to add the final asset class "alternative investments".

2.3 Valuation Task

The valuation task is designed to examine whether participants have a higher valuation for self-built portfolios compared to not self-built portfolios. In order to ensure that participants provide their true valuation, we use, similar to Norton et al. (2012) and Franke et al. (2010), the incentive-compatible Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964). For this purpose, participants are initially endowed with the portfolio ($t = 0$) and have to decide at which price they would be willing to sell the portfolio right away. If they keep the portfolio, their personal payoff from the valuation task is solely determined by the currently unknown payoff of the portfolio in one month ($t = 1$). Otherwise, the personal payoff will depend on the current selling price in $t = 0$. We tell participants that there is no additional period to be played after $t = 1$. Since the value of a financial portfolio depends on all expected future discounted cash-flows and is reflected in the selling price, the portfolio's one-time "payoff" in $t = 1$ in our setting can be simply interpreted as the selling price of the portfolio in one month.

In order to value the portfolio, participants are provided with a histogram that shows the potential future payoffs of the portfolio in $t = 1$. We simulate the potential future payoffs of the portfolio in $t = 1$ by applying the actual historical returns of each portfolio to a nominal portfolio value in $t = 0$. We use a nominal portfolio value of 123 instead of a round-number value to avoid any strong anchoring effects. To help participants understand the underlying distribution, we show them the frequency histogram of the realizations of the portfolio payoffs. The histograms of portfolio RedStone and portfolio SilverTree are depicted in Figure 4 and Figure 5. Participants can get further information on how many times a payoff is realized by hovering over the respective histogram bar with their mouse cursor. We track those movements to obtain a measure of information processing.

Figure 4: Valuation Task - SilverTree

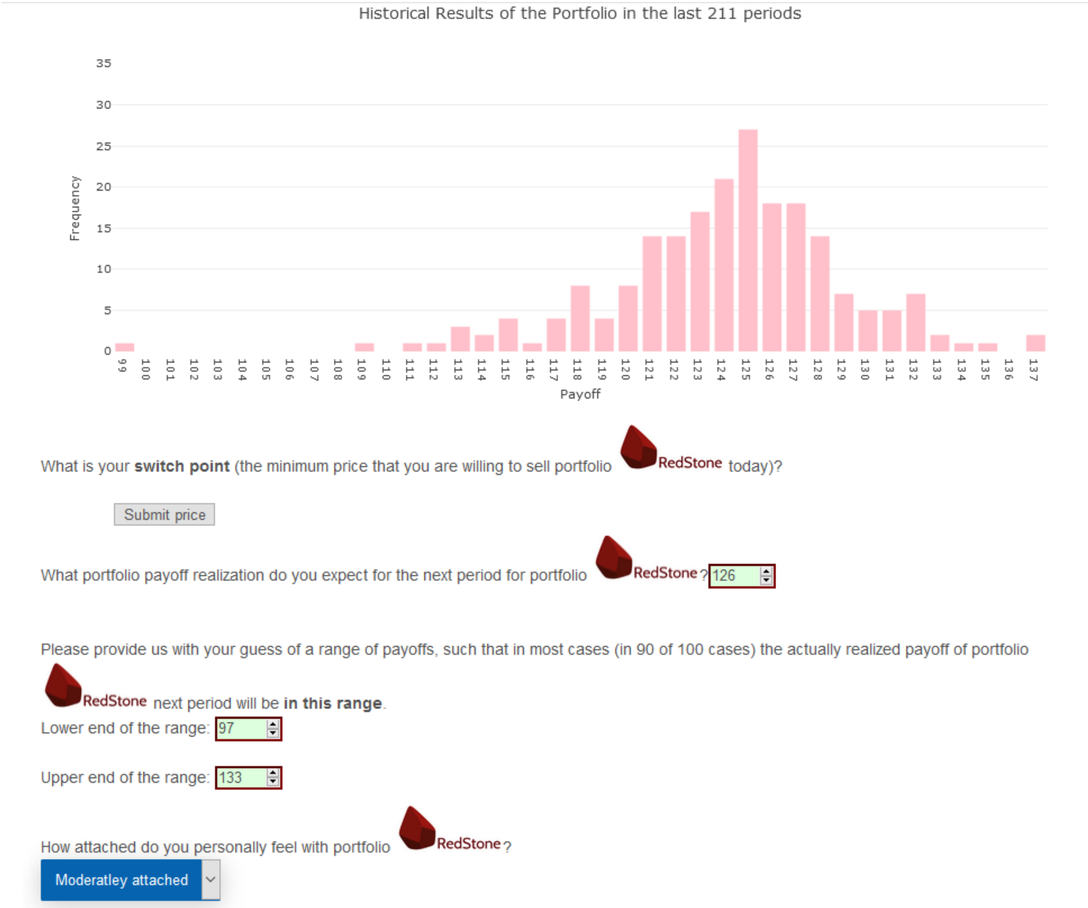


In this figure, we depict a screenshot of the valuation task (in this example, for portfolio SilverTree). In this screenshot, the participant has not yet submitted their valuation.

Participants then decide whether to keep the portfolio and get exposure to the uncertain portfolio realization in one month ($t = 1$) or to sell the portfolio and get the *selling price* without any additional potential payoff in $t = 1$. We tell participants the distribution of the potential selling price so that they can formulate their *minimum selling price*. We randomly draw the selling price in $t = 0$ from a uniform distribution, with support between 90 and 150.[6] If the *randomly drawn selling price* is above the participant's *minimum selling price*, the participant has to sell the portfolio and gets the drawn selling price. If the *randomly drawn selling price* is below the participant's *minimum selling price*, they have to keep the portfolio and their payoff solely depends on the realization of the portfolio's payoff in $t = 1$. The price at which a participant is indifferent between the two options determines their subjective value of

[6] This range covers all potential payoff outcomes of the two portfolios and hence provides a reasonable range for any price that a real buyer would be willing to pay for the portfolios. Note that any potential anchoring effects that might be associated with providing a price range (see, for instance, Wertenbroch and Skiera, 2002 and Bohm et al., 1997) will be the same for treatment and control groups.

Figure 5: Valuation Task - RedStone



In this figure, we depict a screenshot of the valuation task (in this example for portfolio RedStone). In this screenshot, the participant has already submitted their valuation and needs to provide their belief upon the realization of the portfolio in the next period, as well as their attachment towards the portfolio.

keeping the portfolio.

After eliciting the valuations for the portfolios, we collect beliefs about the portfolios to learn more about the potential drivers of the IKEA effect in the context of risky financial portfolios. More precisely, participants might overestimate the expected payoff or underestimate the risk of the self-built portfolio. For this reason, we ask participants to provide an estimate for the expected portfolio payoff in one month as well as a 90% confidence interval around this estimate. Participants subsequently do this after submitting the valuation so that there are no framing or other spillover effects. We then compare these measures between participants who self-built the portfolio and those who did not. A difference in the expected outcome would be in favor of a cash-flow channel (i.e., optimism/better-than-average effect, see for instance Svenson, 1981 and Taylor and Brown, 1988). Differences in the width of the confidence interval between treatment and control group would support an overconfidence/underestimation of risk channel (i.e., miscalibration, see, for instance, Moore and Healy, 2008). If there are no effects on beliefs, this would rather suggest that there is a standalone effect of self-building related to psychological ownership driving potential differences in valuations. We illustrate the valuation task before participants are being asked about their beliefs in Figure 4. Figure 5 illustrates the valuation task after participants have submitted the minimum selling price and been asked about their beliefs.

2.4 Trading Task

In the trading task, we examine how self-building a portfolio affects the way new signals are processed as well as future trading decisions. Participants are told they hold the portfolio at $t = 0$ at a given initial valuation. Afterwards, participants receive a new signal about the value of their position ($t = 1$). They can decide to either sell the portfolio at this price (i.e., realizing the potential paper gain/loss) or keep the portfolio for another period. Participants are told that there is no additional period to be played after $t = 2$.

We show participants four different scenarios about the new signals in $t = 1$: Large negative, small negative, small positive, and large positive return.[7] If participants do not sell the portfolio in $t = 1$, we determine the value of the position at the next period ($t = 2$) from the actual return realization. Specifically, since the four signals in $t = 1$ correspond to real-life points in time, we can simply use the actual return realization of the following month ($t = 2$). We make participants aware of this procedure to increase the importance of the task.

We assume that participants use the provided initial value of the position in $t = 0$ as a reference point. In order to encourage this behavior, we explicitly tell participants the gain or loss compared to the initial value that they are currently holding the portfolio for. Since they do not have any other reasonable reference points and their personal payoff solely depends on the displayed gains/losses, we believe that participants have a strong reason to use these gains/losses for their mental gains/losses.

We design this task with the purpose of abstracting from confounding factors in order to focus on our essential research question regarding trading decisions: do people sell a portfolio depending on the prior realization of the portfolio? There are, however, various alternative designs we could have used, e.g., using multiple periods, having a basket of assets (see, for instance, Weber and Camerer, 1998, Chang et al., 2016, or Fischbacher et al., 2017) or allowing participants to sell individual parts of their portfolio (i.e., changing or "breaking up" the built portfolio). While these rich designs would give more external validity, they would come at the risk of losing internal validity, i.e., they would be prone to multiple alternative explanations and confounds. Hence, in case of a null effect we would not be able to identify whether this result is driven by these additional dimensions. We therefore decided to use a simple, concise, and clean design in order to clearly identify a potential IKEA effect in trading behavior.

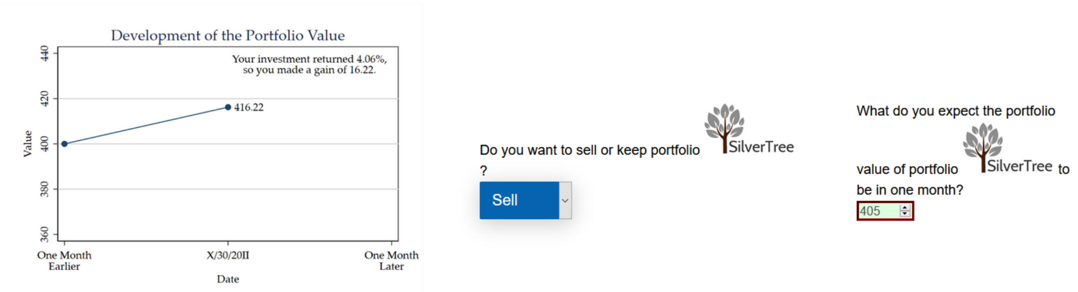
Another reason for using a static decision setting is that the experiment overall is already relatively long and rather complicated. Amongst our participants, the median answer to the question on how complex participants considered the task to be was "rather complex" (4 within a range from 1-5). Moreover, participants on average take about 46 minutes to complete the experiment which is rather long for an online experiment. Adding even more complex tasks and settings with multiple rounds and assets would further complicate the experiment for participants

[7] More precisely, for portfolio RedStone, the corresponding return signals are -5.06%, -2.04%, 2.02%, and 5.01%. For portfolio SilverTree, the corresponding return signals are -4.09%, -1.02%, 1.05%, and 4.06%. Note that we use return signals that are close to the historical 5%, 20%, 80%, and 95% quantiles of the respective distributions in order to increase external validity. Hence, there is sufficient variation in gains and losses.

and could hence detriment the quality of the insights.

Lastly, we also collect beliefs about the expected value of the portfolio in the next period ($t = 2$) after receiving the new signal in $t = 1$. For this purpose, we ask participants to indicate which value they expect the portfolio to have in the next period (only discrete number inputs are allowed). We illustrate the trading task in Figure 6 for the case of a paper gain of 4%.

Figure 6: Trading Task – Large Positive Signal



In this figure, we depict a screenshot of the trading task (in this example, for the "large positive return" signal for Portfolio SilverTree). In this screenshot, the participant has decided to sell the portfolio and indicated to expect the portfolio to have a value of 405 in the next month.

2.5 Additional Control Variables

In order to improve the efficiency of our estimates, to validate the randomization, and to analyze heterogeneous treatment effects, we survey a number of control variables. At the very beginning of the experiment, we assess demographic characteristics (see Appendix E.1). At the end of the experiment, participants have to fill out a short survey. We carry out this survey before determining the final personal payoffs in order to avoid any spillover effects from the payoff realization on perceived self-assessments. We elicit financial literacy (from 0-6 based on the number of correct answers to 6 questions from the National Financial Capability Study by the FINRA Investor Education Foundation), numeracy (from 0-1 based on a single question from the Berlin Numeracy Test in Cokely et al., 2012), and attributes about the real-world investment behavior of participants (see Appendix E.22).Moreover, we ask participants how they perceived the self-building task. More precisely, we ask them "how enjoyable was the portfolio building?", "how complex was the portfolio building?", "how much effort did you have to put into the construction of your portfolio?", and "when I look at the portfolio I have built I feel proud of having accomplished something" (all Likert-scales from 1-5). Finally, we ask participants whether they have a "hard time giving up possessions".

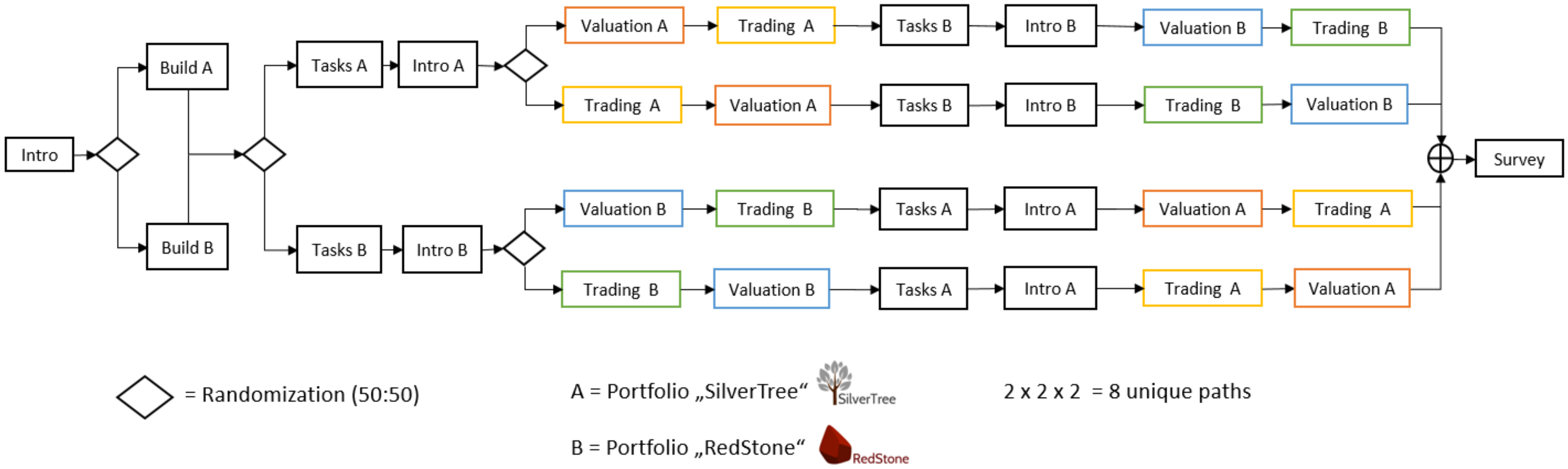
2.6 Procedure

At the very beginning of our experiment, we ask all participants to give consent to take part in the study. Subsequently, we ask them to answer demographic questions before they are being confronted with an attention check. Only participants answering the attention check correctly are allowed to proceed with the study. Then, we give participants a general introduction into the experiment and ask them to build one specific target portfolio. After the successful completion of this task, participants are presented with a portfolio. To account for order effects, we randomize the order of the portfolios for the tasks (i.e., whether a participant first has to do tasks for the self-built or the not self-built portfolio). It might be that the attachment towards the self-built portfolio that is built up during the initial self-building process is weakening over time. If participants first do the tasks for the other portfolio and then for the self-built portfolio, the IKEA effect might vanish. However, our estimates of the treatment effect are similar across both possible orderings.

After having made all relevant decisions for the first portfolio, participants are confronted with the second portfolio. For each portfolio, participants have to make all decisions for the valuation and the trading task (i.e., every participant makes all decisions for both distinct portfolios while one of them is self-built and the other is not). After the first valuation task, participants have to answer a second attention check. Just as before, only participants answering the attention check correctly are allowed to proceed with the study. To account for order effects between tasks, we also randomize the order of the two tasks (valuation and trading). However, each participant first works on the two tasks for one portfolio and then on the two tasks for the other portfolio (see also Figure 7). We do this to avoid that participants have to mentally switch between the two portfolios too many times which might confuse them. Note that there is no information provided between the tasks so that the order of the two tasks should not matter. Empirically, we can confirm that order effects do not play a relevant role. After having made the decisions for the two tasks, participants are asked to answer the post-experimental questions (see Appendix E.22).

We illustrate the complete experimental design with all randomizations in Figure 7.

Figure 7: Experimental Design With All Randomizations



In this figure, we depict the complete experimental design with all randomizations. "A" corresponds to portfolio SilverTree and "B" corresponds to portfolio RedStone. We describe the portfolio self-building process of "build A(B)" as well as the valuation and trading tasks in section 2.

3 Data

3.1 Recruitment

Participants were recruited via Amazon's Mechanical Turk (MTurk) which is an online labor market and frequently used for conducting experiments in economics and finance.[8] One reason for recruiting participants via MTurk is that the samples tend to be more representative of the US population than conventional student samples by being more diverse in terms of age, ethnicity, education, and geographical location (Buhrmester et al., 2011; Paolacci et al., 2010). Several studies show that the results obtained in MTurk are very similar to results typically obtained in laboratory experiments (Horton et al., 2011; Snowberg and Yariv, 2021). Several papers also point out that this similarity can be found even in complex tasks like auctions. For example, Lee et al. (2018) successfully replicate procurement auction experiments, Hafenbrädl and Woike (2018) replicate dollar auctions, and Mill and Morgan (2020) also find patterns of overbidding in first-price auctions with MTurk participants. Similarly, Arechar et al. (2018) show that even interactive experiments can be conducted online very reliably and that behavioral patterns of public good games observed in the laboratory can be replicated by using an online experiment with a MTurk sample.

To ensure a high-quality sample (i.e., participants understanding the task and paying attention), we restrict eligibility criteria (Arechar et al., 2018). We restrict recruitment to US-based individuals with an approval rate of 97% or higher.[9] Moreover, we restrict recruiting to individuals with approved Human Intelligence Tasks (HITs) of more than 500. Individuals are not allowed to take part via mobile phones or VPN clients to reduce inattentiveness and to prevent multiple participation in the study. Further, individuals have to pass a Captcha and two attention checks to take part (for details, see Instructions (Screen 4 and Screen 16)).

We pre-registered to recruit 500 participants to ensure that even with a small effect size (Cohen's d = 0.2) we are able to find an effect with a power of 99% at a 5% significance level.[10]

Our study was called 2097 times by potential experimental participants. 766 of those participants either used a mobile phone or a VPN client server, and were not allowed to take part in this study to ensure attentiveness and to exclude bots. 168 participants out of the remaining 1331 participants tried to do the study several times (most of these participants failed the attention check and still tried to redo the experiment). Further, 179 (417) participants failed the first (second) attention check and were not allowed to continue. 71 participants aborted the study before reaching the questionnaire and were hence dropped from the analysis as these participants did not make all relevant choices. All in all, we have data from 496 participants

[8] For example: Jordan et al. (2016); Peysakhovich et al. (2014); Rand et al. (2014); Kumar et al. (2015); Duarte et al. (2012); Kuziemko et al. (2015); Heimer and Imas (2021); Hartzmark and Sussman (2019); Bazley et al. (2021); Snowberg and Yariv (2021); Horton et al. (2011); Arechar et al. (2018).

[9] Participants' location is verified through their IP addresses. Requesters can review the work done by MTurk workers and decide to approve or reject the work. Approved work is paid as indicated in the contract, and rejected work is not paid. Hence, higher approval rates of workers indicate a higher quality of work.

[10] Cohen's d is a common measure for the effect size when comparing means. It denotes the change resulting from treatment relative to one standard deviation of the outcome variable in the data. Thus, a Cohen's d of 0.9 indicates that the treatment has increased the dependent variable by 0.9 standard deviations. Typically, a Cohen's d less than 0.2 is considered a "negligible" effect size (Cohen, 2013). A Cohen's d less than 0.5 is a "small" and Cohen's d less than 0.8 is a "medium" effect size, while a Cohen's d more than 0.8 is considered a "large" effect size.

that we can use.

