Categorization and Learning from Financial Information

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This paper examines the role of coarse categories in individuals' learning from financial information. In particular, we (i) test theoretical predictions about categorical over- and underreaction to information by Mullainathan (2002) in an investment context, (ii) explore differences in category-based belief formation and (iii) link category-based beliefs to investment behavior. Our findings document that information aggregation along prominent categories in financial markets, such as industries, can affect people's beliefs and investment decision-making. Interestingly, we find differences across category types. Subjects form category-based beliefs when the observed stock belongs to "good" stock categories associated with gains. People then overreact to category changes, form overly optimistic beliefs, and invest significantly more in the stock. Yet, we find the opposite pattern if the stock belongs to "bad" stock categories associated with losses. People then seem to be generally sensitive to the stock's outcomes. Category changes do not distort their beliefs.

1 Introduction

It has been argued that investors first categorize assets into broad classes based on common characteristics, such as into value stocks, growth stocks, or small-cap stocks, and then move funds across these classes, called "style investing" (Barberis and Shleifer, 2003). Style investing has important implications for asset prices, as styles become popular and unpopular and thus drive excessive return comovement of firms within specific classes (Barberis et al., 2005; Green and Hwang, 2009). Theory suggests that style-level demand for these assets emerges from the fact that investors form beliefs about the future performance of assets at the category level (Barberis and Shleifer, 2003). An important empirical question remains how people form category-based beliefs about investments and whether they are linked to suboptimal investment decisions.

This study examines the role of coarse categories in individuals' learning from financial information. In particular, we test theoretical predictions by Mullainathan (2002) about individuals' under- and overreaction to new information when forming beliefs applied to an investment context. Importantly, we investigate differences in individuals' category-based belief formation and relate their beliefs to investment decisions. Our experimental results document a categroy-based belief distortion, which affects investment decisions. Yet, this depends on the type of category and the type of information associated with it. The findings enhance the understanding of how people learn from financial information when information aggregation along prominent categories in financial markets, such as industries, is present.

People often rely on categories when they interpret information. In general, this tendency can be very useful, as it allows individuals to assess large amounts of information by focusing on a specific level of detail and ignoring specialization of lower levels. One of the most important functions of categorization is its role in learning (Anderson, 1991). Categorization allows the prediction of unseen features of an object by relating to features of an object's category. In this vein, a Bayesian account suggests that people consider all the categories an object could belong to when they make inferences about that object. However, the crux is that psychology literature shows that people use a simple heuristic in which they consider only the most likely category and ignore alternative categories, which distorts their inferences (Malt et al., 1995; Murphy and Ross, 1994).

This insight from psychology is used in economic theory to study belief formation in economic choice. A failure to account for alternative categories can create over-generalized beliefs, for example stereotypical beliefs (Bordalo et al., 2016). Closest to this study is theoretical work by Mullainathan (2002). He formalizes human categorical thinking as a simplification of Bayesian updating in which people use coarse categories to make inferences. A category corresponds to a specific probability distribution over single units. Assuming people can only hold a finite subset of beliefs for making predictions, Mullainathan (2002) suggests that individulas use that probability distribution associated with the category to make predictions for particular units. He introduces a mechanism which can explain under- and overreaction to new information: People update the assigned category only when they see enough information to suggest that an alternative category better fits the observed information. Applying this framework to financial markets, the model can explain investor under- and overreaction to news.

This study uses an experimental approach to examine the role of coarse categories in individuals' learning from financial information and subsequent investment decisions. The experiment is designed to (i) test the theoretical predictions by Mullainathan (2002) in an investment context as well as to (ii) explore differences in category-based belief formation and (iii) to link category-based beliefs to investment behavior. Our design thereby exploits advantages of laboratory experiments to directly elicit subjective beliefs and compare subjects' beliefs and choices to a Bayesian benchmark. This allows us to draw clear conclusions about subjects' deviations from objectively correct beliefs and choices.

In the main task, subjects choose to invest either in a risky asset or a risk-free asset Kuhnen (2015). The risky asset is a stock that generates positive and negative outcomes, i.e., stock returns, with a specific probability. Subjects do not initially know the likelihood of the stock to generate a positive or negative outcome, but can make inferences about the probability from observing outcomes. The stock belongs to one of several different stock categories (industries in our experiment) that determines how likely the stock generates a positive rather than a negative outcome. The subjects do not know to which category the stock belongs to before they see any outcomes. To identify whether subjects ignore alternative categories and form biased category-based beliefs, we provide subjects with category-level information, i.e., the probability distributions of the categories, and let them observe the stock's return before eliciting their beliefs about the stock's future outcome. The key idea of the experimental design is a manipulation of the categories' level of coarseness. We compare subjects' beliefs in this treatment to beliefs stated in a condition in which subjects see more disaggregated information based on finer categories, but still face the identical learning environment. To relate subjects' category-based beliefs to their future investment behavior, we ask them to make investment decisions after observing each stock outcome.

We have three main findings. First, when coarse categories are present, subjects form more *pessimistic* beliefs about the stock investment on average. Yet, as proposed by the theoretical model by Mullainathan (2002), we find evidence for overreaction to new information in case the new information is suggestive of a "category change." That is, if an observed outcome of the stock should objectively change the belief about the stock's industry belongig, subjects updated their beliefs too strongly and formed overly *optimistic* beliefs about the stock's future outcomes. Second, this overreaction varies across different category types. Category-based belief formation in accordance with the model predictions by Mullainathan (2002) is observed for "good" stock categories associated with gains. However an opposite belief pattern emerges for "bad" stock categories associated with losses. Third, subjects' overreaction to category changes is associated with higher stock investments. Interestingly, this tendency correlates with fewer suboptimal investment decisions in our experimental setting.

