Return Predictability, Expectations, and Investment: Experimental Evidence*

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Abstract

We design an experiment to study how investors form their expectations and make risky investments under different market conditions. Together with the past realizations of a risky asset, our subjects observe a signal a that, in some rounds, helps predict future returns. When subjects perceive a as useless, they irrationally extrapolate from recent return realizations. When they perceive a as useful, instead, they correctly incorporate it and extrapolate much less. We interpret those findings in a forecast model in which subjects have imperfect ability to detect predictability and face uncertainty about the correlation between signal a and future returns. We also find that the level of risky investment and its elasticity to forecasts are larger when a is perceived as useful, suggesting that subjects recognize that predictability in our setting reduces risk. Yet, the elasticity of investments to forecasts remains low – a puzzle relative to their high risky investment.

Keywords: Return Predictability, Expectations, Long-Term Investment, Extrapolation, Model Uncertainty.
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1 Introduction

How do investors form expectations about risk and returns? How do these expectations affect their investment decisions? We investigate these questions in an experimental asset market in which we let subjects have access to information that may or may not be helpful to predict future returns.

Subjects in our experiment have access to the history of realized returns of a risky asset. Observing past returns may affect their expectations of future returns; in particular, it may induce them to extrapolate from past returns. For example, investors may think that if prices have gone up yesterday, they are likely to go up again today. Surveys of investors' expectations have documented various forms of extrapolation. Moreover, extrapolation has been shown to influence investment decisions, leading to important effects on investors' welfare and on market dynamics. Motivated by this evidence, several scholars have proposed asset pricing models featuring extrapolative investors.[1]

While extrapolating from past returns is not rational in our setting (and typically also in actual financial markets), we let our subjects have access to the time series of another variable which, in some treatments, provides useful information to forecast future returns. We build on a large literature on return predictability in financial markets, which has documented for example that the ratio between dividend and prices in the stock market is positively correlated with subsequent returns. The observation dates back to Fama and French (1988) and Campbell and Shiller (1988); more recently, Golez and Koudijs (2018) have shown a significant relation between dividend yields and returns five years ahead in several countries and over five centuries of data.

Predictability in financial markets has important implications, motivating a fundamental debate on the notion of market efficiency and on the quest for asset pricing models with time-varying expected returns (Cochrane (2011), Campbell (2014)). For our purposes, a key observation is that predictability can affect not only expectations but also investment decisions. In particular, predictability may induce larger investment in risky assets, especially so for investors with longer time horizons (Campbell and Viceira (2002)).

[1] Survey evidence include Shiller (2000); Dominitz and Manski (2011); Greenwood and Shleifer (2014), Landier, Ma and Thesmar (2019). The effects of extrapolative investment are shown e.g. in Benartzi (2001), Greenwood and Nagel (2009), Bianchi (2018). Models based on extrapolative investors include De Long, Shleifer, Summers and Waldmann (1990), Barberis, Shleifer and Vishny (1998), Rabin (2002), Rabin and Vayanos (2010), Bianchi and Jehiel (2015), Bianchi and Jehiel (2020).

Our first key question is how investors form expectations when, on top of the history of returns, they observe a predictive variable such as the dividend price ratio. It has been long documented that agents tend to perceive regularities in the data, even when facing completely i.i.d. processes (Chapman (1967), Tversky and Kahneman (1973), Whitson and Galinsky (2008)), and extrapolation may in part respond to such a desire. Under this perspective, one may ask whether extrapolative tendencies are robust when a (simple) rational forecasting model is made available to agents. We elicit investors' expectations while exogenously varying the information that they have access to: in some treatments, the additional variable provided to investors is uncorrelated to future returns; in other treatments, it has a significant predictive power.

Our second key question is how expectations, possibly influenced by the perception of return predictability, are incorporated into investment decisions. We observe the extent to which investors rely on their expectations when deciding the fraction of wealth invested in the risky asset, and whether return predictability affects both the level of investment and its sensitivity to expectations. This allows us to test, in an experimental setting, the implications of predictability for portfolio choices. More broadly, this allows us to derive estimates of investment elasticities to expectations, a key ingredient in most asset pricing models. A classic question, dating back at least to Shiller (1981), is whether volatility in stock prices is too large relative to fundamentals, and whether erratic investors' expectations – Keynes' animal spirits - may significantly contribute to such volatility. The experimental setting is particularly useful as it allows not only to directly observe expectations and investment, but also to abstract from frictions that may contribute to portfolio inertia.

We design our experiment to specifically address the two questions of interest stated above. As mentioned, in every round, subjects are provided with a visual graph of past simulated realizations of a risky index returns and with the past realizations of another variable (called variable a), which in half of the rounds, helps predicting next-period returns. Subjects are asked to make forecasts of future returns, and they choose how much to allocate to the risky asset from a given wealth endowment. In addition, they state whether they view the information in variable a as useful or not. Each round corresponds to a new independent simulation of the same underlying risk and signal distributions, and to a new wealth endowment.

We simulate the process of returns and of the variable a according to a VAR model on US equity markets over 1927-1998, as estimated by Cochrane (2009). The risk index subjects are asked to forecast, and allocate wealth to, mimics US equity returns five-year averages, and the signal provided via variable a has the same predictive power in our experiment as the US market price-dividend ratio over the next five-year index returns.

We find, first, that subjects extrapolate from past returns, consistently

with existing literature. However, this tendency is considerably reduced -in some cases, it is completely eliminated- when subjects perceive predictability. In rounds perceived as predictable, variations in forecasts correctly load on the conditional expectation, i.e. the predictive variable a. The load is however significantly lower than one.