3.2 Demographics

The age of our participants ranges from 18 to 79 years (median = 35). 55% of our participants were female and 76% of participants reported to have at least a Bachelor's degree as the highest qualification. Furthermore, our participants seem to be quite experienced with financial products. 57% of our participants indicated to have invested in equity, 35% in other financial instruments (bonds, options, etc.), and 60% of our participants indicated to be interested in financial markets. Even more interesting is that our sample seems to be substantially more financially literate than the US population. While in a representative sample of the US population respondents on average answered three out of six financial literacy questions correctly, participants in our sample answered 4.36 questions correctly which is very similar to 4.12, the number of correctly answered questions by US *investors*.[11] Thus, our sample is much more similar to US *investors* than a representative sample of the US population which denotes an advantage in our setting as our results are more likely to generalize to actual investors. This rather surprising characteristic might be driven by two reasons. First, participants on MTurk might be more familiar with the financial literacy questions as many experiments (including experiments on financial literacy) are conducted on MTurk. The other reason for the similarity of participants on MTurk with US *investors* might be selection as participants with lower financially literacy might select themselves out of the experiment.[12] We don't find very compelling evidence for the first channel. Specifically, we can see that participants who indicated to spend more time working on MTurk (and thus are more likely to have encountered these types of questions) are performing worse in the financial literacy questionnaire than participants who indicated to spend less time working on MTurk (β=-0.28,t(494)=-4.45, $p \leq 0.001$).[13] This negative correlation rather indicates that participants who are working more on MTurk might also be less attentive. This is also what we see if we compare participants who fail our attention checks to participants who pass our attention checks. Specifically, we find that participants who have indicated to spend more time working on MTurk fail our attention checks significantly more often (β=0.10,t(989)=6.44, $p \leq 0.001$). Thus, a selection channel seems a more natural explanation as of why our sample resembles US *investors*. To test this channel, we look at the time as well as the number of approaches participants need to finish the portfolio-building task. We find that participants who finish our experiment (and thus never fail any attention check) are faster (β=-29.88,t(656)=-4.30, $p \leq 0.001$) and need fewer approaches (β=-4.05,t(656)=-4.79, $p \leq 0.001$) to finish the portfolio-building task compared to participants who started the task but drop out later in the experiment. While these results suggest a potential selection effect, this finding can also be explained by attentiveness as less attentive participants would need more approaches and therefore more time. Furthermore, we observe that participants in our sample

[11] For comparison, please see the FINRA Investors in the United States Report (2019): `https://www.usfinancialcapability.org/downloads/NFCS_2018_Inv_Survey_Full_Report.pdf` and the FINRA 2018 National Financial Capability Study: `https://www.usfinancialcapability.org/downloads/NFCS_2018_Report_Natl_Findings.pdf`.

[12] We thank an anonymous referee for this insightful comment.

[13] An alternative way to examine this channel would be to focus on the time participants need to answer the financial literacy questions. Unfortunately, we did not collect this kind of data for these questions.

claim to be well educated and quite active in financial markets (see above) which is consistent with the observation that they are also more financially literate.

Overall, we believe that having a sample that is more representative of actual US investors is an advantage since it increases external validity. Nevertheless, we still have sufficient variation in financial literacy within our sample (standard deviation = 1.44, range 0-6) in order to examine potential interaction effects between financial literacy and an IKEA effect.

3.3 Payment

We tell participants that their personal compensation is based on a fixed component (1.50 USD) as well as on the amount of Wonderland Coins (WC), a fictional currency that they earn during the following tasks. The translation from Wonderland Coins to US Dollars is as follows: US Dollars = (Wonderland Coins - 90) * 0.12. We ensure that the payoffs in the tasks are at least 90 so that no participant ends up with a negative performance-based compensation in order to keep our promise to participants that they earn at least the fixed part of their compensation. To avoid wealth effects, we randomly select one of the tasks to determine the performance-based component at the end of the experiment.

For the valuation task, participants either receive the current selling price if they decide to sell the portfolio or receive the future price realization (drawn from the distribution shown in the histogram) if they decide to keep the portfolio for another period. For the trading task, we endow participants with 130 WC. This ensures comparability between the valuation and trading task. It also ensures that no participant ends up with a negative performance-based compensation. We then tell them that they invested 400 WC in the portfolio at $t = 0$ and that their personal payoff consists of the initial endowment of 130 WC as well as the potential gains or losses they make during the following trading decisions. On average, participants needed 46 minutes to finish our experiment, and earned on average \$5.94 which is substantially better than a target payment of about \$6 per hour for typical US-based MTurk workers (see Berg, 2015).

4 Results

In the result section, we first focus on the properties of the self-building task, i.e., the treatment. Second, we have a look at valuation decisions before coming to trading decisions.

4.1 Properties of the Treatment

First of all, we examine how participants perceived the portfolio-building task in Figure 8. The figure illustrates the responses to the questions regarding the complexity, enjoyment, necessary effort, and feeling of accomplishment of the portfolio-building task. The exact wording of those questions is included in the figure. Franke and Schreier (2010) show that process effort and enjoyment are important value drivers of self-designed products. Hence, any valid self-building treatment should sufficiently stimulate these perceptions. Amongst our participants, the median answer to the question on how complex participants considered the task to be was "rather complex"[14] and most participants stated that they had to put "rather much" effort into the construction of the portfolio.[15] Further, participants said "it was fun"[16] to construct the portfolio and the median participant "agreed" when they were asked whether they felt proud of accomplishing the construction.[17] These results address the potential concern that participants might dislike the building process when customization and assembling are segregated (Buechel and Janiszewski, 2014). In fact, the feeling of accomplishment that is created by our task seems to be comparable or even stronger than in Franke et al. (2010) where participants on average indicated a feeling of accomplishment of 3.39 out of 7 although there was an additional possibility to customize. Overall, these findings show a desirable combination of properties which makes us feel confident to conclude that the self-building treatment is valid and reasonably strong.

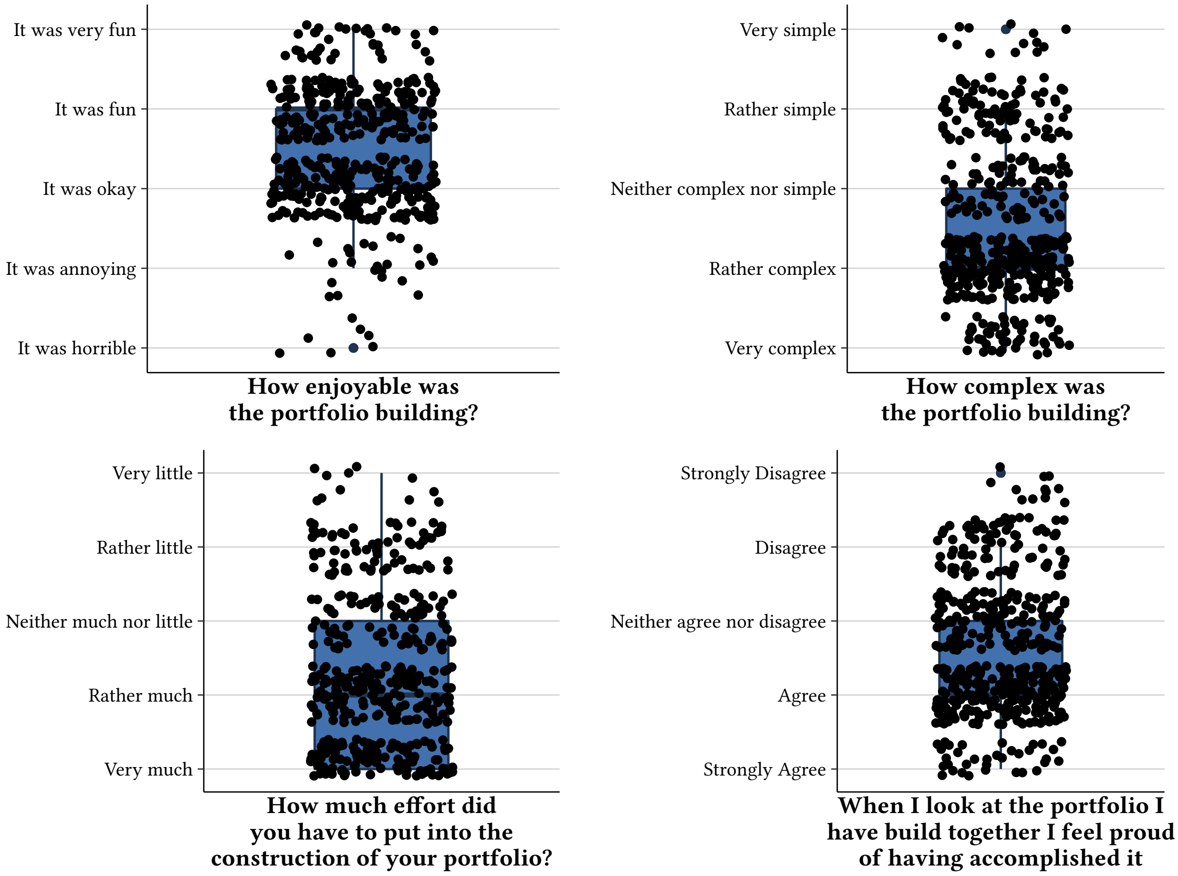


Figure 8: Properties of the Portfolio-building Task

This figure depicts the answers and corresponding summary statistics to questions focusing on the properties of the portfolio-building task. The individual questions are included under each segment of the figure. Black dots represent individual answers. Blue boxes show the box plot. For optical reasons, the responses are jittered.

[14]Based on the Wilcoxon signed-rank test on the median response participants considered the task neither very complex $Z = 87153$, $p \leq 0.001$ nor very simple $Z = 0$, $p \leq 0.001$.

[15]Based on the Wilcoxon signed-rank test on the median response participants did not put very much $Z = 51040$, $p \leq 0.001$ nor very little $Z = 0$, $p \leq 0.001$ effort into the task.

[16]Based on the Wilcoxon signed-rank test on the median response participants considered the task neither to be very fun $Z = 118341$, $p \leq 0.001$ nor to be horrible $Z = 0$, $p \leq 0.001$.

[17]Based on the Wilcoxon signed-rank test on the median response participants neither strongly agree $Z = 96141$, $p \leq 0.001$ nor strongly disagree $Z = 0$, $p \leq 0.001$ on whether they felt proud for accomplishing the construction.

Participants were also asked how attached they feel to the portfolio they have constructed as well as to the not self-built portfolio. Note that this question was asked after the valuation task to reduce possible experimenter demand and anchoring effects. The attachment results are shown in Figure 9. The median participant indicated to feel "moderately attached" to the self-built portfolio while only feeling "slightly attached" to the not self-built portfolio. This difference is statistically highly significant (paired Wilcoxon signed-rank test: $Z = 34230$, $p \leq 0.001$). Hence, self-building a portfolio leads to higher subjective attachment towards this portfolio. Nevertheless, although an increase in attachment of one point on the Likert scale for the median participant indicates a substantial effect size, the level of generated attachment is "moderate". Given that this effect only stems from self-building without any customization, it still seems remarkable. Moreover, this effect seems to be comparable to the results of Norton et al. (2012) where participants provided a rating on how much they liked IKEA boxes on a 1-7 Likert scale (3.81 for self-built and 2.5 for not self-built).

However, as the elicitation of the feeling of attachment cannot really be incentivized, this effect has to be considered with caution. In particular, we cannot exclude the possibility that an experimenter demand effect is driving this result. However, recent studies show that demand effects are rather weak. For example, Mummolo and Peterson (2018) document that even financial incentives to respond in line with researchers' expectations fail to consistently induce experimenter demand effect in survey experiments. Similar findings are reported in de Quidt et al. (2018) for economic games.

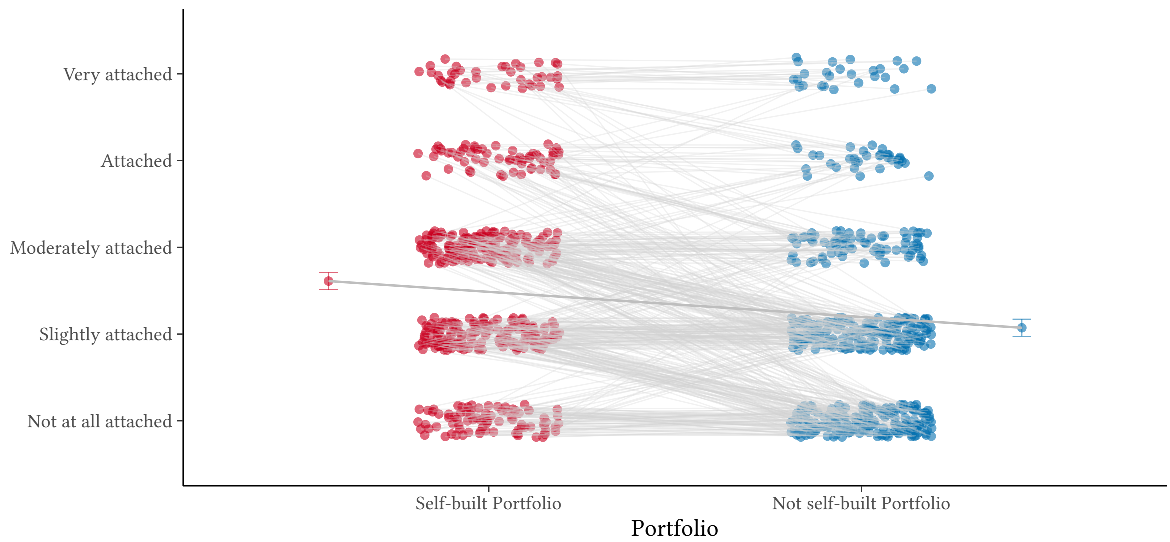


Figure 9: Reported Attachment to Portfolios

This figure presents the answers to the question "How attached are you with the portfolio?" for both the self-built and the not self-built portfolio. Dots denote individual responses. Grey lines show the participant-specific changes. Red dots denote the responses for the self-built portfolio while blue dotes denote the not self-built portfolio. For optical reasons, the responses are jittered. T-Bars denote the 95% confidence intervals around the mean responses by portfolio which are shown on the very left and very right.

4.2 Valuation of the Portfolios

In this subsection, we examine the effect of self-building on the valuation of the portfolios. To determine the participants' valuation of each portfolio, we obtain the individual lowest price that had to be offered so that a participant is willing to sell the portfolio, i.e., the minimum selling price based on the BDM-mechanism described in section 2.3. Figure 10 shows the indicated minimum selling price of the portfolio. The average minimum selling price (M = 124.21; SD = 5.59) is indistinguishable from the mean payoff of the portfolio ($t(492) = 1.2$, $p \geq 0.05$) indicating that on average, participants used the information provided reasonably.

Most importantly, we find no significant difference between self-built portfolios (M = 124.13; SD = 5.28) and not self-built portfolios (M = 124.30; SD = 5.88) ($t(990) = 0.5$, $p \geq 0.05$, d = 0.0 [-0.16,0.09] (negligible)). Also disaggregating the data reveals that there is no significant difference in terms of valuation between self-built portfolios and not self-built portfolios for both SilverTree ($t(494) = 0.8$, $p \geq 0.05$, d = 0.1 [-0.11,0.25] (negligible)) and RedStone ($t(494) = 1.3$, $p \geq 0.05$, d = 0.1 [-0.29,0.06] (negligible)). This null finding is estimated very precisely, and the effect size is remarkably small, indicating that even if we incorrectly do not reject the null hypothesis, the extent of this effect would be tiny. Specifically, it would imply that self-building decreases the valuation by only -0.14 [-0.53,0.25]% – an economically irrelevant effect. Note that this null effect is not driven by a lack of variance within participants (i.e., participants choosing one valuation and sticking to it for both portfolios). In particular, we see that 80 % of participants change their valuation between the two portfolios and the within-subject variation is on average 15.16. Table 1 reports the results of mixed-effects regression, accounting for participant-specific effects.[18] We can see that self-building has no influence on the minimum selling price even when controlling for beliefs, attachment, and socio-economic demographics.

However, we can see that the valuation of the portfolio correlates with multiple relevant variables. Specifically, we see that the valuation is highly correlated with the belief regarding the future realization. We can also see that the expressed willingness to take financial risk and financial literacy are positively correlated with the valuation of the portfolio.[19]

In Appendix C.1 we also take a closer look at participants' beliefs. In line with the previous results, we find no differences in beliefs between the self-built and the not self-built portfolio. Specifically, there are neither differences in the beliefs about the mean payoff nor in the beliefs about the payoff's confidence interval. This finding is consistent with the results described above.

We also look at the information processing during the task (i.e., how often participants hovered over payoff bars in the histogram of the respective portfolio's payoffs) in Appendix C.3

[18] The mixed-effects regression is sometimes also referred to as a "random effects" regression. We use a model with random and fixed effects. The random effects are described by random intercepts to account for participant-specific effects. The fixed effects include a dummy that takes on a value of one if the participant has self-built the respective portfolio as well as several controls. Instead of a mixed-effects regression, we could also use a regression where we account for each participant with a participant-specific dummy. The results do not change when using the latter approach.

[19] Note that we use financial literacy only as a linear predictor in the regression. Such a linear relationship is not straightforward and a non-linear linear relationship might be more instructive. Thus, we also estimate a model where financial literacy enters as a quadratic predictor. We find that such a model does not perform better than a model with a linear relationship χ^2(df=1)= 2.349, $p \geq 0.05$. The relationship between financial literacy and the valuation also remains the same using this alternative model (i.e., the linear part remains positive and significant while the quadratic part is insignificant and close to zero).

and find no significant differences there as well. Specifically, there is no difference between the two portfolios with regard to how often participants have hovered over below and above median payoff information. Again, this finding is consistent with the "absence" of the effects discussed above.

Finally, one might be concerned that extreme valuations (potential outliers) could drive the null effects. However, given the precision (i.e., low standard errors) of our estimates, this does not seem to be an issue. Moreover, in unreported analyses we winsorize valuations at the 1% and 2.5% level, respectively, and also exclude the 1% most extreme valuations. Results remain unchanged. If anything, estimates get closer to zero and standard errors get even smaller. This finding is also robust in a variety of additional specifications (for instance, dropping participants who take an extremely short or long time to complete the tasks, focusing on participants who do/do not have a difference in their attachment between the self-built and not self-built portfolio, focusing on participants who do/do not perceive self-building annoying).

To further provide evidence on the "absence" of the effect, we use the method suggested in Harvey (2017) and recently applied in Focke et al. (2019). This method basically asks which t-statistic is needed to reject an effect at common probabilities that the null is true (i.e., the α-level which is typically 10%, 5%, 1% and 0.1%) given a prior odd the existence of the effect. For example, Harvey (2017) show that if we assume that there is a strong prior against an independent variable X influencing a dependent variable Y (i.e., the odds are 49 to 1), we need a t-statistic of 3.70 to reject the null hypothesis (i.e., no effect of X on Y) at the 5% level compared to a t-statistic of about 2 that is typically required (see table III in Harvey, 2017). Thus, to provide evidence on the "absence" of the IKEA effect in financial portfolios, we need to define a typical magnitude of the effect. In order to do so, we survey the literature on the IKEA effect and find that self-building increases the valuation of the product by about 40 to 60% of the standard deviation. To be conservative, we assume that a "meaningful" effect leads to an increase of 30% of the standard deviation (i.e., a Cohen's d of 0.3). Using this 30% standard deviation increase as the null, we obtain a t-statistic of 4.96 for our observed 0.92% standard deviation change. Thus, we can reject the null hypothesis (i.e., a meaningful increase) at the 0.1% level for a variety of priors. This is true even if we assume that a null effect is a long-shot (i.e., the prior belief is 99 to 1 against finding an effect different from a 30% standard deviation increase). Thus, we can confidently say that we find a clear null effect. Overall, our evidence hitherto indicates that there is no economically meaningful IKEA effect for self-built portfolios.