There is a rich strand of finance literature on return comovement. Several studies examine common factors in asset returns and whether the sensitivity to these factors can explain average rates of return. For example, characteristics such as firm size and book-to-market ratio appear to explain cross-sectional variation in stock returns in excess of the covariance structure of returns (Daniel and Titman, 1997). Motivated by strong common factors in the returns of specific asset categories, Barberis et al. (2005) ask the question why patterns of comovement in asset returns arise. Beyond traditional theory stating that comovement in returns reflect only correlation in fundamentals, they reveal the importance of market frictions and investor sentiment for common return movement. Examining leading and lagged returns of S&P 500 and non-S&P 500 stocks, Barberis et al. (2005) make the first attempt to disentangle different friction- and sentiment-based explanations of comovement and determining the importance of behavioral explanations. One of the most prominent behavioral explanations is investor category-learning (Barberis and Shleifer, 2003). This is supported by empirical evidence on investor reactions to mere category changes with no fundamental linkage. Cooper et al. (2001) document a remarkably high stock price reaction for firms' change to dotcom names during the Internet bubble period and Rashes, 2001 finds excessive comovement between stocks with similar ticker symbols.

Our study contributes to this strand of research by (i) isolating category-based beliefs as a source of such behavioral patterns observed in financial markets as well as (ii) uncovering differences in the formation of category-based beliefs, which helps explain different reactions to categorical information. We find that subjects form category-based beliefs as predicted by Mullainathan (2002) when the observed stock belongs to "good" stock categories associated with gains. People then overreact to category changes, form overly optimistic beliefs, and invest significantly more in the stock compared to a situation with no category change, but the same quality of the stock. Yet, our results indicate that this depends on the type of category and the type of information associated with it. We find the opposite result if the stock belongs to "bad" stock categories associated with losses. People then seem to be sensitive to the stock's outcome and even overreact to negative information with too pessimistic beliefs if there is no category change. This can explain the overreaction to firms' change to dotcom names during the Internet bubble period with high returns Cooper et al. (2001), but suggests that, in contrast, this pattern could be weaker or even diminshed for stock categories associated with negative returns.

This paper also contributes to specific work on investor category learning. Previous literature links category learning to investors' attentional constraints. Peng and Xiong (2006) present a model in which investors allocate attention across fundamental factors and show that an attention-constrained investor tends to pay more attention to market- and sector-level factors than to firm-specific factors, leading to category-learning. Indeed, Drake et al. (2017) empirically show that investors focus on market and sector-wide information which is then associated with excess return comovement. In addition, Yuan (2015) reports that market-wide events raising the attention level investors pay to their portfolios, cause them to become more active in information processing and trading. However, our experimental results show that category learning in an investment context even occurs in settings in which subjects do not face attention constraints. We thus provide evidence for categorical thinking by itself being a cognitive limitation beside pure attentional constraints. This is important for the understanding of the underlying mechanism of category learning in financial markets.

Finally, our results contribute to literature on the effect of information aggregation on risk taking. For example, in a financial market context, it has been found that individuals take more investment risk if they observe more aggregated return information, i.e., less frequent return information, long-horizon return information, or return information at the portfolio- rather than at the asset-level (Anagol and Gamble, 2013; Benartzi and Thaler, 1999; Gneezy and Potters, 1997; Haigh and List, 2005; Thaler et al., 1997). These findings are typically explained by myopic loss aversion. We add to this strand of literature by showing evidence for another form of information aggregation affecting risky investment decisions: information aggregation along stock categories, which is very common in financial market media.

2 Theory and Hypotheses

This study is based on a model of human inference in which people rely on coarse categories when forming beliefs (Mullainathan, 2002). Categorical thinking is defined as a simplification of Bayesian updating in which people use coarse categories to make inferences. The model introduces two key features of coarseness into human inference: (i) people tend to group together several different types of objects into one large category and (ii) people do not consider all available categories, when making inferences. Together, these two features are formalized into a simple assumption: people can only hold a finite subset of beliefs for making predictions. Consequently, they choose the most likely category given the observed data and make forecasts solely by using the probability distribution associated with the chosen category, ignoring all other possible categories. They update the assigned category only when they see enough data suggesting that an alternative category better fits the data. As a result, categorical thinking reduces the set of posteriors people can hold compared to Bayesian thinking.

This idea can be applied to the stock market. Suppose an investor aims at evaluating a stock which generates an outcome each period. This outcome is stochastic and can be either good or bad. Imagine the stock can belong either to a good, mediocre, or bad industry. The industry determines the stock's probability to generate a good or bad outcome. A stock of the good industry pays a good outcome with probability $g > 50\%$, a stock of the mediocre industry with probability $m = 50\%$, and a stock of the bad industry with probability $b = 1 - g < 50\%$. The investor observes the stock's outcome each period and wants to forecast the outcome next period. A Bayesian updater counts how many good outcomes are already realized and updates the probability over all possible industries. That is, a Bayesian infers the probability of generating a good outcome for each industry, multiplies by the up dated probabilities, and then adds them together. According to the model by Mullainathan (2002), categorical thinking, in contrast, means choosing the most likely industry based on the observed outcomes and then using that industry's probability of generating a good outcome to make forecasts.

The model generates three predictions about people's beliefs in the face of coarse categories. First, the model suggests that when categories are fine enough, the categorical thinker will approximate the Bayesian probability when making inferences. That is, as the number of available categories increases, the individual's belief approximates the objectively correct Bayesian posterior. Thus, individuals' belief error, measured by the deviation of their subjective beliefs from the objectively correct Bayesian posterior, decreases with an increasing number of categories. Imagine, for example, the extreme case in which the number of categories equals the number of objects that can be assigned to categories. In this case, the beliefs would be identical to the Bayesian posteriors. This notion is captured in our first hypothesis:

Hypothesis 1 (Approximation) A higher number of available categories is positively correlated with a lower belief error.

Further, the model predicts that indviduals change their beliefs rarely, because they are not sensitive enough to small changes in probability. More precisely, they do not respond to new information if it does not lead to a change of category, because it is small enough. In other words, if the observed signals do not suggest a change of category, for example from the mediocre category to the good categroy, people do not update their beliefs. This creates underreaction to new information. In this vein, our second hypothesis is as follows:

Hypothesis 2 (Underreaction) Individuals do not update their beliefs in response to single information signals.

By contrast, the model proposes that in case of new information that is large enough to suggest a category change, individuals will respond too strongly, because of an immediate category switch. This creates overreaction to new information. Thus, our third hypothesis is:

Hypothesis 3 (Overreaction) Individuals update their beliefs too strongly in response to information signals consistent with a category change.