We consider alternative treatments in which we make predictability easier or harder to apply, and find that when applying predictability becomes harder, subjects revert to extrapolation; when applying predictability becomes easier, the tendency to extrapolate is reduced even further. Moreover, we observe higher tendency to extrapolate, and lower reliance on the predictive variable a, when subjects have little experience in the experiment (i.e., in earlier rounds), when they take longer time to complete the tasks, and when they have lower ability to correctly assess predictability.

Overall, our results point at the view that extrapolation may just respond to subjects' needs to perceive some pattern in the data. Indeed, as we show, it is precisely subjects who overestimate the occurrence of predictability who also tend to extrapolate more. At the same time, extrapolative tendencies can be minimized by offering them with an alternative and relatively simple rational model. We believe these findings have important implications for the above mentioned literature on extrapolation in financial markets.

Motivated by this evidence, we develop a model of expectation formation which incorporates two forms of uncertainty. First, subjects may be uncertain on whether variable a is actually helpful to predict returns. Second, in case a is indeed predictive, they may be uncertain on what is the exact relation between variable a and expected returns. We assume that subjects process information based on rational expectations about their ability to perceive correlations, without introducing any extrapolation from past returns or other biased perceptions of correlations. We show that our model provides a good fit to the data, thereby suggesting that our subjects are fairly sophisticated in dealing with those forms of uncertainty.

In terms of investment, we find that subjects are more prone to take risk in rounds perceived as predictable than in rounds perceived as i.i.d. Moreover, their investments depend on their own forecasts, and this elasticity is significantly higher when subjects perceive predictability. This is consistent with the view that our subjects perceive that predictability reduces investment risk, which again points at a rather high level of sophistication. In order to form this perception, subjects need to get a sense of the specific form of predictability they are facing: predictability *per se* is not necessarily associated to lower risk; this is so in our setting as it leads to mean reversion in returns.

At the same time, overall elasticities remain small. This is consistent with a number of recent studies (reviewed below), and as mentioned our experimental setting allows us to rule out that these estimates are driven by frictions such as transaction costs, trading constraints, limited attention and

measurement errors in investment. Moreover, we show in a simple Merton-Samuelson investment model, that these elasticities are difficult to reconcile with relatively high levels of risky investment. As we discuss below, these findings have important implications for asset pricing models studying how shocks to expectations translate into price volatilities or other equilibrium outcomes.

Our paper builds on the literature analyzing expectations in surveys and in experimental settings.[2] Our key innovation is the focus on return predictability, while abstracting from an analysis of dynamic expectations (we let our subjects make forecasts over a series of independent rounds). We also relate to the literature documenting how expectations affect stock market investments.[3] The key novelty of our study is to experimentally shock subjects' expectations using predictability, while abstracting from other frictions that may impact how much investments respond to expectations.

2 Experiment

2.1 Design

The purpose of our experiment is to analyze how investors form their forecast and risk taking decisions when market returns become predictable. To do so, we simulate two different risk processes, one loading on a predictive variable and the other a random walk.

In the random walk case, the return process r_t is simulated according to:

$$r_{t+1} = \mu + \epsilon_{t+1}, \tag{1}$$

where $\{\epsilon_t\}$ are i.i.d. normally distributed shocks $\epsilon_t \sim \mathcal{N}(0, \sigma^2)$.

In the predictable case, the return process r_t^p is simulated according to:

$$r_{t+1}^p = a_t + \epsilon_{t+1}^p, \tag{2}$$

where a_t is a predictive variable with mean μ and $\{\epsilon_t^p\}$ are i.i.d. normally distributed shocks $\epsilon_t^p \sim \mathcal{N}(0, \sigma_p^2)$.

For convenience purpose, we refer to the process (1) as the "i.i.d." case and to the process (2) as the "predictable" case. At any time t, the conditional mean in the i.i.d. case, $\mathbb{E}_t(r_{t+1})$, is constant equal to μ, whereas, in the predictable case, the conditional mean $\mathbb{E}_t(r_{t+1}^p)$ is the time-varying a_t.

The predictive process (2) is simulated using the parameters of the return-dividend yield ratios VAR model estimated by Cochrane (2009) on

[2]See e.g. Assenza, Bao, Hommes, Massaro et al. (2014), Manski (2018), Beshears, Choi, Laibson and Madrian (2018) for reviews, and the references mentioned above.

[3]See e.g. Vissing-Jorgensen (2003), Kézdi and Willis (2011), Amromin and Sharpe (2014), Arrondel, Calvo-Pardo and Tas (2014), Merkle and Weber (2014), Drerup, Enke and Von Gaudecker (2017), Das, Kuhnen and Nagel (2020), and the references above.

US equity returns (CRSP data, period 1927-1998): the variable a and its ability to predict the returns r^p mimics dividend yield ratios and their ability to predict market returns over the next five years in the data. The unconditional distributions of the depicted returns are statistically indistinguishable between the two cases, and match the mean and standard deviation of US equity returns averaged over 5-year periods.[4]

In both processes (1) and (2), the unconditional mean of returns is $\mu = 6.07\%$. The conditional variance of returns is however lower in the predictable case. The correlation between shocks to a_t and r_t is negative, which leads to mean reversion in returns. Given our parameters, we have that $Var(r^p_{t+1}) = 0.67 Var(r_{t+1})$. Appendix 9 provides further details of the simulations of processes (1) and (2).

Subjects are provided, at each round of the experiment, with a new simulated snapshot of either the i.i.d. process (1) or the predictable process (2). The snapshots provide the time series of variables r_t and a_{t-1} for a 40-periods history $r_{-40}, ..., r_{-1}$ and $a_{-40}, ..., a_0$. In the predicable treatment, variable a is as informative as the publicly available dividend yield ratios; in the i.i.d. treatment, subjects still observe a signal, simulated to have the same distribution as a, but now uninformative about future returns. Figure 1 in Appendix 9 provides an example of the predictable and of the i.i.d. treatments.