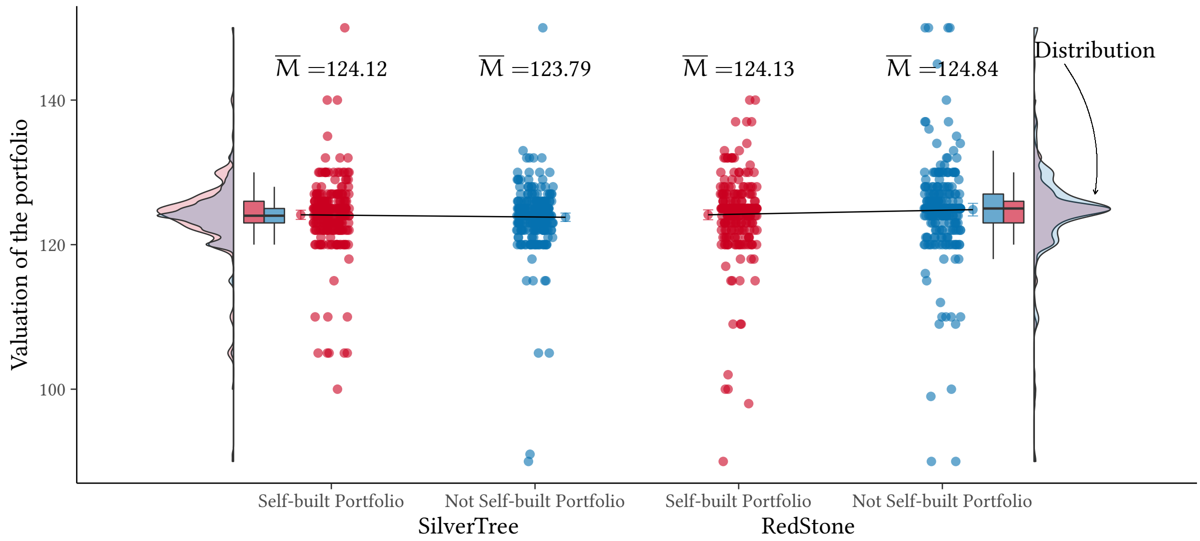


Figure 10: Valuation of the Portfolios

This figure depicts the valuations of the portfolios based on the minimum selling price obtained via the BDM mechanism. Dots denote individual (jittered) responses. The panel on the left/right show the minimum selling prices for portfolio SilverTree/RedStone. The boxes left/right of the dot clouds show the box plots. Left/right of the box plots the distribution for each answer is shown. Red objects denote the responses for the self-built portfolio, while blue objects denote the not self-built portfolio. T-Bars denote the 95% confidence intervals around the mean response, with the black line indicating the average change in responses.

	Valuation of the portfolio (minimum selling price)				
Constant	124.17^{***} (0.25)	124.24^{***} (0.35)	124.25^{***} (0.33)	124.42^{***} (0.55)	117.90^{***} (2.60)
Self-built	0.17 (0.25)	0.57 (0.50)	0.35 (0.48)	0.54 (0.50)	0.16 (0.26)
SilverTree		−0.14 (0.50)	−0.14 (0.47)	−0.13 (0.50)	
Self-built x SilverTree		−0.77 (0.86)	−0.43 (0.81)	−0.79 (0.86)	
Belief			1.38^{***} (0.16)		1.39^{***} (0.16)
Attachment				−0.07 (0.16)	0.06 (0.17)
FinancialLiteracy					0.51^{***} (0.16)
FinancialRisk					0.38^{*} (0.22)
Controls	×	×	×	×	✓
Sbj specific effects	✓	✓	✓	✓	✓
LogLik	-3037.06	-3034.1	-3001.02	-3034.89	-2983.7
Observations	992	992	992	992	992
Akaike Inf. Crit.	6,082.13	6,080.21	6,016.05	6,083.78	6,009.40
Notes:					*p < 0.1; **p < 0.05; ***p < 0.01

Table 1: Valuation of the Portfolios

This table provides the results of mixed-effects regressions of the valuation of a portfolio (the minimum selling price extracted via the BDM mechanism). *Self-built* denotes a dummy that takes on a value of one if the participant has self-built the respective portfolio, and zero otherwise. *SilverTree* denotes a dummy that takes on a value of one for the portfolio SilverTree and zero for RedStone. *Belief* denotes the z-scored beliefs. *Attachment* indicates how attached participants indicated to feel to the respective portfolios. *FinancialLiteracy* indicates the financial literacy score of participants (from 0-6 based on 6 questions as in the National Financial Capability Study (NFCS) by the FINRA Investor Education Foundation). *FinancialRisk* indicates participants' expressed willingness to take financial risk (range: 1-5). Controls include educational attainment, employment status, age, gender, ethnicity, and how many hours participants work online. All regressions account for participant-specific effects.

4.3 Trading

In this subsection, we examine the effect of self-building a portfolio on subsequent trading decisions. In the trading task, for a given portfolio, participants had to decide whether to keep or sell it depending on the prior return realization of the portfolio. Figure 11 shows the decisions on whether to keep or sell the portfolio depending on the prior realization. First, we see that participants are more likely to sell the portfolio in comparison to the other return realizations when the prior realization was very positive (a gain of 4.5%)(M = 0.50; SD = 0.45). If the realization was very negative (a loss of 4.5%)(M = 0.41; SD = 0.44), we see that also a lot of participants were willing to sell the portfolio, however significantly less compared to a very positive prior realization ($t(492) = 2.5$, $p = 0.011$, $d = 0.2$ (small)).[20] Participants were more likely to keep the portfolio if the prior realization was slightly negative (a loss of 1.5%)(M = 0.35; SD = 0.41) compared to a very negative prior realization ($t(492) = 3.9$, $p \leq 0.001$, d = 0.1 (negligible)). Overall, when looking at strong signals, participants are more likely to sell their winner portfolio which is consistent with the disposition effect. Moreover, the finding that the probability to sell increases with the absolute value of the return signal is consistent with the empirically observed V-shaped disposition effect pattern of US retail investors as described by Ben-David and Hirshleifer (2012). Hence, this makes us feel confident to conclude that the trading task provides a valid setting for testing the impact of self-building on trading decisions.

Most importantly, we can again see no significant difference in terms of trading decisions between self-built portfolios (M = 0.36; SD = 0.22) and not self-built portfolios (M = 0.38; SD = 0.21) ($t(984) = 1.0$, $p \geq 0.05$, $d = 0.1$ [-0.19,0.06] (negligible)). This holds true for all of the four possible prior realizations of the respective portfolios.[21] Also disaggregating the data by portfolio reveals that there is no significant difference in terms of trading decisions between self-built portfolios and not self-built portfolios for all four possible prior realizations for both SilverTree[22] and RedStone[23]. This null finding is again estimated very precisely, and the effect size is very small, indicating that even if we incorrectly do not reject the null hypothesis, the extent of this effect would be negligible. Specifically, it would imply that self-building decreases the relative probability of selling by only -3.6 [-8.55,1.36]% – an economically small effect. This relative change is particularly small compared to strong treatment effects observed in literature. However, our effect size is still very small, even compared to non-invasive treatments in previous literature. Chang et al. (2016), for example, merely increase the salience of the own previous buying decision and still find a relative decrease of 37% in the probability to sell an asset held

[20] We use a paired t-test as we average over both portfolio types for every participant (and thus we cannot use a χ^2-test). Using a non-parametric test yields the same results.

[21] Using t-tests to compare the pooled trading decisions between self-built portfolios and not self-built portfolios for all of the four possible prior realizations gives: Very negative (a loss of 4.5%) prior realization: $t(984) = 0.5$, $p \geq 0.05$, $d = 0.0$ (negligible); slightly negative (a loss of 1.5%) prior realization: $t(984) = 0.0$, $p \geq 0.05$, $d = 0.0$ (negligible); very positive (a gain of 4.5%) prior realization: $t(984) = 0.7$, $p \geq 0.05$, $d = 0.0$ (negligible); slightly positive (a gain of 1.5%) prior realization: $t(984) = 0.6$, $p \geq 0.05$, $d = 0.0$ (negligible);

[22] Using t-tests we obtain: Very negative (a loss of 4.5%) prior realization: $t(493) = 1.0$, $p \geq 0.05$, $d = 0.1$ (negligible); slightly negative (a loss of 1.5%) prior realization: $t(493) = 0.7$, $p \geq 0.05$, $d = 0.1$ (negligible); very positive (a gain of 4.5%) prior realization: $t(493) = 1.1$, $p \geq 0.05$, $d = 0.1$ (negligible); slightly positive (a gain of 1.5%) prior realization: $t(493) = 1.2$, $p \geq 0.05$, $d = 0.1$ (negligible);

[23] Using t-tests we obtain: Very negative (a loss of 4.5%) prior realization: $t(493) = 0.1$, $p \geq 0.05$, $d = 0.0$ (negligible); slightly negative (a loss of 1.5%) prior realization: $t(493) = 0.5$, $p \geq 0.05$, $d = 0.0$ (negligible); very positive (a gain of 4.5%) prior realization: $t(493) = 0.0$, $p \geq 0.05$, $d = 0.0$ (negligible); slightly positive (a gain of 1.5%) prior realization: $t(493) = 0.1$, $p \geq 0.05$, $d = 0.0$ (negligible);

at a loss.

Table 2 and Table 3 reports on linear-probability mixed-effects regressions accounting for participant-specific effects, both pooled over all prior realizations and separately for each prior realization. Similar results are obtained when logit models are used instead. We can see in both tables that self-building has no influence on the trading decisions even when controlling for beliefs, attachment, and socio-economic demographics.

In Appendix C.2, we also take a closer look at participants' beliefs. We again find no difference in beliefs between the self-built and the not self-built portfolio. Specifically, there are no differences in the belief about the mean future realization conditional on whether the portfolio was self-built for of any of the four prior realizations. We also find no effect on the belief about the confidence interval on the mean future realization, which is consistent with the results described above. It is, however, worth mentioning that the beliefs are highly correlated with the trading decisions which indicates that beliefs are not randomly expressed but are rather consistent with the behavioral measures.

This finding is robust in a variety of additional specifications (for instance, excluding extreme valuations, dropping participants who take an extremely short or long time to complete the tasks, focusing on participants who do/do not have a difference in their attachment between the self-built and not self-built portfolio, focusing on participants who do/do not found self-building annoying). Just as before, we can see that the trading decisions are correlated with multiple relevant variables. Specifically, we see that the valuation is highly correlated with the belief regarding the future realization. Participants believing that the future realization is higher are less willing to sell the portfolio. We also see that the expressed willingness to take financial risk and financial literacy are negatively correlated with the valuation of the portfolio.[24] Thus, participants who are willing to take more risks are also less likely to sell the portfolio.

[24] Note that we again use financial literacy only as a linear predictor in the regression which is again not straightforward, in particular in light of a disposition effect. However, we again find that a more complex model does not perform better than a model with a linear relationship (χ^2(df=1)= 1.233, $p \geq 0.05$). Moreover, in Table 3 we estimate the propensity to sell conditional on the prior realizations. The results suggest that the effect of financial literacy on behavior is only very slightly different when facing a winning versus a losing stock.

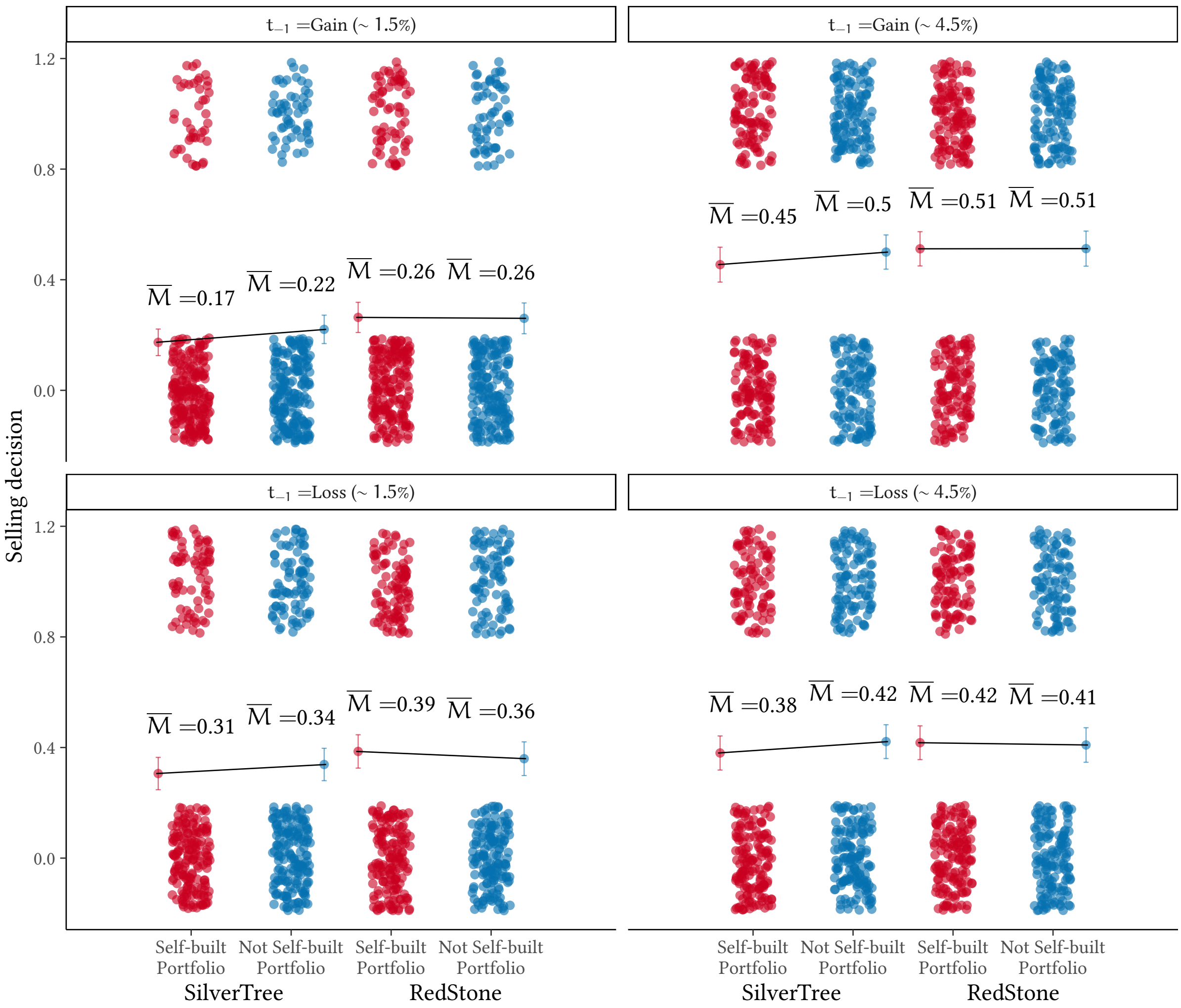


Figure 11: Propensity to Sell Portfolios

Dots denote individual (jittered) responses. This figure shows the individual (binary) decisions to buy or sell a portfolio as well as the mean and confidence interval conditional on the portfolio type and prior return realization. Individual responses are jittered to enhance visibility. Red objects denote the propensity to sell for the self-built portfolios while blue objects denote the not self-built portfolios. T-Bars denote the 95% confidence intervals around the mean response, with the black line indicating the average change in responses. The top left panel shows the propensity to sell if the prior realization was slightly positive (a gain of 1.5%). The top right panel shows the propensity to sell if the prior realization was very positive (a gain of 4.5%). The bottom left panel shows the propensity to sell if the prior realization was slightly positive (a loss of 1.5%). The bottom right panel shows the propensity to sell if the prior realization was very positive (a loss of 4.5%).

In summary, we document that self-building a portfolio increases the self-reported attachment towards this portfolio. However, this increased attachment does not translate into any changes in behavioral responses. Neither the mean valuation nor trading decisions are impacted by self-building. One possible reason as of why this increased attachment does not translate into any changes in behavioral responses might be a researcher demand effect. The increase in attachment is not particularly strong, and as the elicitation of the feeling of attachment is not incentivized, it is more prone to researcher demand effects.

Nevertheless, there might be heterogeneous treatment effects amongst participants. Our rich sets of variables allows us to examine various data splits. However, we do not find any

	Trading decision				
Constant	0.36^{***} (0.01)	0.39^{***} (0.02)	0.39^{***} (0.02)	0.37^{***} (0.02)	0.45^{***} (0.10)
Self-built	0.02 (0.02)	-0.01 (0.02)	-0.001 (0.02)	-0.01 (0.02)	0.01 (0.01)
SilverTree		-0.07^{***} (0.02)	-0.05^{**} (0.02)	-0.07^{***} (0.02)	
Self-built x SilverTree		0.05 (0.03)	0.02 (0.03)	0.05 (0.03)	
Belief			-0.15^{***} (0.01)		-0.15^{***} (0.01)
Attachment				0.01 (0.01)	-0.003 (0.01)
FinancialLiteracy					-0.02^{***} (0.01)
FinancialRisk					-0.03^{***} (0.01)
Controls	×	×	×	×	✓
Sbj specific effects	✓	✓	✓	✓	✓
LogLik	-2743.65	-2744.62	-2559.95	-2748.05	-2591.14
Observations	3,968	3,968	3,967	3,968	3,967
Akaike Inf. Crit.	5,495.31	5,501.23	5,133.89	5,510.09	5,224.28
Notes:					*p < 0.1;**p < 0.05;***p < 0.01

Table 2: Propensity to Sell Portfolios

This table provides the results of mixed-effects regressions of an indicator variable for the selling decision. *Self-built* denotes a dummy that takes on a value of one if the participant has self-built the respective portfolio, and zero otherwise. *SilverTree* denotes a dummy that takes on a value of one for portfolio SilverTree and zero for RedStone. *Belief* denotes the z-scored beliefs. *Attachment* indicates how attached participants indicated to feel to the respective portfolios. *FinancialLiteracy* indicates the financial literacy score of participants (from 0-6 based on 6 questions as in the National Financial Capability Study (NFCS) by the FINRA Investor Education Foundation). *FinancialRisk* indicates participants' expressed willingness to take financial risk (range: 1-5). Controls include educational attainment, employment status, age, gender, ethnicity, and how many hours participants work online. All regressions account for participant-specific effects.

economically or statistically significant differences across all these non-parametric splits for valuation and trading decisions, as well as for the belief formation in these tasks. More precisely, we test for non-parametric heterogeneous treatment effects by analyzing medium and quantile rank splits with respect to perceived task characteristics (complexity, enjoyment, effort, feeling proud after completion), how well participants understood the tasks, whether participants answered the task comprehension questions correctly, personal characteristics (age, gender, employment, ethnicity), financial literacy, numeracy, how long participants took for the tasks, and self-reported propensity of having a hard time giving up possessions. Hence, it is unlikely that a heterogeneous treatment effect for self-building a portfolio with respect to valuation, trading decisions, and beliefs exists.

5 Discussion and Conclusion

The existence of an "IKEA effect", i.e., a significantly higher valuation for self-built products, has been documented for various consumer goods (e.g., Franke et al., 2010 and Norton et al., 2012). In this paper, we investigate how strong the effect of self-building in the context of financial portfolios is. We argue that it is important to explicitly look at financial portfolios because of their unique characteristics (e.g., their instrumental value with risky monetary payoffs) as well as due to the recently heavily increasing number of self-directed retail investors.

To examine this effect, we compare valuation and trading decisions of investors who self-built a portfolio and investors who did not self-build the same portfolio. Our results show that, although investors feel significantly more attached to their self-built portfolio, there is no

	Trading decision											
	t_{-1} =Loss ($\sim$ 4.5%)			t_{-1} =Loss ($\sim$ 1.5%)			t_{-1} =Gain ($\sim$ 4.5%)			t_{-1} =Gain ($\sim$ 1.5%)		
Constant	0.40*** (0.02)	0.42*** (0.03)	0.55*** (0.21)	0.34*** (0.02)	0.39*** (0.03)	0.66*** (0.22)	0.49*** (0.02)	0.51*** (0.03)	0.27 (0.23)	0.22*** (0.02)	0.26*** (0.03)	0.24 (0.19)
Self-built	0.02 (0.02)	−0.01 (0.04)	0.02 (0.02)	0.002 (0.02)	−0.03 (0.04)	0.01 (0.02)	0.02 (0.02)	0.01 (0.04)	−0.01 (0.02)	0.02 (0.02)	−0.01 (0.04)	0.01 (0.02)
SilverTree		−0.04 (0.04)			−0.08** (0.04)			−0.05 (0.04)			−0.09** (0.04)	
Self-built x SilverTree		0.05 (0.08)			0.07 (0.07)			0.03 (0.08)			0.05 (0.06)	
Belief			−0.24*** (0.02)			−0.15*** (0.02)			−0.19*** (0.02)			−0.11*** (0.02)
Attachment			0.02 (0.01)			0.01 (0.01)			−0.03** (0.01)			−0.01 (0.01)
FinancialLiteracy			−0.03** (0.01)			−0.04*** (0.01)			0.02 (0.01)			−0.03** (0.01)
FinancialRisk			−0.03 (0.02)			−0.03* (0.02)			−0.04* (0.02)			−0.03 (0.02)
Controls	×	×	✓	×	×	✓	×	×	✓	×	×	✓
Sbj specific effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LogLik	-611.37	-615.6	-521.02	-599.87	-601.2	-582.56	-621	-624.07	-581.38	-526.19	-526.13	-534.9
Observations	992	992	992	992	992	992	992	992	992	992	992	991
Akaike Inf. Crit.	1,230.74	1,243.20	1,084.04	1,207.74	1,214.41	1,207.13	1,250.00	1,260.13	1,204.75	1,060.38	1,064.25	1,111.79

Notes: *p < 0.1; **p < 0.05; ***p < 0.01

Table 3: Propensity to Sell Portfolios by Prior Return Realization

This table provides the results of mixed-effects regressions of an indicator variable for the selling decision by prior return realization. *Self-built* denotes a dummy that takes on a value of one if the participant has self-built the respective portfolio, and zero otherwise. *SilverTree* denotes a dummy that takes on a value of one for the portfolio SilverTree and zero for RedStone. *Belief* denotes the z-scored beliefs. *Attachment* indicates how attached to the respective portfolio participants claimed to feel. *FinancialLiteracy* indicates the financial literacy score of participants (from 0-6 based on 6 questions as in the National Financial Capability Study (NFCS) by the FINRA Investor Education Foundation). *FinancialRisk* indicates participants' expressed willingness to take financial risk (range: 1-5). Controls include educational attainment, employment status, age, gender, ethnicity, and how many hours participants work online. All regressions account for participant-specific effects. Columns (1)-(3) depict decisions in case the prior realization was strongly negative (a loss of 4.5%). Columns (4)-(6) depict decisions in case the prior realization was slightly negative (a loss of 1.5%). Columns (7)-(9) depict decisions in case the prior realization was strongly positive (a gain of 4.5%). Columns (10)-(12) depict decisions in case the prior realization was slightly positive (a gain of 1.5%).

economically meaningful difference in valuations between self-built and not self-built portfolios. The high precision of our close to zero estimates indicates that in contrast to consumption goods, an economically significant IKEA effect for financial portfolios does not exist. We neither find that participants have biased beliefs about the fundamental quality of a self-built portfolio (i.e., expected return and risk), nor that there is a value-increasing standalone effect of self-building that might be related to psychological ownership. Moreover, we also do not detect meaningful differences in future trading decisions.