In an experimental setting, we will test these three hypotheses about how coarse categories are associated with individuals' learning from financial information. We will further analyse differences in subjects' belief formation based on category characteristics and relate potential belief biases to subsequent investment decisions.

3 Experiment

A setup to investigate the role of coarse categories in individuals' learning from financial information and its effect on their investment decisions requires (i) categories relevant for inference, (ii) exogenous variation of the coarseness of categories to isolate the category effect, and (iii) an incentive-compatible measure of beliefs and decisions. This section outlines how the experimental setting meets these requirements (Table 4.1 summarizes our experimental conditions).

3.1 Experimental Design

The experimental setting is based on the learning problem subjects face in the study by Kuhnen, 2015.[1] Subjects perform a task consisting of investment choices and belief estimation exercises. In all treatments, subjects repeatedly choose to invest either in a stock with risky outcomes (positive and negative outcomes) or in a bond with known safe outcomes. After each decision, irrespective of whether they chose to invest in the stock or bond, subjects observe the stock's outcome and are asked to provide estimations regarding the stock's probability of paying a positive outcome. Subjects do not initially know the likelihood of the stock to generate a positive or negative outcome, but can make inferences about the probability from its realized outcomes. After that, subjects can again decide to invest in either the stock or bond each period. In total, subjects take part in four learning blocks consisting of six decisions each. Within each learning block, they face the same stock, so that they can learn from its realized outcomes. In all learning blocks, the positive outcome of the stock is 20 EUR and the negative outcome is -5 EUR. The bond has a certain outcome of 6 EUR each period.

In each block, the stock belongs to one of several different stock categories that determines how likely the stock generates a positive rather than a negative outcome. Importantly, the stock categories differ in quality. Comparing the expected outcomes in each category yields to a clear ranking of categories in the sense of first-order stochastic dominance. The coarseness of available categories varies between treatments to isolate category effects. The experimental treatments are implemented across the four learning blocks, i.e., within-subjects, in random order. The categories are implemented as industries. It has been shown that industries are important categories in financial markets (Drake et al., 2017).

In the *Category* treatment, the stock belongs to one of three industries with equal probabil-

[1] The experiment instructions are provided in Appendix 4.A.

ity, either to the "good industry," the "mediocre industry," or the "bad industry." If the stock comes from the good industry, it generates a positive outcome with a 70% probability and a negative outcome with a 30% probability each period. A stock that belongs to the mediocre industry generates positive and negative outcomes with equal probability, i.e., 50%. If the stock belongs to the bad industry, it generates a positive outcome with a 30% probability and a negative outcome with a 70% probability.

Subjects' beliefs and decisions in the *Category* treatment are compared to a condition in which subjects are provided with more disaggregated category information, but still face the identical learning problem. Specifically, the number of available categories increases. In the *Disaggregated* treatment, the stock belongs to one of six industries with equal probability (Table 4.1). This allows to isolate the category effect on subjects' beliefs.

Additionally, we manipulate the symmetry of category sizes by varying the probability that the stock belongs to the good category. Again, the stock can belong to one of three industries, as in the *Category* treatment. Yet, in the *Broad* treatment, the stock has a very high probability to belong to the good industry (80%) and in the *Narrow* treatment it has a very high probability (80%) to belong to the bad industry, i.e., a low probability to belong to the good industry. These variations allow us to isolate relative size effects in subjects' failure to account for alternative categories. This can be of importance in financial markets. Stock categories sometimes group together stocks based on specific characteristics, such as "automobile industry stocks," and sometimes based on general characteristics, such as "value stocks."

Table 4.1: Experimental Conditions

Treatment	Number of categories	Size of categories	Comparison to *Category*
Category	3	Symmetric	-
Disaggregated	6	Symmetric	Isolation of category effect
Broad	3	Asymmetric (high probability of good industry)	Isolation of relative size effect
Narrow	3	Asymmetric (low probability of good industry)	Isolation of relative size effect

Notes: This table provides an overview of the experimental conditions of the experiment with different numbers and sizes of categories. The last column reports the effects isolated by a comparison to the baseline condistion *Category*.

3.2 Belief Elicitation and Behavioral Outcome Measure

In order to investigate category-based beliefs, we elicit subjects' beliefs about the stock's chance of paying a positive outcome, which will serve as one of the key outcome measures of this study. Subjects had to provide an estimate in percent as an integer from 0 to 100 after each new outcome they observe. Initially, subjects do not know this probability. They start with a prior based on information about the possible underlying processes. That is, in the *Category* and the *Disaggregated* treatment, they start with a prior that the stock pays either a positive or negative outcome with equal probability. Because of the asymmetric category sizes in the *Broad* and *Narrow* conditions, the prior increases to 64% in the *Broad* treatment and descreases to 36% in the *Narrow* condition. After observing the realized outcomes, subjects make informed inferences about the stock's probability of paying a positive outcome. A fully rational (Bayesian) subject counts the number of positive outcomes in the course of the periods and updates the probability over all possible industries. That is, a Bayesian infers the probability of generating a good outcome for each industry, multiplies by the updated probabilities, and then adds them together. For example, the value of the objective Bayesian posterior for the stock paying a positive outcome in the *Category* condition can be calculated as:

$$P(P) = P(G) * P(P|G) + \ P(M) * P(P|M) + \ P(B) * P(P|B) \tag{4.1}$$

where $P(P)$ is the probability that the stock pays the positive outcome. $P(G)$, $P(M)$, $P(B)$ denote the probability that the stock belongs to the good, mediocre, and bad industry, respectively. Before observing any outcomes, these are 33%. $P(P|G)$, $P(P|M)$, $P(P|B)$ represent the probability that the stock pays a positive outcome conditional on belonging to the good (70%), mediocre (50%), and bad industry (30%), respectively. Further, the probabilities that the stock belongs to each category after observing stock ouctomes can be calculated as:

$$P(G) = \frac{(1 - P(P|G)^{n-t} * P(P|G)^{t} * P(G)}{P(T)} \tag{4.2}$$

$$P(M) = \frac{(1 - P(P|M)^{n-t} * P(P|M)^{t} * P(M)}{P(T)} \tag{4.3}$$

$$P(B) = \frac{(1 - P(P|M)^{n-t} * P(P|B)^{t} * P(B)}{P(T)} \tag{4.4}$$

where n represents the number of periods so far and t the number of observed positive ouctomes so far. The total probability $P(T)$ is the same in each of the denominators and is the sum of the three numerators of Equations (2) to (4).