Subjects are told that the variable a may or may not be useful to predict returns and that, in all round, the average return is equal to 6.07%. They are not given any other information about the processes (1) and (2). They are placed at $t = 0$, where they see the realization a_0 and they are asked, first, to predict the return r_0 and, second, to report whether variable a is useful to predict returns. Third, they need to allocate their endowment between a riskless asset giving zero returns and the risky asset with returns r_t. Finally, at the end of each round, we provide subjects with feedback on the realized returns, on whether the variable a was useful, and on their investment profit.

Our main goal is to observe i) if subjects correctly identify when the signal a is informative or not; ii) how they form their returns forecasts, in both the i.i.d. and the predictable treatments, and whether they use the available signal a to do so; and iii) how they make risk investment decisions, and whether they use their own forecasts to do so.

[4] We do a Kolmogorov–Smirnov test for distributions on arbitrary pairs of displayed simulated returns from the i.i.d process (1) and the predictable process (2). The average p-value we find is 0.497, so the distributions of returns in the two types of graphs do not significantly differ from each other, given the number of draws displayed in each graphs to the subjects in the experiment.

2.2 Implementation

We have conducted the experiment in two waves. In the first wave (January 2019), we have recruited 58 participants, students in the Master of Finance at Toulouse School of Management (TSM). The second wave (January 2020) includes 36 students from the same Master. The experiment took place in the University computer lab on an application we have built using the Otree framework (Chen, Schonger and Wickens (2016)). After logging in, subjects saw detailed instructions, including a description of the tasks and the payment rules, as included in Figure 2 in Appendix 9.[5]

Subjects are informed that they would play an investment game, and face a variable that may or may not be useful to predict returns. We provide subjects with an example for each type of graph, in the introduction, and tell that the average return is 6.07% in all rounds and that rounds are independent.

In the baseline treatment, common to both waves, we let subjects play for 20 rounds, half are i.i.d. and half are predictable.[6] The order of the graphs is randomized across subjects. Each round includes a Question Page and a Result Page. In the Question Page, subjects are presented a new simulated graph and they are asked to provide a forecast for the next-period risky returns, to state whether they think that variable a was useful to forecast returns, and to allocate a 100 ECU endowment between the riskless asset and the risky asset. Upon submitting their answers, subjects click onto the Result Page, where they see the simulated realization of returns and they are told whether variable a was indeed predictive and whether their forecast was "precise", meaning that it lied in a $(-1\%, +1\%)$ interval of the return realization.[7] They are also shown the realized payoffs of their investment. An example of those pages is provided in Figures 3 and 4, in Appendix 9.

As compensation for participating in the experiment, subjects receive 5 ECU for every correct answer regarding whether the variable a is predictive and 10 ECU for every "precise" forecast; in addition, they receive their full portfolio value from a round that is randomly drawn at the end of the experiment.

We have verified that the simulated data correctly represent either the i.i.d. process (1) or the predictable process (2) by regressing the returns $\{r_t\}$ in each simulation on both the predictive variable $\{a_{t-1}\}$ and on the

[5] They could ask questions at any time during the session. All questions were answered privately.

[6] In addition, in the first wave, we have asked to make 5-period forecasts and investments. In the second wave, we have provided 20 additional rounds. In half of them, we state that variable a is useful and in half of them we state that variable a is not useful to predict returns. These additional treatments are discussed in Section 4.

[7] This chosen interval helped us incentivize subjects, in a clear and easily understandable way, to provide their true expectations. In our sample around 8% of forecasts turned out to be accurate according to this definition.

previous realized returns $\{r_{t-1}\}$. Results are provided in Table 10 in Appendix 9. Regression coefficients of r_t on a_{t-1} are indeed around 1 (and highly significant) in the predictable case and around 0 (and not significant) in the i.i.d. case, while regression coefficients of r_t on r_{t-1} are around 0 (and not significant) in both cases.[8]

2.3 Summary Statistics

In Table 1, we provide some descriptive statistics of the data collected during the experiment. We notice some interesting patterns, which we confirm and interpret in the next analysis.

First, subjects have a good ability to detect predictability. Conditional on being in a predictable round, subjects' answers about the usefulness of variable a are correct 80.6% of the time (see $\Pr(a\ \textit{useful}|\ \textit{predictable})$). Conditional on being in a i.i.d. round, they are correct 70.4% of the time (see $\Pr(a\ \textit{useless}|\ \textit{i.i.d.})$). Both results are significantly greater than 50%, as would implied by random guesses (p-value = 0.00). This also implies that they tend to slightly overestimate the proportion of predictable rounds, estimated to be 55.1% as opposed to the true proportion 50% (the difference is significant with p-value = 0.00).

Though all simulations in which variable a is predictive derived from the same model, one simulated graph may have randomly been "more predictive" than the next, in the sense that the regression of r_t on a_{t-1} may have a higher R^2 (see Table 10 in Appendix 9). We do not find, however, that subjects were more likely to correctly identify variable a as predictable in graphs with larger R^2. The correlation between the probability of noting a as predictable and the R^2 of the regression of r_t on a_{t-1} in a given predictable graph is equal to -0.1.

We also notice that the average forecast is 5.28%, which is significantly below the true mean of 6.07% (p-value = 0.00). That agents tend to make overall pessimistic forecasts, on average below the true statistical mean, is a common feature of survey data; and our result is consistent with evidence in e.g. Dominitz and Manski (2007), Hurd and Rohwedder (2012), Giglio, Maggiori, Stroebel and Utkus (2019). Pessimism in forecasts is however moderated by the perception of predictability: when subjects perceived returns as predictable by variable a, their average forecast is 5.74%, which is significantly larger than 4.72%, the average forecast when they perceive returns as not predictable (p-value = 0.00), and not significantly different from 6.07% (p-value = 0.13).