Why does the IKEA effect not exist for financial portfolios despite the fact that its existence has been documented for other goods? In general, an increase in valuation for self-built goods might be driven by two channels: First, people have biased perceptions about the quality of the self-built good. An overvaluation of financial portfolios might be driven by overestimating expected portfolio returns or underestimating risk. These components are special in the context of risky lotteries, and we are the first to show that there is no direct effect, e.g., via increased overconfidence, of self-building on beliefs about future returns or risk. Hence, self-building does not affect the perception of the objective attributes of a financial portfolio. Second, people derive additional utility from possessing self-built goods as a standalone effect of associating the portfolio with the self. For instance, owning self-built goods can serve as a means of self-expressing yourself (Levy, 1959) or to signal competence to yourself or others (Mochon et al., 2012). Hence, self-building can be an important driver of psychological ownership (Pierce et al., 2003).

In particular, a financial portfolio differs from most other goods in two important dimensions. These dimensions might determine the strength of psychological ownership generated by the self-building process. Firstly, financial portfolios are intangible which makes them more difficult to use for self-expression and showing competence to others. Although participants in Franke et al. (2010) are willing to pay more for intangible T-shirt designs, the final product that buyers can take along is still physical, i.e., a T-shirt with this design.

Secondly, financial portfolios are an intermediate good and serve a utilitarian purpose. According to Dhar and Wertenbroch (2000, p. 61) utilitarian goods are goods "whose consumption is more *cognitively driven*, *instrumental*, and goal oriented and accomplishes a functional or practical task" (see also Strahilevitz and Myers, 1998). If participants' decisions are more cognitively driven for utilitarian goods, they might think more rationally or apply different heuristics in a financial valuation context. Crucially, in contrast to most consumer goods, utility from a financial portfolio is mainly derived from its future *monetary* instrumental value. Of course, investors might also derive additional utility from other aspects of owning a portfolio, e.g., having fun trading the portfolio because they enjoy gambling (Kumar, 2009). Nevertheless, our results suggest that self-building does not directly impact these aspects. In fact, an important ultimate goal of owning a portfolio is to sell it again at a later point, preferably for an adequate gain. This is different to other self-built goods where a higher valuation might reflect the urge to permanently possess your own creations. This reasoning is related to the findings of Novemsky and Kahneman (2005b) who document that exchange goods that are given up "as intended" do not exhibit loss aversion, and argue that intentions to exchange versus to consume a good moderate the endowment effect.[25] Based on this finding, Ariely et al. (2005) argue that "there is less reference dependence for money because money that is held to be spent is perfectly instrumental, making it a utilitarian good". This is in line with the findings of Dhar and Wertenbroch (2000) who document that the magnitude of the endowment effect is weaker for utilitarian than for hedonic goods. Finally, Ariely et al. (2005) and Novemsky and Kahneman (2005a) suggest that it might be more difficult to develop significant emotional attachment to utilitarian goods. Although the self-built boxes in Norton et al. (2012) are also utilitarian to some extent, they are still physical which allows for easier self-expression and showing competence to others. Moreover, they do not have a clear monetary instrumental value that increases the intention to exchange rather than to keep the good in the future. In this context, our results suggest that participants solely focus on the monetary instrumental value of a financial portfolio. Since self-building does also not affect the perceived monetary instrumental value ("quality") of the portfolio via biased beliefs about risk and return, there might be ultimately no effect on valuations and trading decisions.

Why do we still find that participants claim to be more attached to their self-built portfolios? Most importantly, it is not clear that a higher subjective attachment always translates into economically significant higher valuations in terms of monetary units. While there are no economic costs of being more attached to the self-built portfolio, participants seem to solely focus on the instrumental monetary value of their portfolio when doing the incentivized valuation and trading decisions. Consequently, they do not have an economically significant willingness to pay for the additional attachment (e.g., because they anticipate to sell the portfolio in the future anyway).

Overall, we conjecture that the IKEA effect does not exist for intangible instrumental goods

[25] This finding is consistent with the model of Kőszegi and Rabin (2006) where individuals use the expected rather than the current endowment as their reference point. If they have the intention to exchange the good at a later point, the good is no longer part of their reference point. Consequently, they only think about the future monetary value they receive when exchanging the good.

like financial portfolios. Hence, common portfolio self-building opportunities do not seem to affect individual investors' beliefs or decisions directly. Consequently, the self-building process of common self-directed investment opportunities per se does not seem to negatively affect individual investors' welfare as well as the efficiency of financial markets. Nevertheless, self-building still seems to increase perceived subjective attachment to financial portfolios which is remarkable given their utilitarian character.

While we, as is standard in finance experiments, purposefully focused on the two most relevant aspects of a portfolio – the return and the risk – future research might also add further dimensions which might be potential moderators in the context of the IKEA effect. For example, it might be useful to provide investors with other firm-related characteristics such as ESG-measures (see, for instance, Pastor et al., 2021), investor-related aspects such as the possibility to share investment results (with peers or anonymously, see, for instance, Hirshleifer, 2020 and Ammann and Schaub, 2021) or the purpose of the investment (see, for instance, Aspara and Hoffmann, 2015).

Our findings might also be an interesting starting point when thinking about using portfolio self-building devices as a means to let investors customize, stimulate learning, and increase the low participation rate of individual investors in stock markets (Mankiw and Zeldes, 1991). For instance, having the opportunity to self-build a portfolio might attract a new group of retail investors without directly biasing their decisions. This aspect has also implications for retail brokerage firms that might decide to offer self-building tools in order to open new market shares. Of course, such a new group of investors could still differ from current investors with respect to certain characteristics (e.g., risk-taking, cognitive abilities, or how prone they are to behavioral biases) that might then affect financial markets.

However, other important issues of self-directed investing besides the self-building process ("IKEA effect") itself might exist. For instance, it remains an open question for future research whether the increased customization that usually goes along with these self-building tools actually benefits or hurts individual investors after accounting for costs, re-balancing and market timing decisions as well as for potentially non-optimal asset choices. In this case, self-directed investors might make non-optimal decisions due to the influence of other behavioral biases (e.g., being influenced by sentiment (Baker and Wurgler, 2006), choosing attention-grabbing assets (Barber and Odean, 2008) or neglecting correlations (Kroll et al., 1988)) or being overconfident about their own stock pickings. However, such effects could potentially be reduced if investors were appropriately assisted during the self-building process by providing them with instructions and guidance, e.g., by robo-advisors (D'Acunto et al., 2019).

While we purposefully used a rather stylized and concentrated task to elicit trading behavior in order to keep the design clean and neat, future research might also use different tasks to study trading behavior. In particular, it might be fruitful to focus on potential long term effects of the IKEA effect which might arise only in a trading task with multiple periods. Similarly, it would be interesting to learn whether an IKEA effect might be created by allowing participants to trade multiple portfolios at the same time.

Another interesting avenue of future research might use our findings to investigate which factors are essential in the emergence of the IKEA effect. While we focus on intangible instrumental goods, this new research could systematically add features (e.g., social aspects or tangibility) to eventually moderate an IKEA effect (which has been found in more tangible, consumer goods). While such an avenue would go beyond the scope of the current paper, it would potentially provide a valuable contribution to the literature on understanding the drivers of the IKEA effect.[26]

One concern the reader might have is that our null effect might be driven by a rather high similarity between the portfolio RedStone and SilverTree with regard to their return and volatility. As already mentioned earlier (section 2.2.2), our variation in returns between the portfolio RedStone and SilverTree is already close to the maximum variation of returns one could have in a clean design based on real-life data. Thus, it seems unlikely that a treatment with a slightly lower similarity between the portfolio RedStone and SilverTree would change much. Moreover, although the mean return and the standard deviation are relatively close to each other, the used empirical return distributions also differ with respect to other dimensions (e.g., the mode, skewness, kurtosis, minimum and maximum values) which is saliently displayed in the provided graphical histograms. Importantly, all these other dimensions (even if not explicitly highlighted in the written descriptions) are still relevant for the personal payoff of participants. Another argument against the concern that the similarity of the two portfolios might drive the null effect is that we compare the changes in behavior between self-built and not self-built portfolios *for each portfolio separately.* Thus, if an IKEA effect would exist in our setting, we should be able to detect this effect irrespective of how close RedStone and SilverTree are in terms of risk and return as the comparison of self-built versus not self-built within one portfolio type does not depend on the behavior in the respective other portfolio type. Our design requires two portfolios to cleanly identify the effect of self-building and to avoid alternative drivers such as learning and effort effects. However, the mere existence of another portfolio should not alter the emergence of an IKEA effect.

Nevertheless, one way how the mere existence of another portfolio *might* change the IKEA effect is through anchoring. Specifically, the concern could be that self-building does change the behavior (valuation and trading) but that the existence of another portfolio anchors participants to provide the same valuation for both portfolios (which could mechanically erase the IKEA effect). We believe this to be rather unlikely as we can see that 80 % of participants change their valuation between the two portfolios and that within-subject variation in valuations is rather substantial (on average 15.16). Thus, our data indicates that a potential anchoring effect would only be applicable to a very limited extent. Finally, even if we were to assume that 20% of participants are anchored, we can examine whether the IKEA effect emerges for participants who change their valuation between portfolios. We again find no such effect (see Appendix D).

All in all, this paper presents the first empirical investigation of self-building opportunities on financial decision-making. We show that self-building a financial portfolio does not directly change investors' behavior, and conclude that the self-building process of common self-directed investment opportunities per se does not directly distort financial markets.

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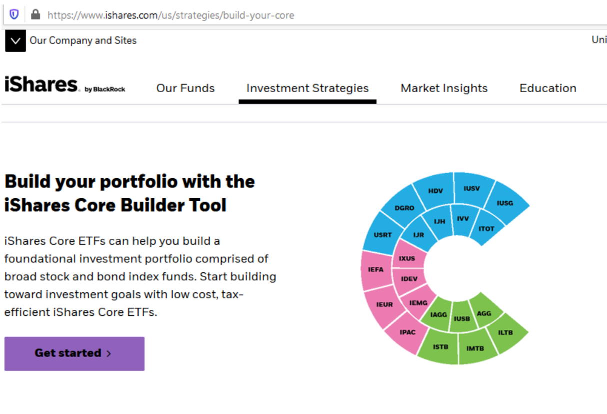
A Additional Figures

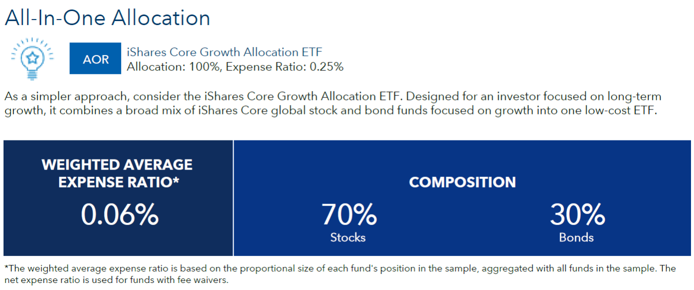
Figure 12: Real-Life Example: iShares Portfolio Builder

(a) Core Portfolio Builder Tool



(b) Selection of Portfolio Components

(c) Alternative Pre-Built Solution



In this figure, we depict a screenshot of the product homepage of one of the largest ETF providers (Morningstar, 2019), BlackRock (see `https://www.blackrock.com/tools/core-builder/us#/`, accessed 21 May 2020). In Panel A of Figure 12, customers can use a portfolio builder tool to create their own "iShares" portfolio by specifying the weights of individual asset-class ETFs (Panel B). Alternatively, on the same page, they can buy a comparable pre-built portfolio (Panel C).

B Summary Statistics

Table 4 summarizes all relevant variables by portfolio.

		Self-built: Redstone (N=254)	Self-built: SilverTree (N=242)	Total (N=496)	p value
Gender		0.55 (0.50)	0.54 (0.50)	0.55 (0.50)	0.826
Age		39.00 (11.98)	39.23 (11.62)	39.11 (11.79)	0.830
Ethnicity					0.664
	African American	29 (11.4%)	21 (8.7%)	50 (10.1%)	
	Asian	23 (9.1%)	17 (7.0%)	40 (8.1%)	
	Hispanic	11 (4.3%)	13 (5.4%)	24 (4.8%)	
	Native American	2 (0.8%)	1 (0.4%)	3 (0.6%)	
	White	189 (74.4%)	190 (78.5%)	379 (76.4%)	
Degree					0.873
	PhD	8 (3.1%)	6 (2.5%)	14 (2.8%)	
	GED	3 (1.2%)	1 (0.4%)	4 (0.8%)	
	HighSchool	45 (17.7%)	51 (21.1%)	96 (19.4%)	
	College	9 (3.5%)	10 (4.1%)	19 (3.8%)	
	BA	138 (54.3%)	122 (50.4%)	260 (52.4%)	
	MA	42 (16.5%)	42 (17.4%)	84 (16.9%)	
	Professional	9 (3.5%)	10 (4.1%)	19 (3.8%)	
Job					0.478
	Employed Full Time	161 (63.4%)	162 (66.9%)	323 (65.1%)	
	Employed Half Time	23 (9.1%)	26 (10.7%)	49 (9.9%)	
	Out of work	23 (9.1%)	20 (8.3%)	43 (8.7%)	
	Self-employed	17 (6.7%)	18 (7.4%)	35 (7.1%)	
	Student	9 (3.5%)	4 (1.7%)	13 (2.6%)	
	Unable to work	21 (8.3%)	12 (5.0%)	33 (6.7%)	
Income					0.512
	≤75k	106 (41.7%)	94 (38.8%)	200 (40.3%)	
	>75k	148 (58.3%)	148 (61.2%)	296 (59.7%)	
HoursWorkOnline		16.51 (15.14)	17.62 (15.14)	17.05 (15.13)	0.415
ComplicatedTask		2.50 (1.12)	2.51 (1.06)	2.51 (1.09)	0.965
EffortBuilding		2.20 (1.22)	2.21 (1.14)	2.21 (1.18)	0.925
ProudBuilding		2.56 (1.00)	2.59 (1.02)	2.57 (1.01)	0.760
EnjoyableBuilding		3.57 (0.87)	3.56 (0.84)	3.56 (0.86)	0.906
GeneralAttachment		2.96 (1.16)	2.85 (1.13)	2.90 (1.15)	0.287
StatsKnowledge		2.86 (0.94)	2.91 (0.94)	2.88 (0.94)	0.548
FinancialRisk		3.06 (0.98)	2.98 (0.92)	3.02 (0.95)	0.351
ExperienceStocks		0.55 (0.50)	0.58 (0.49)	0.57 (0.50)	0.481
ExperienceOtherFin		0.34 (0.48)	0.35 (0.48)	0.35 (0.48)	0.839
ExperienceSelfBuild		0.28 (0.45)	0.29 (0.45)	0.28 (0.45)	0.814
ExperienceMutualFund		0.49 (0.50)	0.51 (0.50)	0.50 (0.50)	0.653
ExperienceFinMarkets		0.61 (0.49)	0.58 (0.49)	0.60 (0.49)	0.532
ExperienceStatsCourse		0.45 (0.50)	0.49 (0.50)	0.47 (0.50)	0.438
ExperienceEconFinance		0.41 (0.49)	0.45 (0.50)	0.43 (0.50)	0.408
UnderstandingValuati		3.60 (0.81)	3.58 (0.78)	3.59 (0.79)	0.780
UnderstandingTrading		3.63 (0.84)	3.63 (0.79)	3.63 (0.81)	0.977
FinancialLiteracy		4.35 (1.33)	4.38 (1.54)	4.36 (1.44)	0.795
AttachDiff		0.52 (0.98)	0.56 (1.00)	0.54 (0.99)	0.668
HowOftenClicked		6.45 (5.45)	7.60 (11.35)	7.01 (8.84)	0.150
HowOftenHintTaken		0.03 (0.08)	0.04 (0.12)	0.04 (0.10)	0.143
HowOftenInfoClicked		0.17 (0.26)	0.18 (0.28)	0.18 (0.27)	0.580
ResponseTimeTer		51.40 (41.91)	59.52 (79.37)	55.36 (63.10)	0.153
CorrectTQ		1.27 (1.19)	1.17 (1.07)	1.22 (1.13)	0.295
TimeTQ		174.84 (180.34)	199.24 (329.97)	186.77 (264.31)	0.305
TimeNeededOverall		47.02 (30.72)	45.80 (26.19)	46.43 (28.58)	0.634

Table 4: Summary Statistics

Gender denotes a dummy that takes on a value of one if the participant is female. *Age* indicates the participants' age. *Ethnicity* denotes the participants' ethnicity. *Degree* indicates the participants' highest achieved degree. *Job* indicates the participants' current job. *Income* indicates the participants' household income in 2019. *HoursWorkOnline* indicates the number of hours a participant spends on online work per week. *ComplicatedTask* indicates how complex participants considered the portfolio-building task (range: 1-5). *EffortBuilding* indicates how much effort participants had to put into the portfolio-building task (range: 1-5). *ProudBuilding* indicates how proud participants are of having accomplished the portfolio-building task (range: 1-5). *EnjoyableBuilding* indicates how much participants enjoyed the portfolio-building task (range: 1-5). *GeneralAttachment* indicates how attached participants are to the self-built portfolio (range: 1-5). *StatsKnowledge* indicates how participants evaluate their knowledge about statistics (range: 1-5). *FinancialRisk* indicates participants' expressed willingness to take financial risk (range: 1-5). *ExperienceStocks* denotes a dummy that takes on a value of one if the participant has prior experience with investing in stock. *ExperienceOtherFin* denotes a dummy that takes on a value of one if the participant has prior experience with investing in other financial market instruments. *ExperienceSelfBuild* denotes a dummy that takes on a value of one if the participant has invested in a self-built financial portfolios. *ExperienceMutualFund* denotes a dummy that takes on a value of one if the participant has invested in a financial portfolio that was built by someone else. *ExperienceFinMarkets* denotes a dummy that takes on a value of one if the participant is generally interested in financial markets. *ExperienceStatsCourse* denotes a dummy that takes on a value of one if the participant has attended a university statistics course. *ExperienceEconFinance* denotes a dummy that takes on a value of one if the participant has attended a university Economics or Finance course. *UnderstandingValuati* indicates how participants evaluate their understanding of the valuation-task (range: 1-5). *UnderstandingTrading* indicates how participants evaluate their understanding of the trading-task (range: 1-5). *FinancialLiteracy* indicates the financial literacy score of participants (range: 0-6) *AttachDiff* indicates the difference in attachment between the self-built and the other portfolio. *HowOftenClicked* indicates how often participants needed to click to solve the first part of the portfolio-building task (on average over the five asset classes). *HowOftenHintTaken* indicates how often participants have taken a hint to solve the first part of the portfolio-building task (on average over the five asset classes). *HowOftenInfoClicked* indicates how often participants have looked up additional information during the first part of the portfolio-building task (on average over the five asset classes). *ResponseTimeTer* indicates how long participants needed to solve the first part of the portfolio-building task (on average over the five asset classes). *CorrectTQBDM* indicates how many control questions participants had answered correctly (range: 0-4). *TimeTQ* indicates how much time participants needed to answer the control questions. *TimeNeededOverall* indicates how much time participants needed for the whole experiment. For *Gender*, *Age*, *Degree*, *Job* and *Income* we tabulate the absolute and relative (in brackets) frequencies. For all other variables, we tabulate the mean and standard deviation (in brackets).