In an additional step, subjects are asked to rate their confidence regarding the belief estimates after indicating them. After each probability estimate they provide a confidence number from one to nine, with one meaning not confident at all and nine meaning very confident.

To relate subjects' category-based beliefs to their investment behavior, we ask them to repeat their investment decision after observing the stock's outcome each period. These decisions will serve as the second key outcome measure of this study. Subjects again choose to invest in either the stock they have observed or the bond. Risk-neutral subjects should compare the expected outcomes of the two assets and invest in the asset with a higher expected value. In our main treatment conditions *Category* and *Disaggregated*, a risk-neutral Bayesian subject should always invest in the stock if the number of realized positive outcomes leads to a Bayesian posterior about the stock paying a positive outcome of 50% or greater.[2] In the result section we will discuss our results with regard to a range of reasonable risk attitude parameters of subjects.

3.3 Incentives and Procedures

This study uses two key outcome measures, namely subjects' beliefs and investment decisions. Both measures are incentivized. Subjects are paid a show-up fee of 15 EUR for participating in the study. Further, we randomly draw 1 out of 10 participants each session (with maximum 30 participants per session) who are paid based on their performance in one of the experimental tasks. They can earn more than 100 EUR in each task. For each drawn subject, the computer randomly decides which task determines his or her payment. It has been shown that paying a subset of participants is an effective payment scheme for economic experiments (Charness et al., 2016; Cubitt et al., 1998; Hey and Lee, 2005; Starmer and Sugden, 1991). In the belief elicitation task, subjects' earnings are determined by the accuracy of their probability estimates. They can earn 20 EUR for a probability estimate within 5 percent of the correct objective Bayesian value each period, in total up to 120 EUR. With respect to subjects' investment decisions, they can earn an initial endowment of 35 EUR plus their accumulated investment outcomes over a horizon of 6 periods. The investment outcome can be 6 EUR from

[2] In the *Broad* and *Narrow* treatment, these values deviate slightly with the necessary Bayesian posterior being 53% in the *Broad* condition and 47% in the *Narrow* condition.

investing in the bond or either 20 EUR or -5 EUR from investing in the stock each period.

The experiment was conducted with 129 subjects, mostly business and economics students, from the University of Hamburg. On average, subjects earned 27.98 EUR. For each subject, the experimental session took about 1.5 hours. In order to ensure that subjects understand the experimental design, we use four introductory comprehension questions that have to be answered correctly before proceeding with the experiment (Appendix 4.A). At the end of the four learning blocks, subjects are informed about their accuracy of estimates, their investment outcomes, and their resulting task earnings. The experiment is followed by a questionnaire with background and control questions. We elicited subjects' general risk preferences (Dohmen et al., 2011), financial literacy, and stock market participation. Further, subjects were asked to indicate their age, gender, and highest level of education. The experiment is programmed and conducted with z-Tree (Fischbacher, 2007) and the experimental sessions were organized and administrated with the software hroot (Bock et al., 2014). Ethical approval for the experiment was obtained from the University of Hamburg Experimental Laboratory Committee.

4 Results

The results from this experiment document that coarse categories affect subjects' learning from financial information and subsequent investment decisions. When coarse categories are present, subjects form in general more pessimistic beliefs about the stock investment. Yet, in accordance with the theoretical model by Mullainathan (2002), we find evidence for overreaction to new information in case that information is suggestive of a category change. In that case, subjects update their beliefs too strongly and form overly optimistic beliefs about the stock's future outcomes. This overreaction varies across different category types and impacts subsequent decisions to invest in the stock.

4.1 Category-Based Beliefs

We find that (i) subjects' beliefs are systematically distorted when coarse categories are present, (ii) the belief distortion decreases with finer categories, and (iii) the predicted overreaction to information after a category change varies across category types. Together these results provide experimental support for the model propositions by Mullainathan (2002), but uncover variation across different category types.

Based on our belief elicitation in the experiment, subjects' belief distortion is estimated by taking the difference between subject's indicated subjective probability that the stock pays a positive outcome and the actual, objectively correct, Bayesian probability in each period. If subjects were perfectly correct about the probability, their subjective belief would equal the Bayesian posterior and their belief distortion would be zero. A positive belief distortion means that the subject is too optimistic about the probability and indicated a subjective probability that is higher then the actual Bayesian probability; a negative belief distortion means that the subject is too pessimistic about the probability and indicated a lower probability than the actual Bayesian probability. In this section, we compare subjects' belief distortion across our treatment conditions as well as different category states.

To start, we compare subjects' belief distortion in the *Category* treatment to their belief distortion in the *Disaggregated* treatment. This allows us to isolate the effect of coarse categories on subjects' beliefs compared to a situation with more finer categories present. Table 4.2 presents subjects' beliefs and deviations from the Bayesian probabilities separately for our two treatments. The table further reports T-tests for the difference between subjective probabilities and objective Bayesian probabilities. The results show that in our *Category* treatment, subjects have distorted beliefs about the stock paying a positive outcome in the next period. On average, they have too pessimistic beliefs compared to the actual Bayesian probability (T-test, $p < 0.1$). In the *Disaggregated* condition, in contrast, subjects' belief distortion decreases and gets insignificant. This is in line with our first hypothesis (approximation). In case of a higher number of available categories, subjects' beliefs approximate to the objective Bayesian posterior. Moreover, to test the relative size effects in subjects' failure to account for alternative categories, the table displays subjects' belief distortion in the *Broad* and *Narrow* condition. Table 4.2 illustrates that in the *Broad* condition, in which the probability of the good industry is in general higher, subjects exhibit overly pessimistic beliefs (T-test, $p < 0.001$). By contrast, subjects do not show distorted beliefs in the *Narrow* condition, in which the probability of the good industry is in general lower. Thus, the results suggest that the category effect is even stronger in case of asymmetric category sizes, when the "good" industry is broad, i.e., has a high probability. Please refer to Section 4.4.2 for an analysis considering category characteristics in more detail.