[8] In two outlier i.i.d simulations, r_{t-1} is *negatively* correlated to r_t with p-value around 5%. We find that subjects displayed the same forecast biases in these two outlier rounds; and extrapolated from past returns to next-period returns no less strongly than in other i.i.d rounds.

Moreover, forecasts tend to be more accurate in rounds where a is perceived as useful. The variable *Forecast Distance* reports the distance between the subject's forecast and the returns effectively realized in the next period. On average, the distance is 7.7% in rounds perceived as predictable and 10.1% in rounds perceived as i.i.d. (p-value = 0.00).

Finally, subjects' risk allocations follow the same patterns as their forecasts. The average allocation is 48.6 ECU when returns were perceived as predictable, significantly higher than the 40.6 ECU average investment when returns were perceived as i.i.d. (p-value = 0.00).

3 Main Results

We now provide the main results of our analysis regarding subjects' forecasts and risky investments. The interpretation of these results is in Section 6.

3.1 Forecasts

The simulated returns subjects observe in each graph have a simple rational expectation rule: when returns are simulated from the i.i.d. process (1), the best forecast for next-period return is always the unconditional mean $\mu = 6.07\%$; when returns are simulated from the predictable process (2), the best forecast for next-period return is the last realized value of variable a. For any graph g of simulated returns:

$$\begin{cases} \mathbb{E}\left(r_g \mid_{\text{i.i.d.}}\right) & = \mu \\ \mathbb{E}\left(r_g \mid_{\text{predictable}}\right) & = a_g \end{cases}, \tag{3}$$

where a_g is the latest realized value of variable a in graph g (to simplify the notations, we write a_g, r_g instead of $r_{0,g}, a_{0,g}$).

3.1.1 Predictive Variable

To evaluate how subjects' forecasts relate to the rational expectation rule of Equation (3), we consider the following regression:

$$F_{i,l} = \alpha_i + \alpha_2 P_{i,l} + \beta_1 a_g + \beta_2 a_g P_{i,l} + \eta_l + \epsilon_{i,l}, \tag{4}$$

where $F_{i,l}$ is the forecast on next period returns made by subject i in round l (while facing graph g), $P_{i,l}$ is a dummy taking value 1 if subject i believes that returns are predictable by variable a in round l and taking value 0 otherwise, α_i and η_l are respectively individual and round fixed effects.

The results of regression (4) are presented in Table 2. In column 1, we include no fixed effects; in column 2, we add individual fixed effects; in column 3, we add round fixed effects. Results in all these specifications are

robust: subjects' forecasts for next period returns load on variable a only when it is perceived as predictive. The same result appears in columns 4 and 5, where we split the sample according to the values of $P_{i,l}$.[9]

This is a first key result of our experiment: subjects are fairly competent at spotting when a given signal helps predict next period returns (as mentioned their probability of correctly identifying variable a as useful is 80.6%), and they are rational in that they then, and only then, use said signal to make their own forecasts of returns.

This behavior is qualitatively consistent with the rational expectations of Equation (3), but the estimates for coefficient β_2 are significantly lower than 1. Relative to Equation (3), subjects under-react to the value of a_g, even when they perceive that a is predictive. A 1% increase in a_g, corresponding to a 1% increase in the rational expectation of next-period return r_g, would result in a 0.36% increase in subjects' forecasts (considering e.g. the estimates in column 4). We come back to these results in Section 6.1.

3.1.2 Past Returns

While we show in Table 2 that subjects rely on variable a if (and only if) they deem it as predictive, they may also seek other information when forming their expectations. In particular, previous work in the literature suggest that they may use past realized returns to predict next-period returns (see e.g. Shiller (2000), Dominitz and Manski (2011), Greenwood and Shleifer (2014), and Landier et al. (2019)). As mentioned, there is no rational basis for such extrapolative forecasts in US equity markets: annual returns are not positively autocorrelated in the data. Further, as shown in Table 10 in Appendix 9, r_{t-1} does not help positively predict r_t in any of the simulations of returns in our experiment. Any form of extrapolative forecast can therefore be deemed as irrational in the context of our experiment.

To evaluate subjects' tendency to extrapolate, we include the last realized return $r_{-1,g}$ as regressor in specification (4) together with its interaction with the dummy $P_{i,l}$. The results are presented in Table 3. Consistently with previous works, in column 1, we show that subjects rely on past returns in their forecast: a 1% increase in $r_{-1,g}$ would result in a 0.12% increase in subjects' forecasts. In column 2, however, we observe a stark difference in extrapolative behaviors depending on whether a is perceived as predictive. When subjects perceive a as useless, they heavily rely on past returns: a 1% increase in $r_{-1,g}$ increases forecasts by 0.19%. When a is perceived as useful, the effect is much weaker: a 1% increase in $r_{-1,g}$ increases fore-

[9] In column 5, the number of subjects is 93 since one subject declares variable a as useful in 19 out of 20 rounds. When we restrict to $P_{i,l} = 0$, the subject has only one observation and since our regression includes individual fixed effects and standard errors are clustered at the individual level, singleton groups are dropped (hence the missing observation in column 5).

casts by 0.03%, which is not significantly different from zero (p-value=0.33). A purely extrapolative model would not predict any systematic difference depending the perception about a, suggesting that the way in which our subjects make forecasts cannot be simply described as extrapolative.

The result is confirmed in column 3, where we include also variable a_g and its interaction with $P_{i,l}$, and in columns 4 and 5, where we split the sample according to the value of $P_{i,l}$. The load on a_g is similar to the one estimated in Table 2 (if anything, it is larger). The load on $r_{-1,g}$ is significantly reduced in graphs in which a is perceived as predictive.