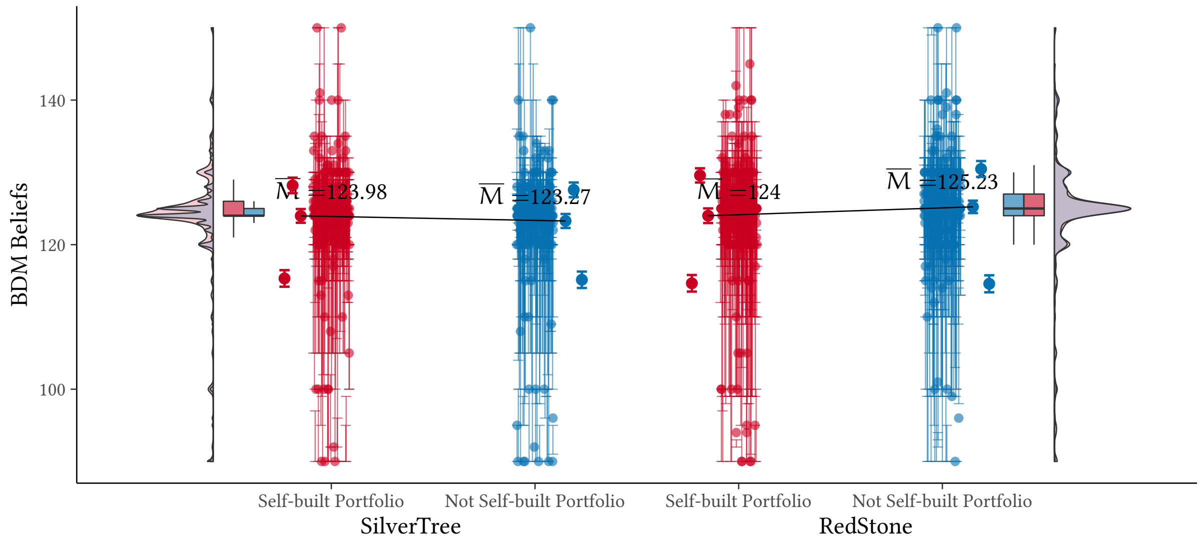


Figure 13: Beliefs Upon the Payoff of the Portfolio
Dots with surrounding tunnels denote individual belief responses, where the upper/lower end of the tunnel denotes the belief of the upper/lower end of the belief of the 95% confidence interval and where the dots denote the mean belief of a given participant. The boxes show the box plots. Left/right of the box plots, the distribution for each answer is shown for the portfolio SilverTree/RedStone. Red objects denote the responses for the self-built portfolio, while blue objects denote the responses for the not self-built portfolio. T-Bars indicate the 95% confidence intervals around the mean responses for the upper and lower end of the belief of the 95% confidence interval (top and bottom T-Bars) and the mean belief (middle T-Bars). The black line indicates the average change in mean belief responses.

C Beliefs

C.1 Beliefs Upon Payoff in Subsequent Period for the Valuation task

In this subsection, we take a look at the participants' belief of how the portfolio will develop in the subsequent period for the valuation task. Figure 13 shows the results. First of all, we see that the belief is indistinguishable from the mean payoff of the portfolio ($t(492) = 0.5$, $p \geq 0.05$). More importantly, we can see, as with the valuations, no significant difference between self-built and not self-built portfolios ($t(990) = 0.5$, $p \geq 0.05$, $d = 0.0$ (negligible)). This effect prevails even if we control for attachment and socio-economic demographics. Overall, this result is consistent with the documented null effect of self-building on the valuation of the portfolios.

C.2 Beliefs concerning the Future Realization in the Trading Task.

Next, we look at the beliefs concerning the future realization of the portfolio in the trading task. Figure 14 depicts the belief upon the future realization of the portfolio depending on the prior realization. First we see that the participants believe the portfolio to have a similar realization in the subsequent period similar to the prior realization ($t(491) = 0.8$, $p \geq 0.05$). In fact, the belief upon the future realization in the subsequent period is indistinguishable from the prior realization for all four prior realizations.

More importantly we again can see no significant difference between self-built portfolios ($M = 399.93$; $SD = 12.18$) and not self-built portfolios ($M = 399.15$; $SD = 14.75$) ($t(984) = 0.9$, $p \geq 0.05$, $d = 0.1$ (negligible)). This again holds true for all four possible prior realizations of the respective portfolios.[27] This effect prevails again even if control for attachment and socio-economic demographics. Overall, this result is consistent with the previous finding that self-building does not affect trading decisions after receiving new signals.

C.3 Information Processing

Lastly, we take a look at the information processing underlying the valuation decision. More specifically, we study how often participants have viewed winning information (i.e., the probabilities of payoffs above the mean) and losing information (i.e., the probabilities of payoffs below the mean). Figure 15 shows how often participants have hovered over winning and losing information. Firstly, we see that participants have hovered substantially more over winning (M = 10.97; SD = 11.80) compared to losing (M = 8.08; SD = 9.24) information ($t(492) = 8.3$, $p \leq 0.001$, $d = 0.3$ (small)). More interestingly, we can see no significant difference between self-built and not self-built portfolios ($t(984) = 0.0$, $p \geq 0.05$, $d = 0.0$ (negligible)).

D Additional Tables

Tables 5 and 6 display the effect of self-building on both the valuation and trading behavior for participants who value SilverTree and RedStone differently.

[27] Very negative (a loss of 4.5%) prior realization: $t(984) = 0.6$, $p \geq 0.05$, $d = 0.0$ (negligible); slightly negative (a loss of 1.5%) prior realization: $t(984) = 0.2$, $p \geq 0.05$, $d = 0.0$ (negligible); very positive (a gain of 4.5%) prior realization: $t(984) = 0.9$, $p \geq 0.05$, $d = 0.1$ (negligible); slightly positive (a gain of 1.5%) prior realization: $t(983) = 1.0$, $p \geq 0.05$, $d = 0.1$ (negligible).

	Valuation of the portfolio (minimum selling price)				
	Pooled	RedStone		SilverTree	
Constant	124.25*** (0.28)	124.50*** (0.43)	116.06*** (4.58)	123.88*** (0.34)	121.30*** (3.65)
Self-built	0.22 (0.31)	0.47 (0.60)	−0.12 (0.52)	0.19 (0.47)	0.28 (0.48)
Belief			2.04*** (0.25)		0.87*** (0.24)
Attachment			0.02 (0.28)		−0.07 (0.23)
FinancialLiteracy			0.28 (0.21)		0.50*** (0.18)
FinancialRisk			0.65** (0.32)		0.01 (0.26)
Controls	×	×	✓	×	✓
Sbj specific effects	✓	✓	✓	✓	✓
LogLik	-2460.67	-1292.05	-1238.45	-1177.89	-1155.41
Observations	794	397	397	397	397
Akaike Inf. Crit.	4,929.35	2,592.11	2,518.90	2,363.77	2,352.82
Notes:					*p $<$ 0.1;**p $<$ 0.05;***p $<$ 0.01

Table 5: Regressions on the Valuation of the Portfolio for Participants Who Change Their Valuation Between the Two Portfolios.

Self-built denotes a dummy that takes on a value of one if the participant has self-built the respective portfolio, and zero otherwise. *SilverTree* denotes a dummy that takes on a value of one for the portfolio SilverTree, and zero for RedStone. *Belief* denotes the z-scored beliefs. *Attachment* indicates how attached participants indicated to feel to the respective portfolio. *FinancialLiteracy* indicates the financial literacy score of participants (from 0-6 based on 6 questions as in the National Financial Capability Study (NFCS) by the FINRA Investor Education Foundation). *FinancialRisk* indicates participants' expressed willingness to take financial risk (range: 1-5). Controls include educational attainment, employment status, age, gender, ethnicity, and how many hours participants work online. All regressions account for participant-specific effects. Column (1) shows the pooled data. Columns (2-3) shows the behavior in the portfolio RedStone and Columns (4-5) shows the behavior in the portfolio SilverTree. This table displays the behavior of participants who indicated to have a different valuation between RedStone and SilverTree, only.

	Trading decision											
	t_{-1} =Loss ($\sim$ 4.5%)			t_{-1} =Loss ($\sim$ 1.5%)			t_{-1} =Gain ($\sim$ 4.5%)			t_{-1} =Gain ($\sim$ 1.5%)		
Constant	0.42^{***} (0.02)	0.46^{***} (0.03)	0.74^{***} (0.28)	0.36^{***} (0.02)	0.41^{***} (0.03)	0.61^{**} (0.30)	0.47^{***} (0.03)	0.49^{***} (0.03)	0.18 (0.32)	0.21^{***} (0.02)	0.26^{***} (0.03)	0.32 (0.26)
Self-built	0.02 (0.02)	−0.04 (0.05)	0.02 (0.02)	0.01 (0.02)	−0.03 (0.05)	0.01 (0.02)	0.03 (0.02)	0.02 (0.05)	−0.004 (0.02)	0.03 (0.02)	−0.001 (0.04)	0.02 (0.02)
SilverTree		-0.10^{**} (0.05)			-0.11^{**} (0.05)			−0.03 (0.05)			-0.09^{**} (0.04)	
Self-built x SilverTree		0.12 (0.09)			0.08 (0.08)			0.01 (0.09)			0.06 (0.07)	
Belief			-0.23^{***} (0.02)			-0.14^{***} (0.02)			-0.18^{***} (0.02)			-0.11^{***} (0.02)
Attachment			0.02 (0.01)			0.02 (0.02)			-0.04^{**} (0.02)			−0.01 (0.01)
FinancialLiteracy			−0.02 (0.01)			-0.04^{**} (0.02)			0.03^{*} (0.02)			-0.04^{***} (0.01)
FinancialRisk			-0.04^{*} (0.02)			-0.05^{**} (0.02)			−0.02 (0.02)			−0.03 (0.02)
Controls	×	×	✓	×	×	✓	×	×	✓	×	×	✓
Sbj specific effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LogLik	-502.61	-504.67	-439.14	-486.22	-486.26	-477.39	-491.21	-495.01	-465.06	-414.07	-415.11	-423.55
Observations	794	794	794	794	794	794	794	794	794	794	794	794
Akaike Inf. Crit.	1,013.22	1,021.33	920.27	980.44	984.52	996.79	990.42	1,002.03	972.13	836.15	842.21	889.11

Notes: *p < 0.1;**p < 0.05;***p < 0.01

Table 6: Regressions on the Propensity to Sell by Prior Realization for Participants Who Change Their Valuation Between the Two Portfolios.

Self-built denotes a dummy that takes on a value of one if the participant has self-built the respective portfolio, and zero otherwise. *SilverTree* denotes a dummy that takes on a value of one for the portfolio SilverTree, and zero for RedStone. *Belief* denotes the z-scored beliefs. *Attachment* indicates how attached participants indicated to feel to the respective portfolios. *FinancialLiteracy* indicates the financial literacy score of participants (from 0-6 based on 6 questions as in the National Financial Capability Study (NFCS) by the FINRA Investor Education Foundation). *FinancialRisk* indicates participants' expressed willingness to take financial risk (range: 1-5). Controls include educational attainment, employment status, age, gender, ethnicity, and how many hours participants work online. All regression account for participant-specific effects. Columns (1)-(3) depict decisions in case the prior realization was strongly negative (a loss of 4.5%). Columns (4)-(6) depict decisions in case the prior realization was slightly negative (a loss of 1.5%). Columns (7)-(9) depict decisions in case the prior realization was strongly positive (a gain of 4.5%). Columns (10)-(12) depict decisions in case the prior realization was slightly positive (a gain of 1.5%). This table displays the behavior of participants who indicated to have a different valuation between RedStone and SilverTree, only.

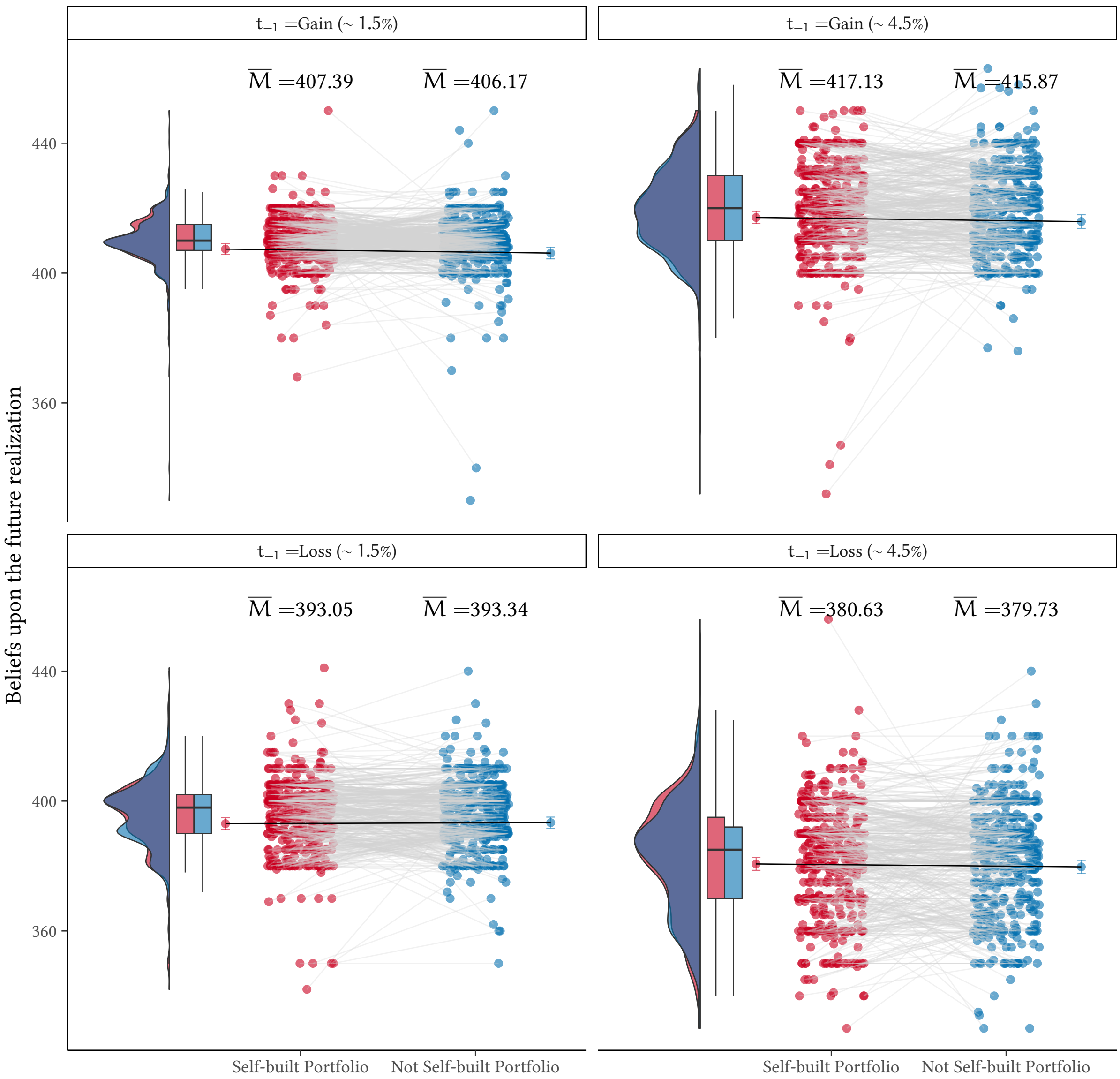


Figure 14: Beliefs Upon the Future Realization of the Portfolio.
Dots denote individual (jittered) beliefs upon the future realization of the portfolio. Grey lines show the participant-specifc changes. The boxes left of the dot clouds show the box plots. Left of the boxplots the distribution is shown. Red objects denote the beliefs for the self-built portfolios while blue objects denote the not self-built portfolios. T-Bars denote the 95% confidence intervals around the mean response, with the black line indicating the average change in responses. The top left panel show the trading decisions if the prior realization was slightly positive (a gain of 1.5%). The top right panel shows the trading decisions if the prior realization was very positive (a gain of 4.5%). The bottom left panel shows the trading decisions if the prior realization was slightly positive (a loss of 1.5%). The bottom right panel shows the trading decisions if the prior realization was very positive (a loss of 4.5%).

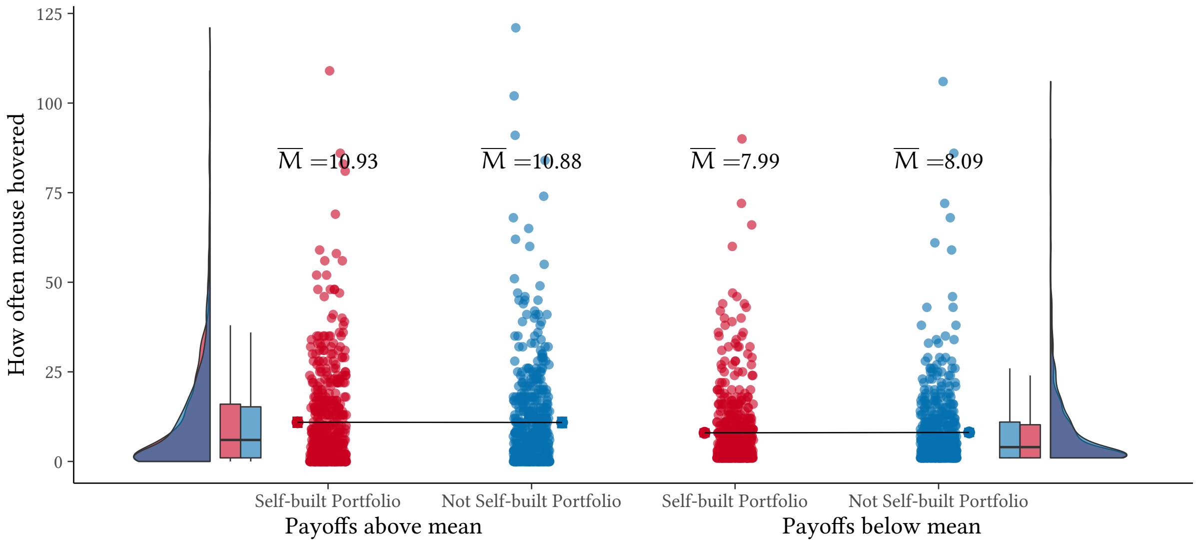


Figure 15: Information Acquisition

Dots denote individual hovering behavior (jittered). The left panel shows how often winning information (i.e., payoffs above the mean payoff of the portfolio) was hovered over. The right panel shows how often losing information (i.e., payoffs below the mean payoff of the portfolio) was hovered over. The boxes left/right of the dot clouds show the boxplots. Left/right of the box plots the distribution is shown. Red objects denote the responses for the self-built portfolio, while blue objects denote the not self-built portfolio. T-Bars indicate the 95% confidence intervals around the mean responses. The black line indicates the average change in mean hovering behavior.

E Online Appendix: Instructions

Below we display the original instructions. Figure 16 shows the flow of the instructions in this section.