Next, we are interested in whether subjects' belief distortions are actually related to category-level probabilities, i.e. whether subjects form beliefs at the level of the industry rather than on the individual stock level. Table 4.3 indicates that subjects rely more on category-level probabilities in case of coarse categories compared to more finer categories being present. We

Table 4.2: Belief Distortion by Treatment

Treatment	Subjective belief	Bayesian posterior	Belief distortion	Difference (T-test)
Category	49.49	50.30	-0.82	p = 0.085
Disaggregated	48.34	48.97	-0.62	p = 0.190
Broad	61.16	64.08	-2.92	p = 0.000
Narrow	36.75	36.31	0.44	p = 0.399

Notes: This table displays subjects' beliefs and deviations from the Bayesian posteriors in the different experimental conditions in percent (from 1 to 100). Subjects' belief distortion is estimated each period at the individual level by subtracting the objectively correct Bayesian probability from subject's indicated probability that the stock pays a positive outcome. The table reports mean values and and T-test results of the difference in means between the two probabilities.

use subjects' belief distortion as dependent variable. The category-level probability serves as independent variable. The category-level probability is the general probability that the stock pays a positive outcome based solely on the characteristics of the industry suggested by the observed outcomes, ignoring that the stock can belong to alternative industries. For example, if the suggested industry was the good industry, the category-level probability is always 70%, irrespective of how likely the stock might belong to alternative industries. We control for subject fixed effects. Column 1 shows that on average subjects' belief distortion is correlated with the category-level probability. This correlation is stronger in our treatments with coarse categories (column 2) and diminishes in our treatment with disaggregated information (column 3).

Further, we test whether subjects' belief distortions are related to category changes, in our experimental setting a change of industry classification. Mullainathan (2002) proposes that subjects first underreact to single signal information that do not lead to any change of category and then overreact in case there is a consistent series of information signals suggesting a category change. First, the regression models in Table 4.4 show subjects' belief distortion seperately for suggested category changes and no suggested category changes by the observed outcomes. We use subjects' belief distortion as dependent variable. A treatment dummy serves as independent variable. The dummy variable is equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. We control for subject fixed effects. The two regression models present results seperately for the case of a suggested category change (column 1) and no suggested category change (column 2) by the observed outcomes. The results indicate that subjects in the *Category* condition have

Table 4.3: Category-Based Belief Distortion

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is subject's belief distortion estimated each period by subtracting the objectively correct Bayesian probability from subject's indicated probability that the stock pays a positive outcome in percent (from 1 to 100), *Belief Distortion*. *Category Probability* is the general probability that the stock pays a positive outcome based solely on the characteristics of the industry suggested by the observed outcomes, ignoring that the stock can belong to alternative industries. *Subject* is a dummy variable controlling for subject fixed effects. The models report results for the full sample (column 1), the category conditions, i.e., the *Category*, *Broad*, and *Narrow* conditions (column 2), and the *Disaggregated* condition (column 3). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief Distortion	(2) Belief Distortion (Category Cond.)	(3) Belief Distortion (Disaggregated)
Category Probability	-0.043*	-0.054**	-0.026
	(-1.71)	(-2.16)	(-0.42)
Constant	2.441*	3.896***	-1.507
	(1.77)	(3.12)	(-0.36)
Subject	Yes	Yes	Yes
N	3,086	2,312	774
R^2	0.20	0.30	0.46

a significantly higher belief distortion compared to subjects in the *Disaggregated* condition when the observed outcomes suggest a category change. The belief distortion increases by 3.3 percentage points ($p < 0.01$). In case of no category change, there is no significant difference in belief distortion between the conditions. The coefficients of the two models are significantly different (Wald test, $p < 0.05$). Thus, subjects show a significantly higher belief distortion in the *Category* condition than in the *Disaggregated* condition after a category change compared to the case of no category change. This result is in line with our hypothesis 3 (overreaction), but not supportive of our hypothesis 2 (underreaction).

These experimental results provide supportive evidence for some of the key model predictions by Mullainathan (2002). The next section focuses on differences in the observed overreaction to category changes to take a closer look at situations in which the model predictions hold.

4.2 Differences in Belief Formation: The Role of Category Types

In this section we show that the observed overreaction to new information after a category change is related to the respective category type. Table 4.5 provides an overview of subjects' belief distortion for different category types. The table reports subjects' beliefs and deviations from the Bayesian probabilities separately for different category types suggested by the observed outcomes. C* represents the suggested category type by the observed information, i.e.,

Table 4.4: Belief Distortion and Category Changes

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is subject's belief distortion estimated each period by subtracting the objectively correct Bayesian probability from subject's indicated probability that the stock pays a positive outcome in percent (from 1 to 100), *Belief Distortion*. *Category Treatment* is a dummy variable equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. *Subject* is a dummy variable controlling for subject fixed effects. The models report results for observations with stock outcomes that suggest a category change (column 1) and for observations with stock outcomes that do not suggest a category change (column 2). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief Distortion (Cat. Change)	(2) Belief Distortion (No Cat. Change)
Category Treatment	3.322***	0.063
	(2.67)	(0.08)
Constant	-2.600	-1.291
	(-0.59)	(-0.25)
Subject	Yes	Yes
N	580	968
R^2	0.33	0.35

the good, mediocre, or bad industry.

The results indicate that if the suggested category C* is the good industry, subjects form distorted beliefs after a category change. Subjects' then form overly optimistic beliefs about the stock paying a positive outcome in the future. By contrast, in case of no category change, subjects do not deviate significantly from the Bayesian probability. This result is again in line with our hypothesis 3 (overreaction), but not supportive of our hypothesis 2 (underreaction). That is, subjects tend to overreact to a change to the good industry with too optimistic beliefs that are 3.7% higher than the Bayesian probability (T-test, $p < 0.05$). Yet, they do form correct beliefs without a category change. However, the opposite pattern is observed for subjects' belief if the suggested category C* is the bad industry. Subjects' form their beliefs correctly in case of a change to the bad industry, but overreact to information consistently suggesting that C* is the bad industry. That is, in case of no category change subjects form overly pessimistic beliefs about the stock paying a positive outcome, on average 2.6% lower than the Bayesian probability (T-test, $p < 0.01$). If the suggested category C* is the mediocre industry, subjects form correct beliefs in both cases with and without category change.