This is the second key result of our experiment: subjects remain fairly competent at spotting when variable a is not useful to predict returns (their probability of correctly identifying variable a as useless is 70.4%), but they then, and only then, resort to a "default option" irrational forecast model whereby they extrapolate from past returns.

3.2 Investments

The second core question of interest in our experiment concerns the allocations to risk subjects choose to make, and crucially i) if and how their investment decisions depend on their own forecasts of returns; and ii) if their investments differ across rounds, depending on whether they perceive returns as predictable or not. We analyze the two questions jointly via the regression:

$$\theta_{i,l} = \alpha_i + \alpha_2 P_{i,l} + \varphi_1 F_{i,l} + \varphi_2 F_{i,l} P_{i,l} + \eta_l + \epsilon_{i,l}, \tag{5}$$

where $\theta_{i,l}$ is subject i's investment into the risky fund (out of her 100 ECU endowment) in round l. As before, $F_{i,l}$ is subject i's forecast of next period return, $P_{i,l}$ is a dummy indicating whether subject i believes that returns are predictable by variable a, and α_i, η_l are respectively individual and round fixed effects.

The results of regression (5) are provided in Table 4. We start by considering the direct effect of the forecast $F_{i,l}$ on investment. In column 1, we include no fixed effects; in column 2, we include individual fixed effects; in column 3, we add round fixed effects. The estimated elasticity is stable across specifications: a 1% increase in next-period return forecast translates into an increase of 2.2% in the risky asset. A similar estimate appears in column 4, where instead of including individual fixed effects we regress the change in investment relative to the previous round over the change in forecast over the previous round.

We next consider the effect of predictability. In column 5, we observe that risky investment is significantly larger when returns are perceived as predictable (as also shown in the statistics of Table 1). An increase of 8.68 ECU corresponds to a 21% increase relative to the average investment in

the i.i.d. case (equal to 40.6 ECU). Moreover, in column 6, we observe that subjects rely on their own forecasts more when they perceive returns as predictable: the estimates for φ_2 in Table 4 are also significantly greater than zero. A 1% increase in next-period return forecast translates into an extra 0.66 ECU in the risky asset under predictability, which corresponds to a 37% increase relative to the average elasticity in the i.i.d. case (equal to 1.8 ECU).

That subjects make investment decisions consistent with their own forecasts is a key result, and an important contribution, of our experiment. Indeed, various work in the macroeconomics and finance literature infer general equilibrium pricing implications from investors' beliefs, obtained via surveys of expectations. Such models implicitly assume that investors adjust their risk decisions perfectly in line with their own expectations. The results of Table 4 indicate they actually do so.

Crucially, however, the results of Table 4 also make clear how limited the magnitude to which subjects vary their risk decisions depending on their stated forecasts. A level increase of 1% in their next-period return forecast – i.e. a 19% increase relative to the 5.28% average forecast – translates into an increase of 2.2 ECU, i.e. 4.9% greater risk taking relative to the 45 ECU average. These magnitudes are pretty similar in " perceived i.i.d." and in "perceived predictable" rounds. Elasticities of investments to expectations as low as 0.26 may cast a doubt on the general equilibrium impact of variations in investors' expectations. We discuss these results further in Section 6.2.

4 Additional Treatments

In some replications of our experiment, we have performed some additional treatments. In the first replication (January 2019), we have added a "long-horizon" treatment in which we ask subjects also their forecast and investment for a longer period. As we detail below, while predictability has potentially even stronger effects at longer horizons, applying it becomes more difficult from our subjects' perspective. In the second replication (January 2020), we have added a "reveal" treatment in which we explicitly tell to subjects whether or not variable a is useful to predict returns, thereby removing some uncertainty and making it easier to employ predictability.

Overall, we observe that, when predictability becomes harder to apply, subjects revert to extrapolation. Conversely, in treatments in which applying predictability is easier, the tendency to extrapolate is reduced even further. This confirms our interpretation that extrapolation may just respond to subjects' needs to perceive some pattern in the data and this tendency can be minimized by offering them with an alternative and relatively simple rational model.

We also observe that when choosing their investments, subjects rely more on their forecast in treatments where predictability is easier and much less so when predictability is harder, confirming our findings in Section 3.2 and highlighting again the possibly important effects of predictability on risk taking.

4.1 Longer Horizon

In the "long-horizon" treatment, we ask subjects to provide their forecasts for the average return over the next five periods, and to allocate a portion of another 100 ECU endowment to risk, locked in for five periods, which in our setting corresponds to a 25 years horizon. These questions were asked while subjects faced exactly the same graphs as in the baseline treatment, 10 graphs with predictable returns and 10 graphs with i.i.d. returns.

Predictability has potentially even larger impacts on investment in the five-period than in the one-period horizon. The reason is that the conditional variance of returns is even lower at such horizon.[10] At the same time, if subjects are uncertain about the parameters of the return process, the effect can be even reversed as parameter uncertainty is amplified at longer horizons (Barberis (2000), Pástor and Stambaugh (2012)).