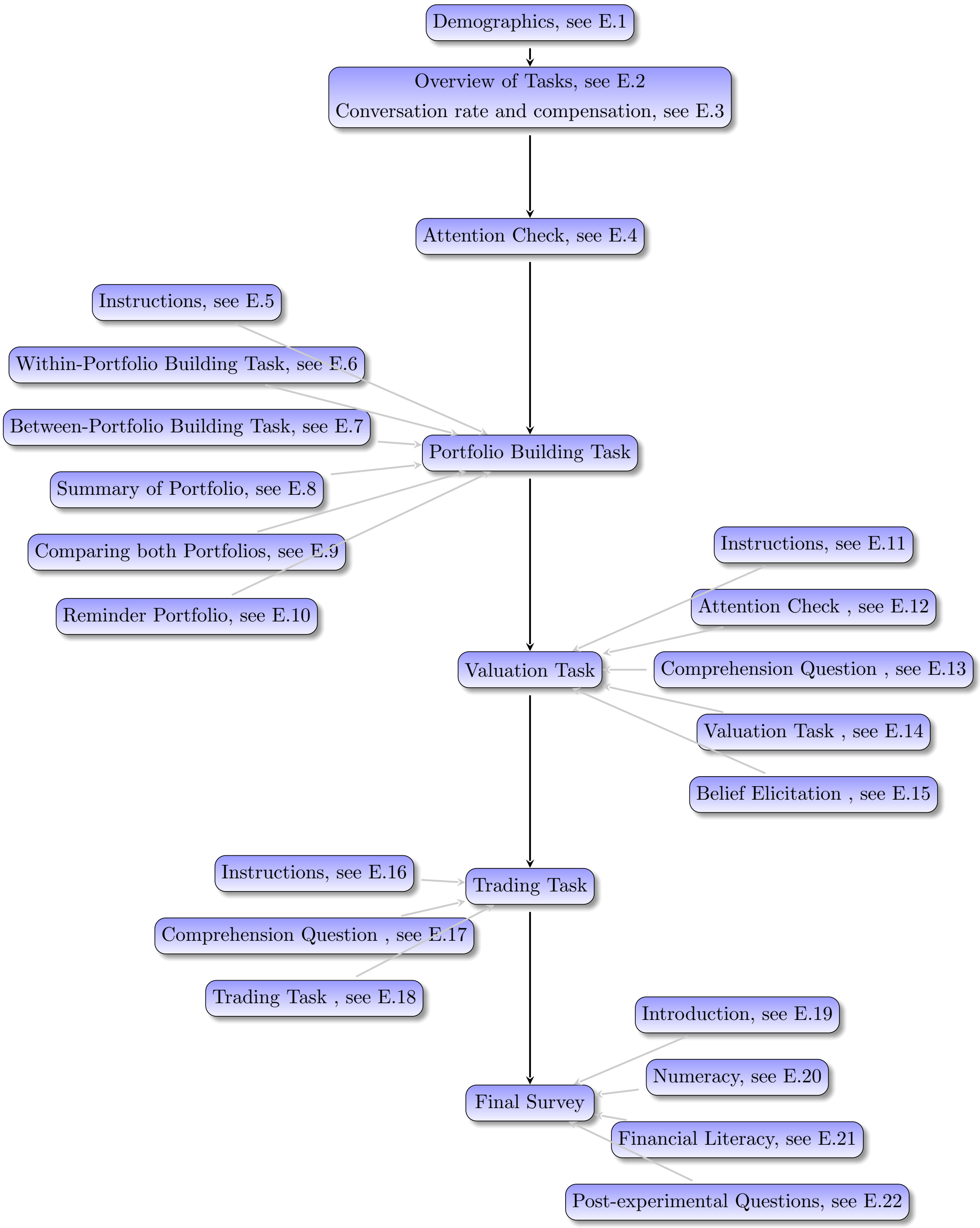


Figure 16: Overview of the Instructions.

E.1 Screen 2: Demographics

Introduction: Demographics

Please answer the following questions about yourself. This information will only be used for statistical purposes.

- "Please indicate your gender assigned at birth." (Answer: "male" or "female")
- "How old are you?"
- "What is your highest educational degree? If you cannot find your degree in the following list, please indicate which degree from the list is closest to your actual degree."
  - Haven't graduated high school.
  - GED
  - High school graduate
  - Currently in college
  - Bachelors
  - Masters
  - Professional degree (JD, MD, MBA)
  - Doctorate
- What is your current employment status?
  - Employed full-time
  - Employed part-time
  - Independent, or business owner
  - Out of work, or seeking work
  - Student
  - Out of labor force (e.g. retired or parent raising one or more children)
- How high was your total household income, before taxes, last year (2019)?
  - $0 - $9,999
  - $10,000 - $14,999
  - $15,000 - $19,999
  - $20,000 - $29,999
  - $30,000 - $39,999
  - $40,000 - $49,999
  - $50,000 - $74,999
  - $75,000 - $99,999
  - $100,000 - $124,999
  - $125,000 - $149,999
  - $150,000 - $199,999
  - $200,000+
- In which state do you live?
- Which of the following best describes your race or ethnicity
  - Hispanic or Latino
  - American Indian or Alaskan Native
  - Asian
  - Native Hawaiian or Other Pacific Islander
  - Black or African American
  - White
- How many hours per week do you spend online doing tasks for money?

E.2 Screen 3 (General Overview Over Our Tasks)

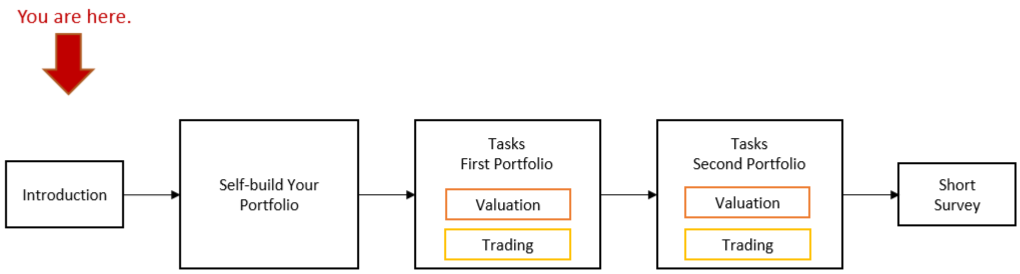
Overview of the Experiment

Before you start with the tasks, here is a short overview of what is to come: First, you will be building a portfolio of financial assets with the help of the instructions provided. More precisely, you will be provided with the structure of a target portfolio and you have to set up this portfolio by combining individual financial assets correctly.

Next, there will be two additional task types. In one task type, you will be asked to value financial portfolios (valuation-task). In the other task type, you will have to make trading decisions about financial portfolios (trading-task). For these two task types, you will not only face the portfolio built previously, but also another portfolio.

Afterwards, there is a short survey that you need to complete in order to get your reward and your bonus payment.

Below you can find a graphical overview of your upcoming tasks:



Note that one of the main guidelines in the experimental economics is that we do NOT deceive participants (see, for example, https://en.wikipedia.org/wiki/Experimental_economics). All rules and restrictions will be implemented in the way we describe them. We go to great lengths to ensure that assignments, randomization of variables and rules are implemented exactly in the way they are presented here to you!

As soon as you leave this screen, the experiment begins.

E.3 Screen 4 (Instructions Compensation)

Your Compensation

In each task, you can earn Wonderland Coins (WC) based on your performance. After the experiment, we will randomly draw one of the tasks and transfer the amount of coins earned in this task to your Wonderland account. We convert the coins in your Wonderland account into US Dollars and this amount will be your performance-based bonus. The overall MTurk bonus payment, in addition to your reward of \$ 1, will be the performance-based bonus plus the fixed bonus of \$ 0.50 for finishing the survey at the end of the experiment. The conversion from Wonderland Coins into US Dollars works as follows:

Performance-Based Bonus in US Dollars = (Wonderland Coins - 90) * 0.12

In total, you can earn between \$1.50 and \$10.50 dollars (reward of \$1.00 + fixed bonus of \$0.50 + performance-based bonus) for participating in the experiment.

E.4 Screen 5 (Preparation Experiment)

Preparation Task

Let us start with a short preparation task.

In this preparation experiment you see several rows of probabilities and payoffs. In the first row you see a probability of 20% and a payoff of \$1.90 for option A. The second row shows a probability of 30% for a payoff of \$1.80 for option B. The third row shows a probability of 40% and a payoff of \$1.70 and so on.

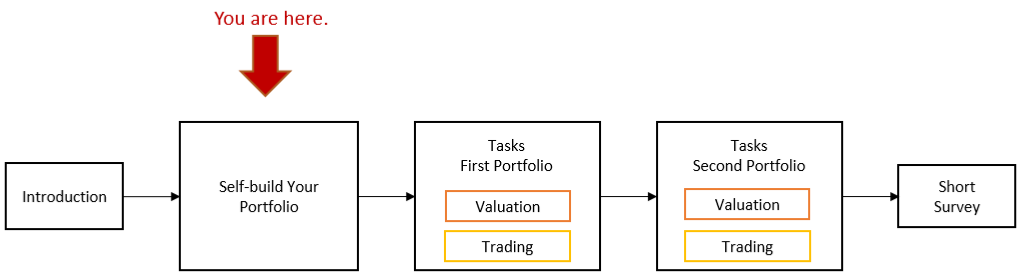
All this is not relevant for your task. The only purpose of this task is to exclude all those workers who do not even read the instructions for the experiment. This is necessary to ensure that only attentive respondents are considered for our study in order to ensure interpretable answers. Your task is to just pick the third row. This way we know you have read the instructions. Choosing any other row will lead to the direct exclusion from the experiment and any payment.

Please choose one option:

- Option A: Probability 20% and \$1.90
- etc.

E.5 Screen 6 (Instructions Portfolio Building)

Building Your Portfolio: Introduction



A portfolio is a mix of financial assets. You now begin to build your portfolio. More precisely, a financial expert will provide you with the final structure of a target portfolio. This portfolio is called “RedStone”/“SilverTree”.

RedStone SilverTree

Your task is to exactly set up portfolio “RedStone”/“SilverTree”by putting together the individual financial assets correctly.

In order to successfully build your portfolio, you should be familiar with the following concepts:

A financial portfolio can be characterized by its **return** and **risk**.

Portfolio Return: The value change of your portfolio relative to the price you paid when you bought it.

Example: You bought a portfolio for 100 Wonderland Coins (WC). After some time, you sell the portfolio for 110 WC. This means that the value of your portfolio has increased by 10 WC. Hence, the return of this portfolio is $\frac{10}{100} = 10\%$.

Portfolio Risk: Portfolio returns are **uncertain**. If a portfolio has an average return of 10% there are some cases where the return is lower than 10% and some cases where the return is higher than 10%. We provide a risk value that captures the likely variation (i.e. what happens in about 70% of cases) around the average return, which is often also called "standard deviation" or "volatility".

Example: You bought a portfolio with a return of 10% and a risk value of 5%. This means that in the past in about 70% of the cases the return was between 5% and 15%.

Adjusting Risk and Return of a Portfolio: By changing the weights of the individual assets in your portfolio you can adjust the return and risk of the portfolio. For instance, if you put a higher weight on an asset that has a high return, you can increase the portfolio return. If you put a higher weight on an asset that has a low risk value, you can reduce the portfolio risk. Usually, there is a trade-off between return and risk. Hence, a portfolio that is more risky is also more likely to provide a higher return.

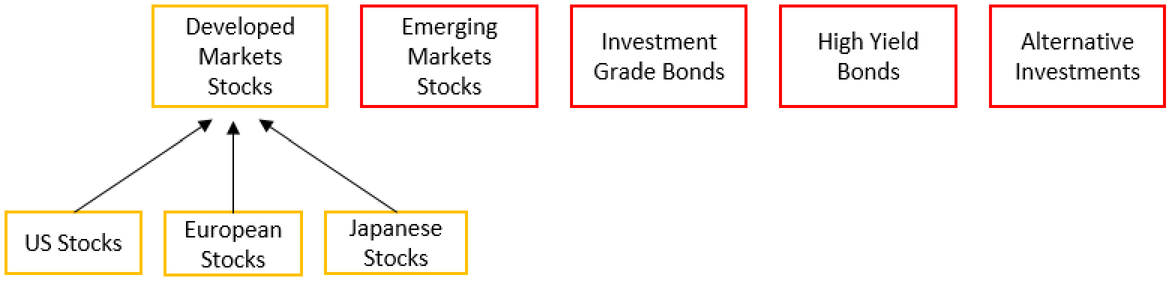
In the following, your target portfolio has a specific return and risk value. Your task is then to set up this portfolio. To do so, you have to select the weights of the individual assets such that your portfolio precisely matches the target return and risk value.

The portfolio you will construct consists of five different broad **asset classes**. These five asset classes are "developed markets stocks", "emerging markets stocks", "investment grade bonds", "high yield bonds", and "alternative investments":

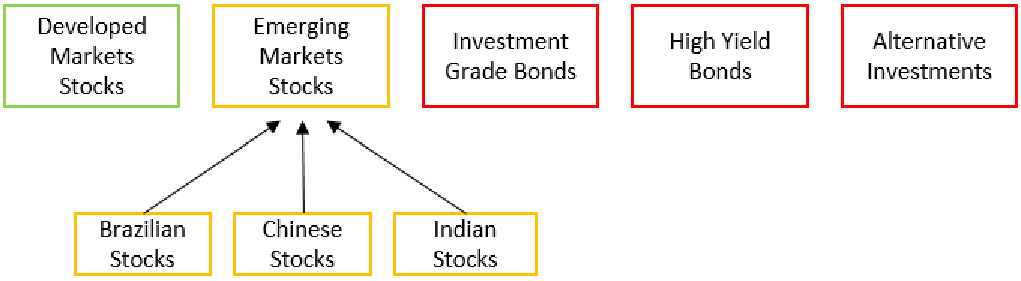
Each *asset class* in turn is constructed separately from three different *assets*. Therefore, the portfolio building process encompasses several steps:

First, you will combine the three different assets within an asset class by determining their weights in the asset class. To guide you, there will be sub-targets for the return and risk value within an asset class that you have to achieve. You will repeat this step five times for the five different asset classes.

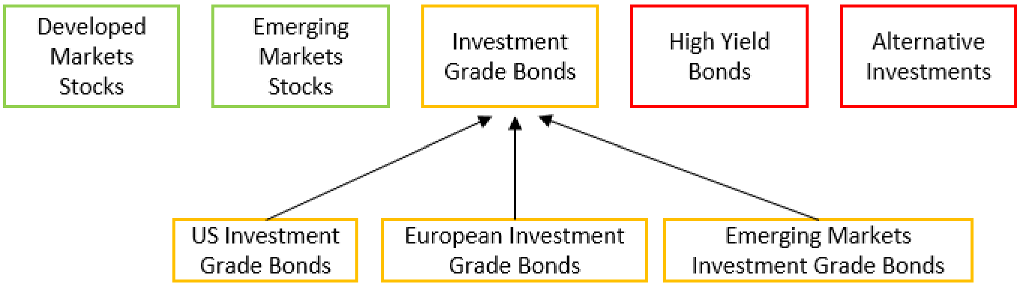
Hence, you will begin with the first asset class "developed markets stocks" and fix the weights of the three included assets "US stocks", "European stocks", and "Japanese stocks":

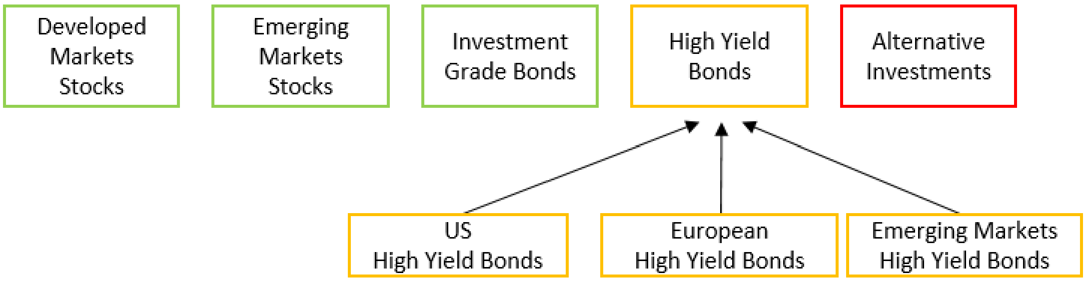


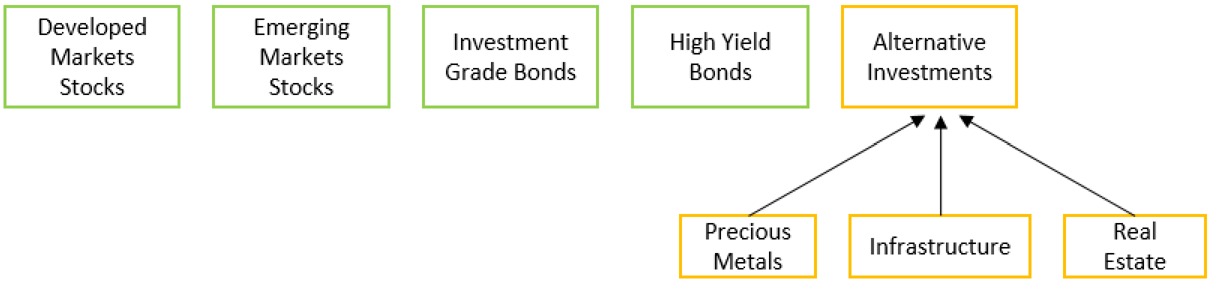
Afterwards, you will continue with the second asset class "emerging markets stocks" for which you have to fix the weights of the three included assets "Brazilian stocks", "Chinese stocks", and "Indian stocks":



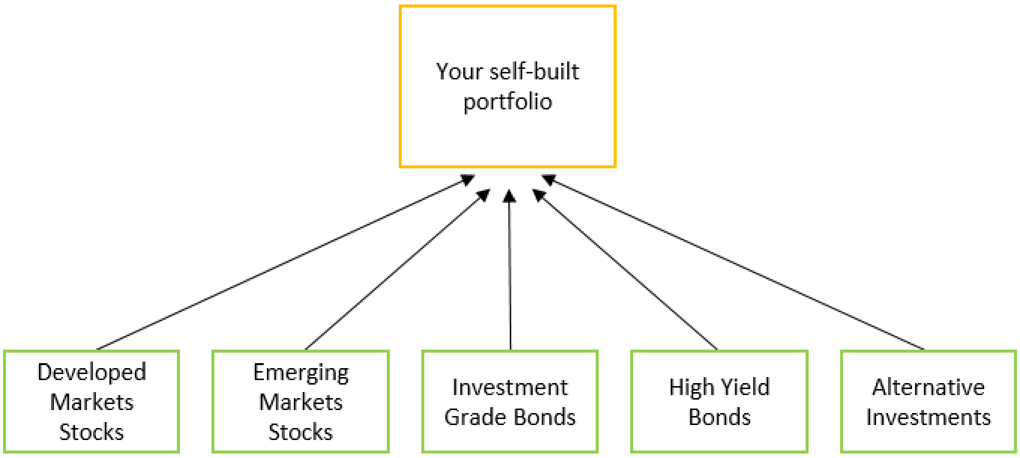
You will continue doing this step-by-step for the remaining three asset classes "investment grade bonds", "high yield bonds", and "alternative investments":







Afterwards, you will put together the five asset classes to form your final portfolio. For this last step, you will have to determine the weights of the five asset classes.



On the next screen you will actually start combining the three assets of the first asset class, "stocks developed markets"!

E.6 Screens 7 - 11 (Within-Portfolio Building Task)

Step X out of 5

You now select the components of **asset class X** for your portfolio "RedStone". In order to match your target portfolio, you have to obtain a **return of Y** and a **risk value of Z** for this asset class.

To do so, you can change the weights of the individual assets by clicking on a point on the triangular grid below. Next to the triangle, you can see the resulting return and risk value for your current selection. After you have achieved the target, you will see a "YES" in the "Target Achieved?" row of the table. You can then proceed by clicking the button that appears below.

- **Developed Markets Stocks:** If you buy a stock you are a partial owner of the company. The return of this investment depends on the performance of the company. The better the company performs, the higher the return. Stocks from developed markets include companies that are based in countries with a high economic output given the size of the population, such as the US, Europe, Japan, Australia, Canada, South Korea, etc..

- **Emerging Markets Stocks:** If you buy a stock you are a partial owner of the company. The return of this investment depends on the performance of the company. The better the company performs, the higher the return and the other way around. Stocks from emerging markets include companies that are based in countries with a low but increasing economic output given the size of the population, such as Brazil, China, India, Russia, Mexico, South Africa, etc..
- **Investment Grade Bonds:** If you buy a bond, you lend money to a company. The company has to pay you back your money plus additional interest when the bond expires. You lose money if the company files for bankruptcy. Investment Grade bonds are bonds from companies that have very sound financials and thus a very small default risk.
- **High Yield Bonds:** If you buy a bond, you lend money to a company. The company has to pay you back your money plus additional interest when the bond expires. You lose money if the company files for bankruptcy. High yield bonds are bonds from companies that have a higher default risk. However, these bonds typically offer higher interest rate payments to compensate for the higher risk.
- **Alternative Investments:** Alternative investments are investments that are different from traditional investments like stocks and bonds. Adding alternative investments to a portfolio helps to further spread the risk of your portfolio across different asset classes.

E.7 Screen 12 (Between-Portfolio Building Task)

Combine the Asset Classes

You have now completed combining the assets within each of the five asset classes of portfolio "RedStone"/"SilverTree". Finally, the last task of the building process is to put together the five classes to form your final portfolio.