Our findings indicate that subjects' overreaction to new information after a category change is associated with the type of category. This could be related to the type of new information subjects observe. Note that in case of C* being the good industry, the new information is always a positive outcome and in case of C* being the bad industry, the new information is always a negative outcome.

Table 4.5: Belief Distortion by Category Type

Category	Subjective belief	Bayesian posterior	Belief distortion	Difference (T-test)
Category change				
C* = good	59.98	56.33	3.65	p = 0.025
C* = mediocre	51.12	49.96	1.16	p = 0.205
C* = bad	41.55	43.21	-1.67	p = 0.498
No category change				
C* = good	58.45	59.77	-1.32	p = 0.122
C* = mediocre	49.74	49.57	0.18	p = 0.877
C* = bad	38.42	41.04	-2.62	p = 0.009

Notes: This table displays subjects' beliefs and deviations from the Bayesian posteriors in the *Category* condition in percent (from 1 to 100). Subjects' belief distortion is estimated each period at the individual level by subtracting the objectively correct Bayesian probability from subject's indicated probability that the stock pays a positive outcome. The table reports mean values and and T-test results of the difference in means between the two probabilities, seperately for observations with stock outcomes that suggest a category change and observations with stock outcomes that do not suggest a category change. Further, the table displays the results seperateley for the different category types, the good industry, the mediocre industry, and the bad industry.

4.3 Consequences for Investment Decisions

So far, the results show that subjects tend to form distorted beliefs based on category-level information. In this section, we link these category effects to behavior. We show that the presence of coarse categories affects investment decisions. We find that in the *Category* condition, subjects' probability to invest in the risky stock is significantly higher than in the *Disaggregated* condition, although the expected outcomes (as well as risk) are identical. Importantly, this increase in probability to invest in the stock is strongest after a category change.

Table 4.6 presents Probit regression models with an investment dummy variable, which is equal to one if the subject invested in the stock and zero otherwise, as dependent variable. A treatment dummy serves as independent variable. The treatment dummy variable is equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. We control for subject fixed effects. The regression models display results for all observations (column 1) and seperately for cases of a suggested category change (column 2) and no suggested category change (column 3) by the observed outcomes. On average, the probability to invest in the stock increases by 6.7% in the *Category* condition compared to the *Disaggregated* condition ($p < 0.01$). Yet, subjects' investment behavior is associated with changes in categories. In case of a category change this increase is 17.9% ($p < 0.01$) and in case of no category change the increase is 4.6% ($p < 0.1$). The coefficients of the two models are significantly different (Wald test, $p < 0.01$). Thus, subjects invest significantly more in the risky stock in the *Category* condition than in the *Disaggregated* condition after a category change compared to the case of no category change.

Table 4.6: Category-Based Investment Decisions

This table contains the coefficients and t-statistics (in parentheses) of Probit regressions in which the dependent variable is a dummy variable which is equal to one if the subject invested in the stock. *Category Treatment* is a dummy variable equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. *Subject* is a dummy variable controlling for subject fixed effects. The models report results for all observations (column 1), for observations with stock outcomes that suggest a category change (column 2) and for observations with stock outcomes that do not suggest a category change (column 3). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Stock Invest	(2) Stock Invest (Cat. Change)	(3) Stock Invest (No Cat. Change)
Category Treatment	0.329***	1.079***	0.262**
	(3.78)	(4.98)	(2.12)
Constant	1.204**	4.883	0.673
	(2.34)	(0.04)	(1.06)
Subject	Yes	Yes	Yes
N	1,056	317	577
Pseudo R^2	0.18	0.25	0.18

Category changes, i.e. observed outcome series with the latest information changing the suggested industry belonging, lead to an increase of stock investings. This investment behavior is in line with our finding of more optimistic beliefs in the *Category* condition after a category change (Table 4.4) and Mullainathan's (2002) idea that people over-respond to a series of outcomes suggesting a category change. Table 4.7 provides further evidence for biased beliefs driving this investment behavior. The table displays the results of Probit regressions models with the investment dummy variable as dependent variable. Subjects' beliefs, i.e., indicated probability estimates during the experiment, serve as independent variable. We control for the objectively correct Bayesian probability and subject fixed effects. The regression models report results for all observations (column 1) and seperately for cases of a suggested category change (column 2) and no suggested category change (column 3) by the observed outcomes. The regression results show that subjects' decision to invest in the stock is positively correlated with their subjective beliefs ($p < 0.01$). This effect is stronger after a category change, but is insignificant for cases with no category change.

A key question is whether this observed investment behavior is associated with actual mistakes. Table 4.8 shows that this is not the case. The table reports results from Probit re-

Table 4.7: Subjective Beliefs and Investment Decisions

This table contains the coefficients and t-statistics (in parentheses) of Probit regressions in which the dependent variable is a dummy variable which is equal to one if the subject invested in the stock. *Bayesian Posterior* is the value of the objective Bayesian probability that the stock pays a positive outcome in percent (from 1 to 100). *Subjective Belief* is the subject's indicated posterior belief that the stock is the good stock in percent (from 1 to 100). *Subject* is a dummy variable controlling for subject fixed effects. The models report results for all observations (column 1), for observations with stock outcomes that suggest a category change (column 2) and for observations with stock outcomes that do not suggest a category change (column 3). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Stock Invest	(2) Stock Invest (Cat. Change)	(3) Stock Invest (No Cat. Change)
Bayesian Posterior	0.022	-0.003	0.052*
	(0.90)	(-0.04)	(1.65)
Subjective Belief	0.020***	0.063***	0.008
	(2.76)	(2.61)	(0.89)
Constant	-1.114	2.311	-2.435
	(-0.90)	(0.00)	(-1.62)
Subject	Yes	Yes	Yes
N	336	43	216
Pseudo R^2	0.22	0.29	0.19