Indeed in our case, while the simulated returns observed in each round have a straightforward rational expectation rule at the one-period horizon (Equation (3)), the rational expectation rule for the predictable returns is far less obvious at the five-period horizon. Making a forecast at long horizons requires estimating the dynamics of the predictive variable a, the process of which was not provided, or even mentioned, in the experiment. When simulating returns from process (2), we follow Cochrane (2009) and simulate the variations of a around its mean μ as a contracting AR(1) process. As detailed in Appendix 9.1, the correct rational expectation rule at the five-period horizon is given by:

$$\begin{cases} \mathbb{E}\left(\overline{r}_{g,5} \mid_{\text{i.i.d.}}\right) & = \mu \\ \mathbb{E}\left(\overline{r}_{g,5} \mid_{\text{predictable}}\right) & = \kappa a_g + (1-\kappa)\mu \end{cases}, \tag{6}$$

where $\overline{r}_{g,5}$ is the average return over five periods starting at $t = 0$, a_g is the last realized value of variable a in graph g, and $\kappa < 1$ depends on the persistence of the variable $(a - \mu)$.[11] To replicate the rational expectations of Equation (6), subjects would thus need to infer either that variable a follows an AR(1), and how persistent it is; or that the past realized $\{a_t\}$ are correlated not only with the returns $\{r_{t+1}\}$ but also with the return averages

[10] From our parameters, as shown in Appendix 9.1, we have $Var_t(r^p_{t+1}) = 0.67 Var_t(r_{t+1})$ for one period and $Var_t(r^p_{t+1}) = 0.61 Var_t(r_{t+1})$ for five periods.

[11] Let $\theta \neq 1$ be the persistence parameter in the AR(1) process of variable $(a-\mu)$. Then $\kappa = \frac{1}{5}\frac{1-\theta^5}{1-\theta}$.

$\{(r_{t+1} + r_{t+2} + r_{t+3} + r_{t+4} + r_{t+5})/5\}$. In this sense, applying predictability is considerably harder here relative to the baseline treatment.

We analyze subjects' forecast and investment following the same analysis as in Section 3, and report our results in Table 5. In columns 1-2, we look at forecasts of the average returns over the next five periods. We observe that subjects stop using variable a to make their long-horizon forecasts, even when they view it as useful. By contrast, they always rely, significantly, on past returns, irrespective of whether they perceive a as predictive. This is in stark contrast to their one-period forecasts (Section 3.1), which as mentioned is likely to reflect the difficulty at correctly identifying the rational expectation rule of Equation (6), compared to the easier rule of Equation (3).

In columns 3-6, we look at the fraction of the endowment invested in the risky asset for the next five periods. We observe that the sensitivity of investment to forecast is still significantly positive, but its magnitude is much smaller than in the one-period case. Estimated elasticities are around 0.7% (0.9% when we regress changes in investment over changes in forecasts relative to the last round), anyway significantly smaller than 2.2% as estimated in Section 3.2. Moreover, and again in contrast with the baseline treatment, both these elasticities and the investment levels do not differ significantly depending on whether variable a is considered predictive. This is again consistent with the view that, even if subjects perceive that a is correlated to returns, they find it hard to use such predictability.

4.2 Revealing Predictability

In the "reveal" treatment, we let subjects face 10 predictable graphs and we explicitly tell them at the beginning of the sequence that in those graphs variable a is useful to predict returns (we call this treatment "Predictive"). We also let them face 10 i.i.d. graphs for which they are told that that a is not useful to predict returns (we call this treatment "Not Predictive"). These sequences are always presented after the baseline treatment in which we do not tell whether a is predictive and the order between "Predictive" and "Not Predictive" is randomized across subjects.

We analyze subjects' forecast and investment following the same analysis as in Section 3, and report our results in Table 6. In columns 1-2, we analyze forecasts of next period returns. In column 1, *Predictive* is a dummy equal to 1 if the treatment is "Predictive" and to zero if subjects are not told whether a is useful (i.e., the baseline treatment). In column 2, *Not Predictive* is a dummy equal to 1 if the treatment is "Not Predictive" and to zero if subjects are not told whether a is useful. We observe that, when a is revealed as predictive, subjects stop relying on past returns to form their forecasts. When *Predictive* equals 1, the coefficient on past return is not significantly different from zero (p-value=0.210). Revealing that a is useful

removes subjects' tendency to extrapolate. Instead, revealing that a is not useful does not affect the tendency to rely on past returns (see column 2). In these columns, the tendency to rely on a is instead not significantly affected by the "reveal" treatment.

In columns 3-4, we analyze risky investments for the next period. We observe that revealing that a is useful increases the elasticities of investment to forecasts. This shows that, consistently with our previous findings, subjects rely more on their forecasts in treatments where predictability is easier to apply.

5 Heterogeneous Behaviors

In Section 4, we have considered treatments where predictability is made harder or easier to apply. At the same time, subjects may find it harder or easier to apply predictability depending on their ability and on the accumulated experience in the experiment. We now explore these potential sources of heterogeneity.

First, we look at whether subjects display different behaviors in early vs. late rounds, thereby uncovering the possible effects of learning. Second, we look at subjects' response time, which may be correlated to how difficult they find it to complete their tasks. Finally, we measure each subject's ability to detect predictability by computing the number of correct answers to the question on whether variable a is predictive. Throughout this section, we restrict to our baseline treatment described in Section 3.

Overall, the picture we draw confirms our previous findings. We observe lower tendency to extrapolate, and higher reliance on variable a, in i) later rounds, ii) responses given with shorter delay, iii) subjects with higher ability to detect predictability. This reinforces the view that extrapolation can be considerably reduced in situations where subjects appreciate the availability of an alternative rational model.

5.1 Learning

In columns 1-2 of Table 7, we explore whether subjects behave differently depending on the experience they have accumulated in our experiment. As mentioned, at the end of each round, we provide to subjects an "answer page" that reports the realized next period returns, whether their forecast was accurate, and whether variable a was predictive. This may induce some learning, and we capture its potential effects simply by looking at the round number in which subjects are playing. In particular, we distinguish between early rounds between 1 and 10 and late rounds between 11 and 20.

In column 1, we observe that in late rounds subjects rely significantly less on past returns, and significantly more on a, when they perceive that a is predictive. In fact, in late rounds and when a is perceived as useful, the

load on past returns is not significantly different from zero (p-value=0.33). The effects in early rounds are weaker, and the load on past returns is always positive.