You can determine the importance of the asset classes by selecting their weights in your final portfolio. This is accomplished by adding the asset classes one-by-one. In each step, you determine the weight of the asset class that is to be added.

The pie chart below and the tables next to it provide you with information on the current composition of your final portfolio as well as return and risk values. You can change the weight of the current asset class with the slider below the pie chart.

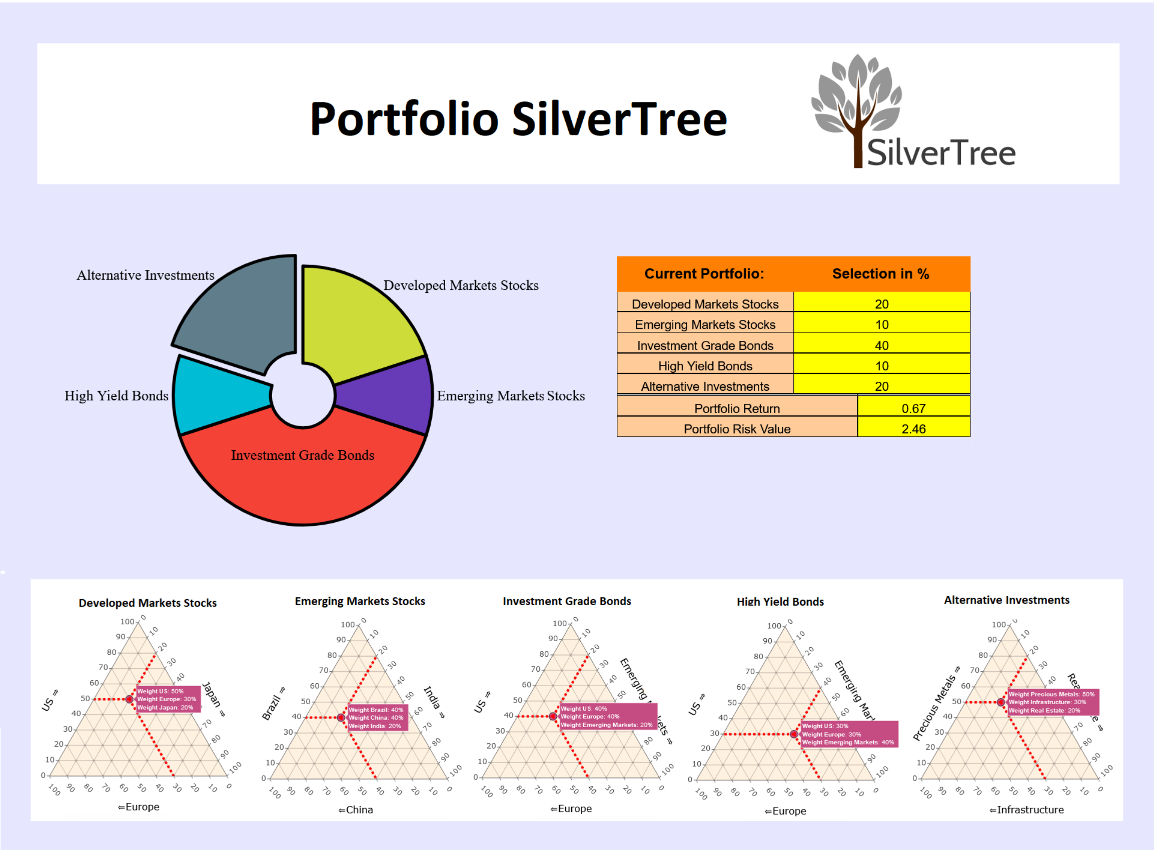
At each step there is a return and risk value target to be obtained. By using the slider, you can change the return and risk value of your selection until you have achieved the target values. After you have achieved the target for the current asset class, you will see a "YES" in the "Target Achieved?" row of the table. You can then proceed to the next asset class by clicking the button that appears below the pie chart. After you have worked through the five asset classes, your portfolio "RedStone"/"SilverTree" is completed and you can proceed by clicking on the next button.

E.8 Screen 13 (Final Screen – Portfolio Self-Building)

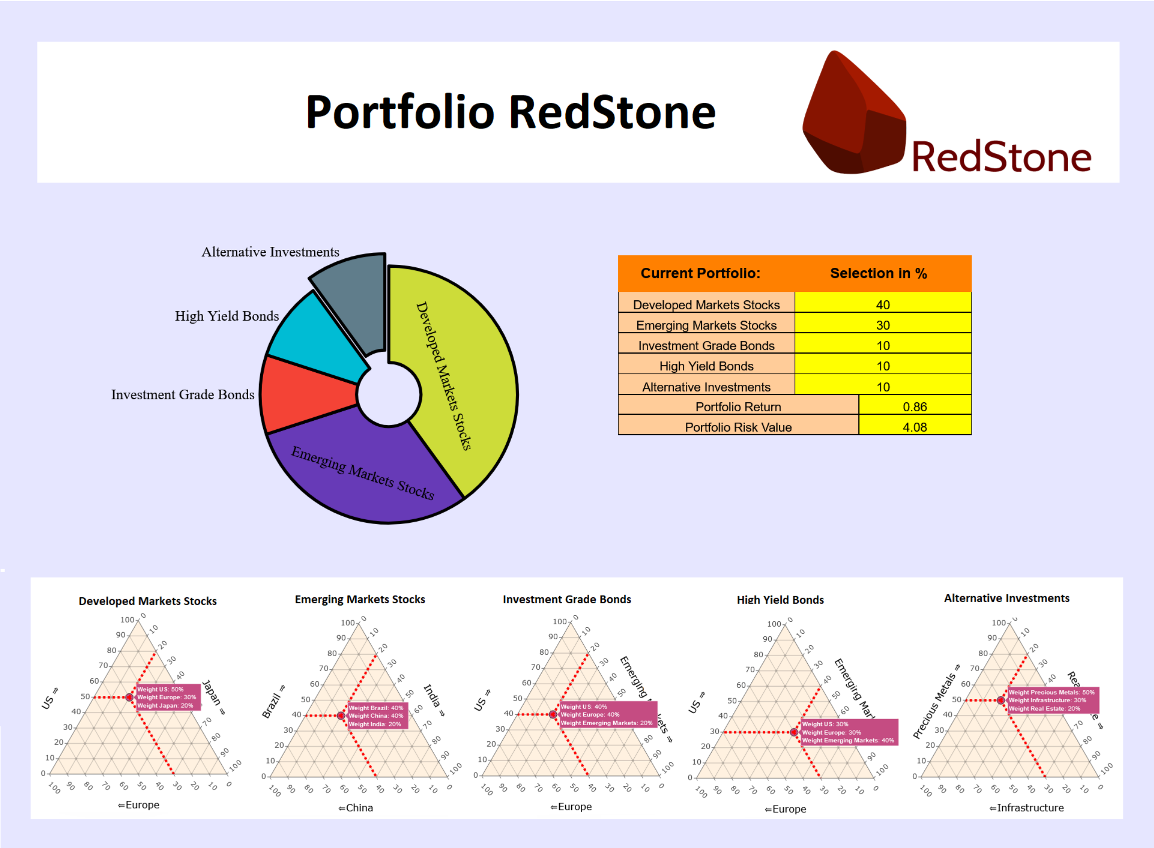
Building Your Portfolio: Summary

You have now successfully finished building your portfolio “RedStone”/“SilverTree”!

Below you can see the final structure of the portfolio that is based on the weights you specified in all the previous steps. Your portfolio “RedStone”/“SilverTree”has an average monthly return of ”0.86%”/”0.67%” and a risk value of ”4.08%”/”2.46%”.



Current Portfolio:	Selection in %
Developed Markets Stocks	20
Emerging Markets Stocks	10
Investment Grade Bonds	40
High Yield Bonds	10
Alternative Investments	20
Portfolio Return	0.67
Portfolio Risk Value	2.46



You can now proceed with the valuation and trading tasks by clicking on the next button. **Remember that these tasks will determine the amount of WC that you earn for your Wonderland account!**

E.9 Screen 14 (Introduction of Not Self-built Portfolio) and Comparison with Self-built Portfolio

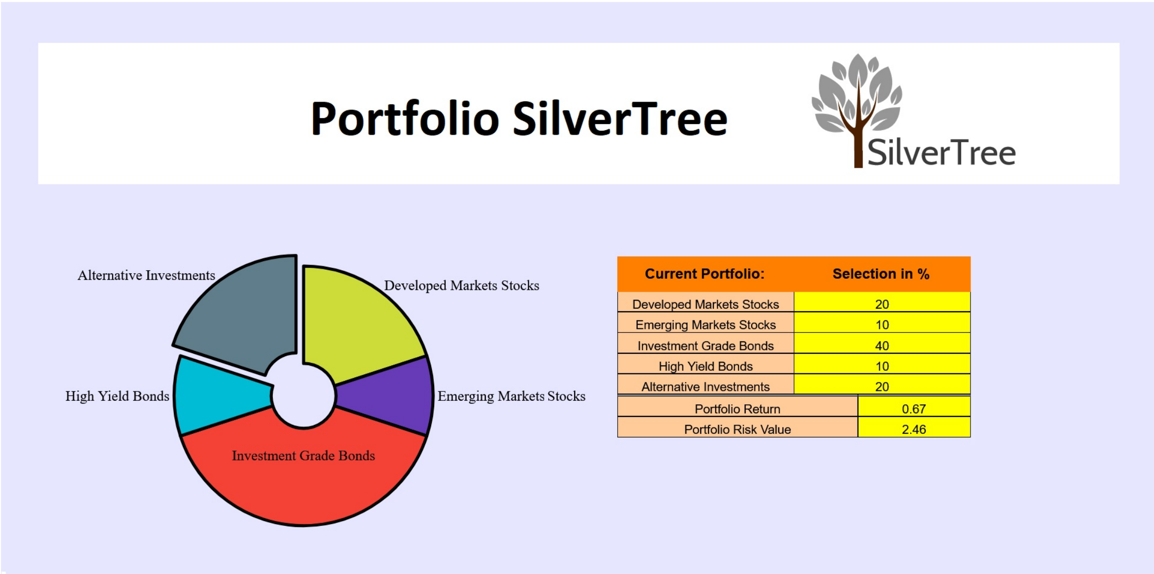
Comparing Your Portfolio to the Second Portfolio

In the following, you will do a valuation and a trading task for your self-built portfolio "RedStone"/"SilverTree" as well as for another portfolio "SilverTree"/"RedStone".

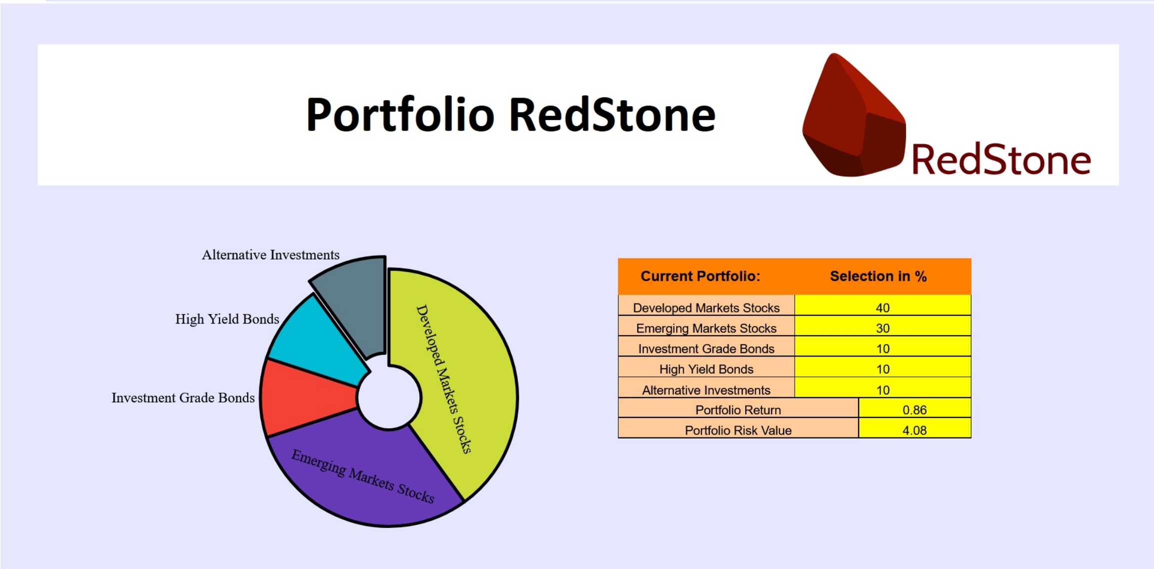
Portfolio "SilverTree"/"RedStone" is a **different portfolio than the one you built before**. It is offered by the same financial expert who also provided you with the target structure of your portfolio "SilverTree"/"RedStone" before. Portfolio "SilverTree"/ "RedStone" consists of the same asset classes as your self-built portfolio. The components of the asset classes and their weights within the respective asset classes are also the same. **However, the weights of the asset classes are different such that the return and risk value of the portfolio are different.**

More precisely, portfolio "SilverTree"/"RedStone" has an average monthly return of "0.67%"/"0.86%" and a risk value of "2.46%"/"4.08%". Hence, portfolio "SilverTree"/"RedStone" has a "lower"/"higher" return but also a "lower"/"higher" risk value than portfolio "RedStone"/"SilverTree". You can find information about the structure of portfolio “SilverTree”/“RedStone”below.

In order to compare the two portfolios, you can once again find information about the structure of portfolio “RedStone”/“SilverTree”, the one you built before, below. Portfolio “RedStone”/“SilverTree”has an average monthly return of ”0.86%”/”0.67%” and a risk value of ”4.08%”/”2.46%”.



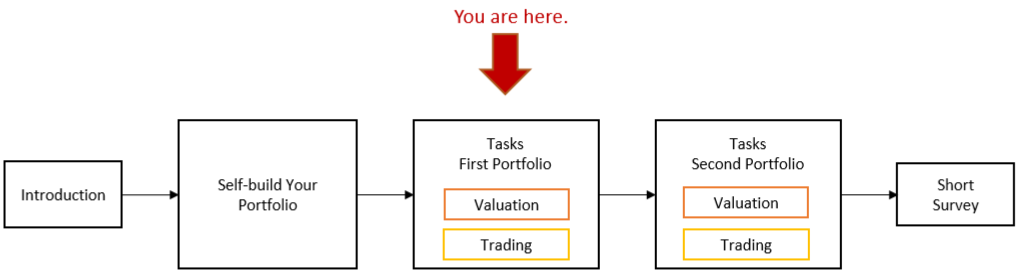
Current Portfolio:	Selection in %
Developed Markets Stocks	20
Emerging Markets Stocks	10
Investment Grade Bonds	40
High Yield Bonds	10
Alternative Investments	20
Portfolio Return	0.67
Portfolio Risk Value	2.46

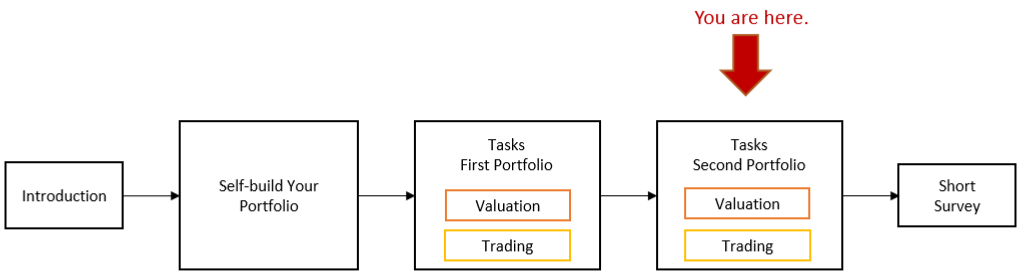


Current Portfolio:	Selection in %
Developed Markets Stocks	40
Emerging Markets Stocks	30
Investment Grade Bonds	10
High Yield Bonds	10
Alternative Investments	10
Portfolio Return	0.86
Portfolio Risk Value	4.08

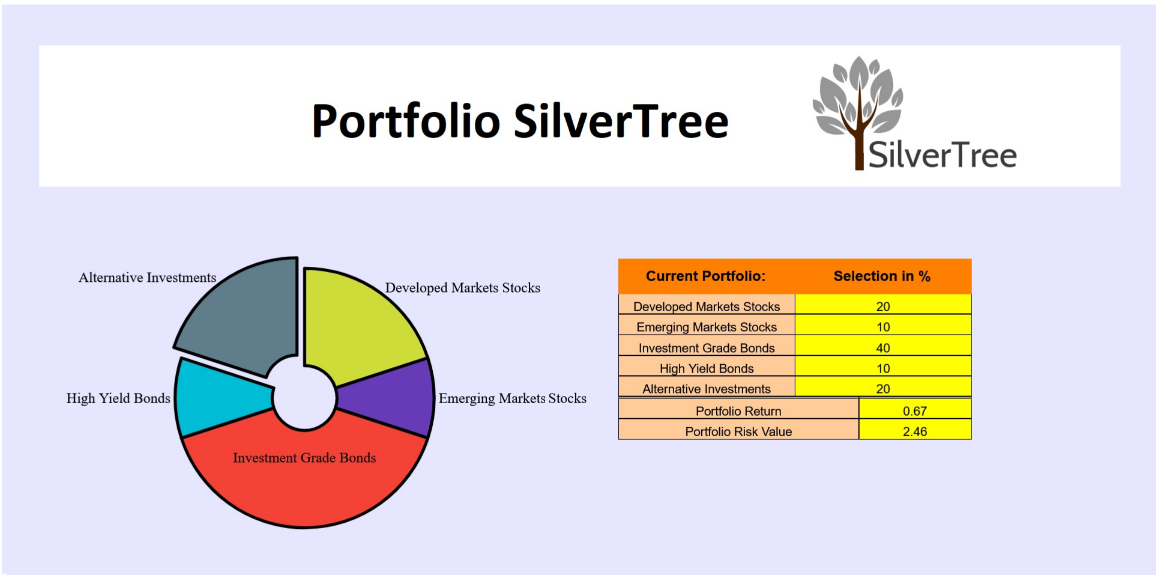
By clicking on the next button you begin with the valuation and trading tasks for each of the two portfolios.

E.10 Screen 15 (Instructions Valuation and Disposition General First Portfolio)

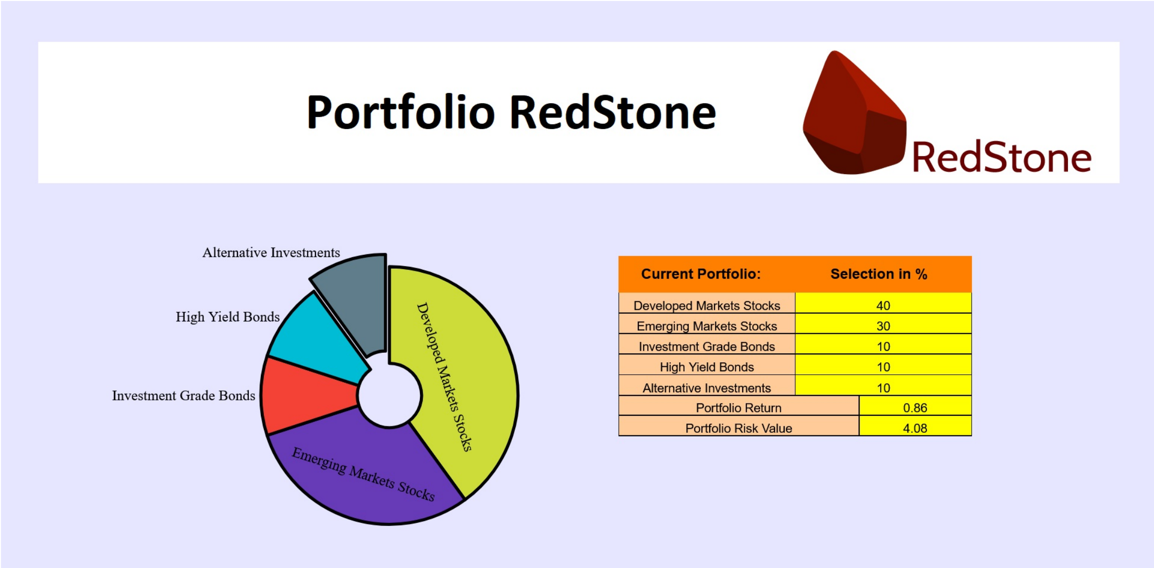




In the following, you will be doing a valuation as well as a trading decision task. [INSERT A OR B] A: You should now consider portfolio "RedStone"/"SilverTree"for these tasks, **the one you built before.** As a reminder, you can once again find information about the structure of the portfolio below. Portfolio "RedStone"/"SilverTree"has an average monthly return of "0.86%"/"0.67%" and a risk value of "4.08%"/"2.46%".