gressions for subjects' suboptimal investment decisions from a Bayesian perspective, assuming risk neutrality. We use two suboptimal choice variables as dependent variables. First, we use a dummy variable for a suboptimal choice to invest in the stock, which is equal to one if the subject chose to invest in the stock, although the stock's expected outcome was lower than the bond's outcome (column 1 and 2). Second, we include regression models with a dummy variable for a suboptimal choice to invest in the bond as a dependent variable. The dummy variable is equal to one if the subject invested in the bond, although the bond's outcome was lower than the stock's expected outcome (column 3 and 4). Results are reportet separately for all observations (column 1 and 3) and observations after a category change (column 2 and 4). As independent variable we use the category treatment dummy variable. Note that we implemented our treatments within-subjects. Although individual risk preferences can explain deviations from this Bayesian benchmark, they cannot explain differences between our treatments. We control for subject fixed effects. The results show that subjects make significantly fewer investment mistakes in the *Category* condition compared to the *Disaggregated* condition, both regarding stock investments (column 1) as well as bond investments (column 3). After a category change this effect is even stronger in case of bond investments (column 4), but diminishes in case of stock investments (column 3). Thus, subjects seem to be more likely to avoid suboptimal investment decisions in the *Category* condition compared to the *Disaggre-*

gated condition, especially they are more likely to avoid suboptimal investments in the bond after a category change.

This findings is based on a comparison to a Bayesian benchmark assuming that subjects behave in a risk neutral manner. As these results imply an increase in risk taking, the finding might change for subjects with strong risk aversion. However, this would only affect the classification of the decision as a mistake, not the treatment effect per se. Note that we compare behavior within-subjects and changes in risk taking across treatments are more likely to be driven by the decision problem compared to personal preferences.

Table 4.8: Suboptimal Investment Decisions

This table contains the coefficients and t-statistics (in parentheses) of Probit regressions in which the dependent variable is a dummy variable which is equal to one if the subject invested in the stock with a lower expected outcome than the bond, *Suboptimal Stock Invest* or a dummy variable which is equal to one if the subject invested in the bond with a lower expected outcome than the stock, *Suboptimal Bond Invest*. *Category Treatment* is a dummy variable equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. *Subject* is a dummy variable controlling for subject fixed effects. The models report results for all observations (column 1 and 3) and for observations with stock outcomes that suggest a category change (column 2 and 4). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Sub. Stock Invest	(2) Sub. Stock Invest (Cat. Ch.)	(3) Sub. Bond Invest	(4) Sub. Bond Invest (Cat. Ch.)
Category Treatment	-0.173*	0.262	-0.185*	-0.792***
	(-1.73)	(0.99)	(-1.92)	(-3.72)
Constant	-4.917	-5.350	-1.279**	-5.123
	(-0.05)	(-0.02)	(-2.47)	(-0.02)
Subject	Yes	Yes	Yes	Yes
N	936	203	876	292
Pseudo R^2	0.16	0.08	0.16	0.20

5 Conclusion

This study uses an experimental approach to examine the role of coarse categories in individuals' learning from financial information and subsequent investment decisions. In particular, we (i) test the theoretical predictions by Mullainathan (2002) in an investment context, (ii) explore differences in category-based belief formation and (iii) link category-based beliefs to investment behavior.

We document that subjects form category-based beliefs as predicted by Mullainathan (2002) when the observed stock belongs to "good" stock categories associated with gains. People then overreact to category changes, form overly optimistic beliefs, and invest significantly more in the stock compared to a situation with no category change, but the same quality of the stock. Yet, we find the opposite result if the stock belongs to bad stock categories associated with losses. People then seem to be sensitive to the stock's outcome and even overreact to negative information with too pessimistic beliefs if there is no category change. Moreover, we observe a stronger category effect in case of asymmetric category sizes. If the "good" stock category is larger relative to other categories, the category-based belief distortion is higher. We further show that subjects' overreaction to category changes is associated with higher stock investments. Interestingly, this tendency correlates with fewer suboptimal investment decisions in our experimental setting.

The study's results enhance the understanding of how people learn from financial information when aggregated category information, such as industry information, is present. This kind of information aggregation along stock categories is very common in financial market media. Further, our study provides experimental evidence of category-based belief distortion in investment decision-making and thereby (i) complements theoretical work on how categorical thinking affects economic choice (Mullainathan, 2002; Mullainathan et al., 2008) and (ii) shows that categorical thinking by itself is a cognitive limitation that influences investor learning beside pure attentional constraints.

The findings documented in this paper open interesting avenues for further research. First, future work could investigate whether our observed effect on investment decisions is robust to making the experimental environment closer to the typical investment environment. For example, it would be interesting to look at whether the results hold for modifying the risky asset's return distribution or the delay between investment choice and return realization as done in the field experimental study by Beshears et al. (2017) with respect to return information aggregation effects. Further, we show differences in subjects' belief formation based on category types. Future research could explore how different market states, i.e., up or down markets, influence category learning. This might uncover important insights into how individuals form expectations and decide to participate in the stock market during different states in financial markets.

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A Appendix

A.1 Experimental Instructions

(translated from German)

Introduction

Welcome to our financial decision making study
For the duration of the study, we ask you to follow a few rules. Should there be questions, please raise your hand and an experimenter will answer your question privately. We ask you not to communicate with each other or use a calculator during the study.

We also ask you to turn off your cell phones and other devices, or at least to put them on silent, and to pack them away with your bag or belongings. We do not want you or other participants to be disturbed or distracted. If you do not adhere to these rules, this will lead to an automatic exclusion from the study and from payment.

The study will last approximately 1.5 hours.

After the study, you will receive a payout for your participation. The actual amount will depend on your decisions in the experiment and luck.

Everyone will earn 15 EUR for participating in this study. In addition, the computer will randomly pick three out of the present participants who get paid his or her earnings from one of the study's tasks.

Please press 'proceed' to continue with the general instructions.

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General Instructions

In this study you complete investment tasks, related to two securities: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff), and will provide estimates as to how good an investment in the risky security is.

Please click 'proceed' to continue with the detailed instructions for the tasks. Take your time to read the instructions carefully. Note that you cannot go back to previous pages. Please let us know if you have any questions.