Considering the effects on investment, we observe that the average investment in late rounds is 4.8 ECU larger than in earlier rounds (p-value=0.05), that is an increase of 10.7% from the average investment of 45 ECU.[12] The sensitivity of investment to forecast does not however vary significantly over rounds (column 2).

5.2 Fast and Slow Responses

We now explore whether forecasts and investments are different depending on how much time subjects take when answering the required questions, which we record for each subject in each round. We construct the dummy *Fast Replies*, which is equal to 1 if the number of seconds the subject takes for submitting the answers in a given round is below the sample median (equal to 61 seconds).

We first notice that *Fast Replies* are associated to a larger probability to a correct response to the question on whether a is predictive (the probability of being correct is increased by 4%, p-value=0.02). In column 3 of Table 7, we show that responding fast is associated to a significantly lower reliance on past returns, and a significantly higher reliance on a, based on the perceived predictability. In fast decisions and when a is perceived as useful, the load on past returns is not significantly different from zero (p-value=0.13). These patterns cannot be observed for slow decisions. Finally, in column 4, we observe that faster decisions are also associated with higher sensitivity of investment to forecast.

5.3 Detection Ability

We can measure subjects' ability detect predictability by looking at the fraction of correct answers to the question on whether a is useful to predict returns in a given round. As mentioned, over the 20 rounds, the average number of correct answers is rather large and exceeding 15. At the individual level, the number of correct answers ranges from 10 (corresponding to purely random answers) to 20. We say a subject has high ability if the number of correct answers is above the sample median, equal to 15.

In columns 5 of Table 7, we observe that high ability subjects display lower loads on past returns, especially so in rounds perceived as predictable. For high ability subjects and when a is perceived as useful, the load on past returns is not significantly different from zero (p-value=0.16). This is not the case for low ability subjects.

[12] At the same time, we observe no time trend in average forecast.

At the same time, the tendency to extrapolate is similar across subjects when *Perceive* is equal to 0. Put differently, subjects with larger tendency to extrapolate are those who more likely to be mistaken when they perceive that a is useful (as opposed to subjects who make mistakes when they perceive that a is not useful). These are subjects who overestimate the occurrence of predictability, which may be driven by a larger desire to perceive patterns in the data. Under this perspective, it appears once again that extrapolation may be a response to subjects' desire to detect correlations.

Finally, in column 6, we observe that the sensitivity of investment to forecast is larger for high ability subjects.

6 Interpretation

In this section, we interpret our main findings first by developing a simple forecast model aimed at uncovering how much sophistication our subjects display. Second, we apply a standard investment model to discuss the implicit risk aversion that can be estimated from their behaviors.

6.1 Forecasts

In order to analyze how forecasts are made, we start by noticing that our subjects face two forms of uncertainty. First, they may not be sure that their assessment on whether a is useful is indeed correct. Second, conditional on perceiving that a is useful, they may not know exactly how to apply variable a. Our subjects are not told that $\mathbb{E}_t(r_{t+1}) = a_t$ when a is useful, they have to infer this relation from the observed graphs. As we highlight below, this inference too is affected by the uncertainty on whether they are correctly perceiving the usefulness of variable a.

We incorporate these two dimensions of uncertainty in the following forecast model. Suppose that subjects have in mind a model to estimate returns when a is useless, which determines an expectation denoted as $\mathbb{E}^u(r_{t+1})$. Subjects have in mind a (possibly different) model to estimate returns when a is useful, which in turn determines an expectation denoted as $\mathbb{E}^p(r_{t+1})$. Their forecast conditional on their perception about a can be written as

$$\begin{cases} \mathbb{E}\left(r_{t+1}\,|_{a\text{ useless}}\right) & = \lambda_u \mathbb{E}^u(r_{t+1}) + (1-\lambda_u)\mathbb{E}^p(r_{t+1}) \\ \mathbb{E}\left(r_{t+1}\,|_{a\text{ useful}}\right) & = \lambda_p \mathbb{E}^p(r_{t+1}) + (1-\lambda_p)\mathbb{E}^u(r_{t+1}) \end{cases},$$

where λ_u is the weight subjects assign to model $E^u(r_{t+1})$ when they perceive that a is useless and λ_p is the weight they assign to model $E^p(r_{t+1})$ when they perceive that a is useful. These weights can be interpreted as the probability that the subject assigns to the fact that a is indeed useful or useless, conditional on the fact that the subject perceives it as such.

Suppose the agent is aware that her ability to perceive predictability may be imperfect, and she determines the weights λ_u, λ_p as posterior probabilities in a standard Bayesian way. Define π as the prior about the proportion of predictable rounds, p as the probability of correctly identifying when a is predictive and q as the probability of correctly identifying when a is not predictive. We have that the probability of declaring that a round is predictable is

$$\hat{\pi} = p\pi + (1-q)(1-\pi),$$

the probability that a is indeed useful conditional on being perceived as such is

$$\Pr(\mathit{predictable} \mid_{a \text{ useful}}) = \frac{p\pi}{\hat{\pi}} = \overline{p}, \tag{7}$$

and the probability that a is indeed not useful conditional on being perceived as such is

$$\Pr(i.i.d. \mid_{a \text{ useless}}) = \frac{q(1-\pi)}{1-\hat{\pi}} = \overline{q}. \tag{8}$$

In this setting, the agent would set

$$\lambda_u = \overline{q} \text{ and } \lambda_p = \overline{p}.$$

Consider now how the subject estimates the models to determine $\mathbb{E}^u(r_{t+1})$, $\mathbb{E}^p(r_{t+1})$. Subjects are told that the average return in each round is equal to $\mu = 6.07\%$. A natural benchmark is then to set

$$\mathbb{E}^u(r_{t+1}) = \mu,$$

as the expectation that subjects hold when a is not useful (notice we do not introduce any tendency to extrapolate from past returns here). Subjects are not told anything about the mapping between a_t and r_{t+1} in the case in which a is useful, we assume they try to estimate a model of the form

$$\mathbb{E}^p(r_{t+1}) = \bar{\theta} a_t + (1-\bar{\theta})\mu,$$

where $\bar{\theta}$ is the estimated weight on a_t. Assuming that subjects indeed perceive that a_t and r_{t+1} are positively correlated, we can set $\bar{\theta} \in (0,1)$.