B: You should now consider portfolio "SilverTree"/"RedStone"for these tasks, the one that is **different than the one you built before.** As a reminder, you can once again find information about the structure of portfolio “RedStone”/“SilverTree”below. Portfolio “RedStone”/“SilverTree”has an average monthly return of ”0.67%”/”0.86%” and a risk value of ”2.46%”/”4.08%”.



E.11 Screen 16 (Instructions Valuation Task)

How to Do the Valuation Task

You will now do the valuation task.

[In second pass: The task is the same as what you have already done for the other portfolio. We provide the instruction below again for your reference. The instructions have not changed.]

Assume that you actually own portfolio “RedStone”/“SilverTree”. You can take one of two actions. Either you sell the portfolio right now or you hold on to it for one more period.

If you hold on to the portfolio, the amount of WC that you can earn for your Wonderland account solely depends on the unknown payoff of the portfolio one period later. There are no additional periods to be played afterwards and you will not have the opportunity to stay invested afterwards. Since the portfolio is risky, the payoff of the portfolio in one period might be larger or smaller than the price you could get if you sell immediately. We will randomly draw a payoff based on the payoffs and probabilities from real-world financial market data. You will be provided with the possible payoffs of the portfolio in the next period and how likely they are as a basis for your decision.

Instead of keeping the portfolio, you might sell the portfolio immediately if you can achieve a price you deem sufficient as a compensation for giving up the portfolio. In this case, the amount of WC that you can earn for your Wonderland account does not depend on the payoff of the portfolio in the next period. Of course, this decision depends on the price that you will get if you sell the portfolio.

For this reason, we would ask you to evaluate the following list of scenarios for the selling price:

Scenario #		Option A		Option B
1	Would you rather:	Keep the portfolio	or	Sell it for 90 WC.
2	Would you rather:	Keep the portfolio	or	Sell it for 91 WC.
3	Would you rather:	Keep the portfolio	or	Sell it for 92 WC.
⋮	⋮	⋮	⋮	⋮
60	Would you rather:	Keep the portfolio	or	Sell it for 149 WC.
61	Would you rather:	Keep the portfolio	or	Sell it for 150 WC.

For each scenario, you pick either Option A (keep the portfolio) or Option B (sell the portfolio for the indicated price). After you answer all 61 scenarios, we will randomly pick **one** scenario that is to be played. Hence, we use the option you chose on **that** one scenario. If you decided to sell the portfolio in **that** scenario, you earn the indicated selling price of **that** scenario for your Wonderland account. If you decided to keep the portfolio in **that** scenario, the amount of WC that you can earn for your Wonderland account solely depends on the unknown payoff of the portfolio one period later. NOTE: To check whether you read the instructions, on the next screen we will ask you how many scenarios, we will randomly pick! The correct answer is "one"! Choosing any other answer will lead to the direct exclusion from the experiment and any payment.

Each scenario is equally likely to be chosen.

We assume you are going to keep the portfolio (Option A) in at least the first few questions when the selling price is low, but at some point switch to sell the portfolio (Option B) when the selling price gets high enough.

So, to save time, just tell us at which selling price you would switch. We can then 'fill out' your answers to all 61 scenarios based on your switch point (choosing Option A for all scenarios before your switch point, and Option B for all scenarios at or after your switch point). Hence, the switch point is the minimum price that you are willing to sell the portfolio for. The higher the number you give as your switch point, the more likely it is that you will not sell the portfolio immediately and thus the unknown payoff next period is relevant to the amount of WC that you can earn. We will still draw one scenario randomly in order to determine the amount of WC that you earn for your Wonderland account.

Example 1:

You provide a switch point of 120 WC. This means that you will sell the portfolio if the selling price is 120 WC or higher. We randomly draw a scenario and the selling price in this scenario is 125 WC. Since you decided to sell the portfolio in this scenario, you have to sell the portfolio and earn the selling price of 125 WC for your Wonderland account.

One period later, the payoff of the portfolio is realized. However, as you have already sold the portfolio, the amount of WC that you can earn for your Wonderland account does not depend on the realization of the portfolio payoff anymore. There are many potential realizations, but here are two exemplary outcomes for illustration.

Outcome 1: The payoff of the portfolio is 135 WC. Hence, you would have earned a **higher** amount of WC for your Wonderland account (135 WC instead of 125 WC) if you had kept the portfolio in this scenario.

Outcome 2: The payoff of the portfolio is 115 WC. Hence, you would have earned a **lower** amount of WC for your Wonderland account (115 WC instead of 125 WC) if you had kept the portfolio in this scenario.

Example 2:

You provide a switch point of 120 WC. This means that you will sell the portfolio if the selling price is 120 WC or higher. We randomly draw a scenario and the selling price in this scenario is 115 WC. Since you decided to keep the portfolio in this scenario, you don't sell and hold on to the portfolio for another period.

One period later, the payoff of the portfolio is realized and determines the amount of WC that you can earn for your Wonderland account. There are many potential realizations, but here are two exemplary outcomes for illustration.

Outcome 1: The payoff of the portfolio is 125 WC. Hence, you earn 125 WC for your Wonderland account in this scenario. Note that if you had sold the portfolio for 115 WC before, you would have earned a **lower** amount for your Wonderland account.

Outcome 2: The payoff of the portfolio is 95 WC. Hence, you earn 95 WC for your Wonderland account in this scenario. Note that if you had sold the portfolio for 115 WC before, you would have earned a **higher** amount of WC for your Wonderland account.

E.12 Screen 17 (Valuation Task – Attention Check)

In case this task will be determining your payoff, how many scenarios are we going to randomly pick?

- Zero
- One
- ⋮
- Ten
- This is a trick question as there are no scenarios in this task

E.13 Screen 18 (Valuation Task – Comprehension Question)

How to Do the Valuation Task (II)

Before the actual valuation, please answer the following two comprehension questions.

Consider the following scenario: you proposed 115 WC as your switch point. The selling price in the randomly chosen scenario turns out to be 120 WC. One period later, the portfolio payoff is 125 WC. What is the amount of WC that you earn for your Wonderland account?

(Enter number as answer.)

Consider the following scenario: you proposed 140 WC as your switch point. The selling price in the randomly chosen scenario turns out to be 120 WC. One period later, the portfolio payoff is 130 WC. What is the amount of WC that you earn for your Wonderland account?

(Enter number as answer.)

Let us assume that we have transferred 130 WC to your Wonderland account for the last scenario. What would be your total bonus payment (fixed + performance-based payment) in US Dollars?

(Enter number as answer.)

You are mistaken!/Correct!

In the first example your proposed switch point is lower than the selling price in the randomly drawn scenario. Thus, you **sell** the portfolio for 120WC and you earn 120 WC for your Wonderland account and you **do not** earn the portfolio payoff of 125WC in the next period for your Wonderland account.

In the second example your proposed switch point is higher than the selling price in the randomly drawn scenario. Thus, you do **not sell** the portfolio and you **do** earn the portfolio payoff of 130 in the next period for your Wonderland account.

As explained in the beginning the translation of Wonderland coins to US Dollars is calculated as follows: US Dollars = (Wonderland Coins - 90) * 0.12 Thus, your performance-based payment in this example is: US Dollars: (130-90)*0.12=40*0.12=$4.80 Your total bonus payment therefore would be $5.30 (fixed bonus payment of $0.50 for the survey at the end of the study + performance-based payment of $4.80)? This bonus payment as well as the $1 reward will be paid to you ONLY if you finish the whole study.

E.14 Screen 19 (Valuation Task)

Valuation Task

The graph below shows which payoffs the portfolio "RedStone"/"SilverTree"has realized in the past to give you an idea of possible realizations in the future. We will randomly draw one of these payoffs based on the historical probabilities to determine the portfolio's payoff in the next period. On the horizontal axis, you can see the different payoff amounts of portfolio "RedStone"/"SilverTree". The height of the bars on the vertical axis shows you how often this payoff amount has realized in the past. You can also directly hover your mouse pointer over the bars to get this information. In total, you have information for the past 211 periods available in the graph.

(GRAPH)

What is your switch point (the minimum price that you are willing to sell portfolio "RedStone"/"SilverTree"for today)?

(Enter number as answer.)

E.15 Screen 20 (Valuation Task – Belief Elicitation)

What portfolio payoff realization do you expect for the next period for portfolio "RedStone"/"SilverTree"?

(Enter number as answer.)

Please provide us with your guess of a range of payoffs, such that in most cases (in 90 of 100 cases) the actually realized payoff of portfolio “RedStone”/“SilverTree”next period will be in this range.

Lower end of range: (Enter number as answer.) Upper end of range: (Enter number as answer.)

”How attached do you personally feel with portfolio “RedStone”/“SilverTree”?” (Five radio buttons from “not attached at all” to “very attached.”)

E.16 Screen 21 (Instructions Trading Task)

How to Do the Trading Task

Next, you will do the trading task.

[In second pass: The task is the same as what you have already done for the other portfolio. We provide the instruction below again for your reference. The instructions have not changed.]

For this task, you are endowed with 130 WC. The amount of WC that you can earn for your Wonderland account is based on this initial endowment and on the gains and losses that you make during the following trading decisions. There will be four trading decisions and we will randomly select which trading decision is used for the calculation of the amount of WC that you can earn for your Wonderland account.

Example 1: You make a gain of 20 WC in the randomly selected trading decision. Hence, the amount of WC that you earn for your Wonderland account is 130 + 20 = 150 WC.
Example 2: You make a loss of 20 WC in the randomly selected trading decision. Hence, the amount of WC that you earn for your Wonderland account is 130 - 20 = 110 WC.

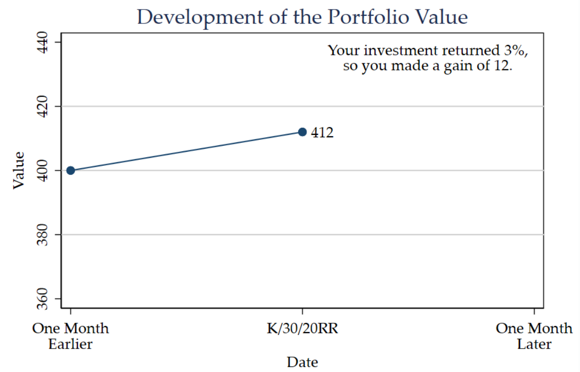
For each of the four trading decisions, you will face a different situation about portfolio “RedStone”/“SilverTree”. All four situations are taken from real world data about the portfolio, such that they describe developments that have actually happened in the past. However, we anonymized the exact dates.

We will put you in the shoes of a real financial market investor at that very point in time. In each situation you have invested 400 WC in portfolio “RedStone”/“SilverTree”one month ago and you can see the development of the portfolio value up until today, the point in time of the scenario.

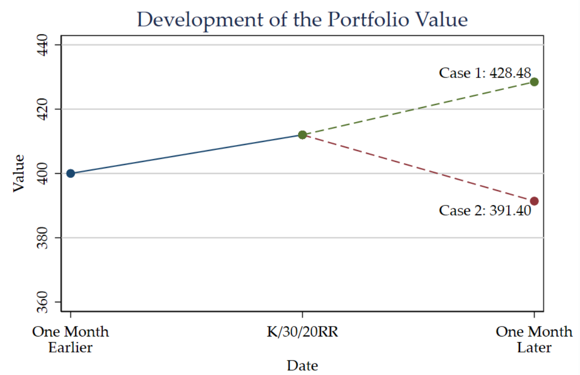
Now, for each situation, you can decide to sell the portfolio for the current market value or hold on to it for another month. If you sell right away, you lock-in the current gain or loss.

Alternatively, if you hold the portfolio for one more month, your payoff depends on the value of the portfolio in one month that is unknown as of today. We will use the actual portfolio value one month later from the real world data as the realization to determine the amount of WC that you can earn for your Wonderland account. There are no additional rounds to be played afterward.
Note: the previously invested 400 WC will be subtracted from the portfolio value to determine your gain and loss (i.e. portfolio value - 400).

Consider the following example as an illustration of the task, your possible actions and the resulting payoff consequences.



In the figure above, we depict the situation about an exemplary portfolio on the 30th of January 2010. In the figure the date will be represented by 30th of month K in year 20RR. This is an anonymized date that stands for an actual date in the past. At this point in time, the value of the portfolio is 412 WC. Hence, you hold the portfolio at a gain of 12 WC, or 3,00%.
Possibility 1: You decide to sell the portfolio for the current price and realize the gain of 12 WC. The amount of WC that you earn for your Wonderland account is your initial endowment plus your gain from the trade, 130 + 12 = 142 WC.
Possibility 2: You decide to hold the portfolio for another month. Hence, the amount of WC that you earn for your Wonderland account depends on the value of the portfolio in one month. To continue the example, we show you two potential cases of this future value:



Case 1: The value of the portfolio in one month has increased by an additional 4% and is now worth 428.48 WC. Hence, you realized a total gain of 28.48 WC. The amount of WC that you earn for your Wonderland account is your initial endowment plus the gain from the trade, 130 + 28.48 = 158.48 WC.
Case 2: The value of the portfolio in one month has decreased by 5% and is now worth 391.40 WC. Hence, you realized a loss of 8.60 WC in total. The amount of WC that you earn for your Wonderland account is your initial endowment minus the loss from the trade, 130 - 8.60 =

121.40 WC.

Remember that for the scenarios you are about to face, we will use the portfolio valuation from the real world data to determine the amount of WC that you earn for your Wonderland account if you keep the portfolio.

E.17 Screen 22 (Trading Task – Comprehension Question/Task)

How to Do the Trading Task II

Before making your trading decisions, please answer the following comprehension question.

Consider the following scenario: You invested 400 WC in the exemplary portfolio one month ago. As of now, the portfolio is worth 410 WC. Unbeknown to you, the portfolio will be worth 405 WC one period later. Further, assume that this task has been drawn to be payoff-relevant for you.

If you decide to sell the portfolio now, what is the amount of WC that you earn for your Wonderland account?

(Enter number as answer.)

If you decide to keep the portfolio, what is the amount of WC that you earn for your Wonderland account?

(Enter number as answer.)

Let us assume that we have transferred 100 WC to your Wonderland account for the last scenario. What would be your total bonus payment (fixed + performance-based payment) in US Dollars? (Enter number as answer.)

You are mistaken!/Correct!

In the first case where you sell the portfolio for 410WC you realized a total gain of 10 WC (current value of 410 WC minus your investment of 400 WC). The amount of WC that you earn for your Wonderland account is your initial endowment (130 WC) plus the gain from the trade (10 WC). Thus, the amount of WC that you earn for your Wonderland account is 130 + 10 = 140 WC.

In the second case where you keep the portfolio for another month the value of the portfolio has decreased by 5 WC and is now worth 405 WC. Hence, you realized a total gain of 5 WC (current value of 405 WC minus your investment of 400 WC). The amount of WC that you earn for your Wonderland account is your initial endowment (130 WC) plus the gain from the trade (5 WC). Thus, the amount of WC that you earn for your Wonderland account is 130 + 5 = 135 WC.

As explained in the beginning the translation of Wonderland coins to US Dollars is calculated as follows: US Dollars = (Wonderland Coins - 90) * 0.12 Thus, your performance-based payment in this example is: US Dollars: (100-90)*0.12=10*0.12=$1.20 Your total bonus payment therefore would be $1.70 (fixed bonus payment of $0.50 for the survey at the end of the study + performance-based payment of $1.20). This bonus payment as well as the $1 reward will be paid to you ONLY if you finish the whole study.

E.18 Screen 23 (Trading Task)

Trading Task

Please decide for each of the following situations whether you want to keep or sell portfolio and what you expect the portfolio value to be in one month.

As a reminder: Portfolio "RedStone"/"SilverTree"has an average monthly return of X% and a risk value of Y%.

For each of the four scenarios:

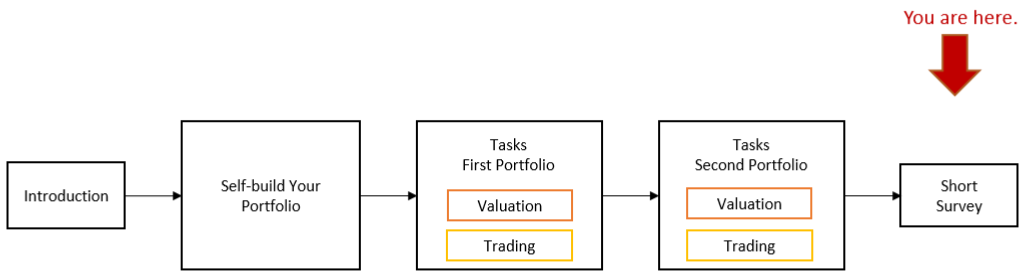
- What do you expect the portfolio value of portfolio "RedStone"/"SilverTree"to be in one month?

[See Figure 6 for a screenshot]

E.19 Survey

Final Survey: Introduction

We now come to the final survey where we would ask you to answer a few questions. This will take not more than 5 minutes. Remember that you have to complete this step in order to receive your compensation. After finishing the survey you will receive detailed information about your overall bonus payment.



E.20 Screen 24: Numeracy (Cokely et al., 2012)

Final Survey (1/3) Note: This is the "Berlin Numeracy Test Single Item (Median Split) Format" that is recommended by Cokely et al. (2012) for a one minute test where researchers are dealing with general population/mechanical turks[28]

[28] See http://www.riskliteracy.org/

- **'Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?'**
  - (Numerical answer between 0 and 50. Correct answer: 30)

E.21 Screen 25: Financial Literacy

Final Survey (2/3)

Note: Correct answers are in italics. Questions are from here: `https://www.usfinancialcapability.org/downloads/NFCS_2018_State_by_State_Qre.pdf`

Item M6 Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

- *More than $102*
- Exactly $102
- Less than $102
- Don't know
- Prefer not to say

Item M7 Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- *Less than today*
- Don't know
- Prefer not to say

Item M8 If interest rates rise, what will typically happen to bond prices?

- They will rise
- *They will fall*
- They will stay the same
- There is no relationship between bond prices and the interest rate
- Don't know
- Prefer not to say

Item M31 Suppose you owe $1,000 on a loan and the interest rate you are charged is 20% per year compounded annually. If you didn't pay anything off, at this interest rate, how many years would it take for the amount you owe to double?

- Less than 2 years
- *At least 2 years but less than 5 years*
- At least 5 years but less than 10 years
- At least 10 years
- Don't know
- Prefer not to say

Following are two statements. Please indicate whether each statement is true or false. If you don't know, just select "don't know."

[Note: We randomize over the ordering of M9 and M10]

Item M9 A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.

– *True*
– False
– Don't know
– Prefer not to say

Item M10 Buying a single company's stock usually provides a safer return than a stock mutual fund.

– True
– *False*
– Don't know
– Prefer not to say

E.22 Screen 26: Post-experimental Questions

Final Survey (3/3)

- "In your experience, how complex was the portfolio-building?" (Five radio buttons from "very complex" to "very simple".)
- "How true is the following statement: I have a hard time giving up possessions" (Five radio buttons from "very true" to "very untrue".)
- "How much effort did you put into the construction of your portfolio?" (Five radio buttons from"very much" to "very little".)
- "When I look at the portfolio I have build together I feel proud of having accomplished it." (Five radio buttons from "strongly agree" to "strongly disagree".)
- "How would you describe your knowledge about statistics?" (Five radio buttons from "very good" to "very bad".)
- Self-reported: "Please estimate your willingness to take financial risk." (Five radio buttons from "not willing to accept any risk" to "willing to accept substantial risk to potentially earn a greater return".)
- "Do you have any experience investing in stocks or equity mutual funds?" (Answer: "yes" or "no".)
- "Do you have any experience investing in other financial market instruments (e.g. bonds, options,...)?" (Answer: "yes" or "no".)
- "Have you ever invested in a self-built financial portfolio?" (Answer: "yes" or "no".)
- "Have you ever invested in a financial portfolio that was built by someone else (e.g. a mutual fund)?" (Answer: "yes" or "no".)
- "Are you generally interested in financial markets?" (Answer: "yes" or "no".)
- "Have you attended a university Statistics course?" (Answer: "yes" or "no".)

- “Have you attended a university Economics or Finance course?” (Answer: “yes” or “no”.)
- “How well did you understand the instructions for the valuation task?” (Five radio buttons from “I did not understand them at all” to “I did understand them perfectly”.)
- “How well did you understand the instructions for the trading task?” (Five radio buttons from “I did not understand them at all” to “I did understand them perfectly”.)
- “How enjoyable was the portfolio building task for you?” (Five radio buttons from “it was horrible” to “it was very fun“.)