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Detailed Instructions

Stages of the Study

The experiment consists of **five stages**.
In each stage, you will decide to invest in one of two securities: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff).

Either way, you start with an endowment of 35 EUR. In addition to this endowment, you will get payoffs from investing.

Each stage consists of 7 investment periods. For each period you can decide wether to invest in the stock or bond, thus you will make 7 decisions. After each period you will earn a payoff from your investment.

Before each block you will be provided with extra information about the stock and the bond. This information can influence your willingness to invest in the stock or bond. **Thus, please read this information carefully – the information is different for each stage.**

If you choose to invest in the bond, you get a payoff of 6 EUR for sure in each period.

If you choose to invest in the stock, you will receive a dividend in every period, which can be either positive or negative. A positive dividend is 20 EUR and a negative dividend is -5 EUR.

At the end of each stage you will have earned your accumulated payoffs from the investment plus your initial endowment of 35 EUR.

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Stock evaluation task

You will then see the dividends of the stock, no matter if you chose to invest in the stock or the bond.

After that, we will ask you to tell us two things:

(1) what you think is the probability that the stock pays a positive outcome (the answer must be a number between 0 and 100);

(2) how much you trust your ability to come up with the correct probability estimate that the stock pays a positive outcome. In other words, we want to know how confident you are that the probability you estimated is correct.

There is always an objective, correct, probability that the stock pays a positive outcome, which depends on the history of dividends paid by the stock already.

If you provide us with a probability estimate that is within 5% of the correct value (e.g., correct probability is 80% and you say 84%, or 75%) you will earn 20 EUR for each correct estimate. In total you can earn up to 120 EUR in this task.

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Your final payment at the end of the study

Your final payment will be:

You will get paid 15 EUR for participating in our study regardless of your task earnings.

In addition, your earnings in one of the experimental tasks can determine your payment. We will randomly draw one of 10 participants out of each session (with maximum 30 participants) who will get paid one of her or his task earnings. The computer will randomly decide which of the above-described tasks will determine the participants' payment. Remember, your task earnings depend on your decisions and answers:

Investment decision in each stage: Your initial endowment of 35 EUR and in each period either 6 EUR from investing in the bond or either 20 EUR or -5 EUR from investing in the stock.

Stock evaluation task in each stage: 20 EUR for each probability estimate that is within 5% of the correct value.

Information Provision

[*Category* condition]

You will soon have the probability to decide to invest either in the stock or bond.

If you decide to invest in a stock you earn the dividend paid by the stock, which can be positive or negative. The positive dividend is 20 EUR and the negative dividend is -5 EUR. The stock belongs to an industry, that determines how likely it is that the stock pays a positive dividend. The stock can belong either to the good, mediocre, or bad industry. A stock from the good industry pays a positive dividend of 20 EUR with a probability of 70% and a negative dividend of -5 EUR with a probability of 30%. A stock from the mediocre industry pays a positive and negative dividend with equal probability, i.e., 50%. If the stock belongs to the bad industry, the stock pays a positive dividend of 20 EUR with a probability of 30% and a negative dividend of -5 EUR with a probability of 70%.

Initially, you won't know to which industry the stock belongs. The probability to belong to the good, mediocre, or bad industry is equal, i.e. 33%.

Please see the overview table below.

Importantly, in each stage, you will observe the same stock during the whole stage. The dividends of the stock are independent from period to period, but come from the same distribution.

Asset	Probability of industry	Industry	Possible outcomes per period	Probabilities for outcomes
Stock	1/3 (33%)	Good industry	20 EUR - 5 EUR	70% 30%
	1/3 (33%)	Mediocre industry	20 EUR - 5 EUR	50% 50%
	1/3 (33%)	Bad industry	20 EUR - 5 EUR	30% 70%
Bond	-	-	6 EUR	100%

That is, the industry of the stock is the same during the whole stage.

If you decide to invest in the bond, each period you will earn 6 EUR for sure.

During each stage, you accumulate your investment outcomes from investing in the stock or bond. These will be added to your initial endowment of 35 EUR.

The stock evaluation depends on what kind of stock outcomes you have already observed. Please refer to the overview table: The initial probability of the stock to pay a positive outcome is 50%, without any doubt. After observing a series of positive outcomes, you might believe that the probability increased to 65%. Yet, how much you trust your ability to come up with the correct probability estimate that the stock pays a positive outcome might vary.

[*Information provision in the other treatments varied according to the number and size of categories. In the next section you find the overview tables with the relevant information.*]

Post-questionnaire

At the end of the experiment, we will ask you some personal questions. Note that all answers will be treated confidentially and will be analyzed anonymously.

A.2 Information Provision Across Treatments

Figure 4.1: Overview Disaggregated condition

Asset	Probability of industry	Industry	Possible outcomes per period	Probabilities for outcomes
Stock	1/6 (17%)	Very good industry	20 EUR - 5 EUR	75% 25%
	1/6 (17%)	Good industry	20 EUR - 5 EUR	65% 35%
	1/6 (17%)	Good - mediocre industry	20 EUR - 5 EUR	55% 45%
	1/6 (17%)	Mediocre - bad industry	20 EUR - 5 EUR	45% 55%
	1/6 (17%)	Bad industry	20 EUR - 5 EUR	35% 65%
	1/6 (17%)	Very bad industry	20 EUR - 5 EUR	25% 75%
Bond	-	-	6 EUR	100%

Figure 4.2: Overview Broad condition

Asset	Probability of industry	Industry	Possible outcomes per period	Probabilities for outcomes
Stock	80%	Good industry	20 EUR - 5 EUR	70% 30%
	10%	Mediocre industry	20 EUR - 5 EUR	50% 50%
	10%	Bad industry	20 EUR - 5 EUR	30% 70%
Bond	-	-	6 EUR	100%

Figure 4.3: Overview Narrow condition

Asset	Probability of industry	Industry	Possible outcomes per period	Probabilities for outcomes
Stock	10%	Good industry	20 EUR - 5 EUR	70% 30%
	10%	Mediocre industry	20 EUR - 5 EUR	50% 50%
	80%	Bad industry	20 EUR - 5 EUR	30% 70%
Bond	-	-	6 EUR	100%