Subjects may try infer the value of $\bar{\theta}$ from the graphs in which they perceive that a is useful. If they take into account that their perception in not perfect, they may also try to extract some information from the graphs in which they perceive that a is useless. Denote with $\bar{\theta}_p$ the average correlation between r_t and a_{t-1} perceived when a is considered useful (recall that subjects observe a 40-periods history, so $t = -40, ..., 0$). Similarly, let $\bar{\theta}_u$ be the average correlation perceived when a is considered useless. The perceived correlation is

$$\bar{\theta} = \frac{\eta_p \bar{\theta}_p + \eta_u \bar{\theta}_u}{\eta_p + \eta_u},$$

where η_p and η_u are the weights the subjects assign to $\bar{\theta}_p$ and $\bar{\theta}_u$, respectively. These weights can be interpreted as the perceived degree of informativeness of $\bar{\theta}_p$ and $\bar{\theta}_u$.

We assume that $\bar{\theta}_p$ and $\bar{\theta}_u$ coincide with the true average correlations in the two sets. That gives

$$\bar{\theta}_p = \frac{\frac{1}{2}p * 1 + \frac{1}{2}(1-q) * 0}{\frac{1}{2}p + \frac{1}{2}(1-q)},$$

where $p/2$ is the fraction of predictable graphs perceived as such and $(1-q)/2$ is the fraction of i.i.d. graphs perceived as predictable. Similarly, we have

$$\bar{\theta}_u = \frac{\frac{1}{2}q * 0 + \frac{1}{2}(1-p) * 1}{\frac{1}{2}q + \frac{1}{2}(1-p)},$$

where $q/2$ is the fraction of i.i.d. graphs perceived as such and $(1-p)/2$ is the fraction of predictable graphs perceived as i.i.d..

We also assume that

$$\eta_p = \overline{p} \text{ and } \eta_u = 1 - \overline{q}.$$

That is, the agent assigns a weight η_p equal to the probability of being right when a is considered (which corresponds to the proportion of true positives) and a weight η_u equal to the probability of being wrong when considering a as useless (which corresponds to the proportion of false negatives).

According to this model, the estimated coefficients in (11) are

$$\alpha_1 = \mu - (1-\overline{q})\bar{\theta}\mu, \text{ and } \alpha_1 + \alpha_2 = \mu - \overline{p}\bar{\theta}\mu, \tag{9}$$

$$\beta_1 = (1-\overline{q})\bar{\theta}, \text{ and } \beta_1 + \beta_2 = \overline{p}\bar{\theta}. \tag{10}$$

As a simple benchmark, we can define an *omniscient* subject who perfectly perceives whether a is useful or not and knows the true models for expected returns. If we set $\pi = 1/2$ and $p = q = 1$, which gives

$$\bar{\theta}^O = \overline{q}^O = \overline{p}^O = 1,$$

and so

$$\begin{cases} \mathbb{E}^O\left(r_{t+1} \mid_{a \text{ useless}}\right) & = \mu \\ \mathbb{E}^O\left(r_{t+1} \mid_{a \text{ useful}}\right) & = a_t \end{cases},$$

as in Equation (3). In the baseline regression

$$F_{i,l} = \alpha_1 + \alpha_2 P_{i,l} + \beta_1 a_g + \beta_2 a_g P_{i,l} + \epsilon_{i,l}, \tag{11}$$

with *omniscient* subjects we would get estimated coefficients as

$$\alpha_1 = \mu = 6.07\%, \alpha_1 + \alpha_2 = 0, \beta_1 = 0, \beta_2 = 1. \tag{12}$$

As noticed, these predictions can be rejected in our data. We observe for example that β_2 is significantly smaller than 1.

Consider instead a subject who has imperfect ability to detect predictability and imperfect knowledge of the return processes. Suppose the subject is *sophisticated* in the sense of being aware of these limitations and who is also *rational* in the sense of holding correct expectations about the proportion of predictable graphs and about the (average) probabilities of correctly identifying when a is predictive and when a is not predictive. For this subject, we can set

$$\pi = 1/2,\ p = 0.8064,\ q = 0.7043.$$

This gives

$$\overline{p} = 0.7317,\ \bar{q} = 0.7843,\ \bar{\theta} = 0.6142, \tag{13}$$

and substituting into (9)-(10), we get the estimated coefficients in (11) as

$$\alpha_1 = 5.2658,\ \alpha_2 = -2.1198,\ \beta_1 = 0.1325,\ \beta_2 = 0.3169. \tag{14}$$

We confront the predictions in (14) with our experimental results in Table 11. In the top panel, we report the estimated coefficients of regression (11) in our data as well as the associated 95% confidence intervals. In the bottom panel, we report the p-value of the t-test of the restrictions in (14) for each estimated coefficient. In column 1, we report estimates on the full sample; in column 2, we restrict to late rounds (those between 11 and 20); in column 3, we restrict to fast decisions (those submitted with a delay below the sample median, equal to 61 seconds); in column 4, we restrict to subjects who have more than 15 correct answers on whether variable a has predictive power (that is the median detection ability). These sample restrictions correspond to the heterogenous behaviors uncovered in Section 5.

We observe that in all these samples we fail to reject that the estimated coefficient is equal to the value predicted in (14), at conventional levels.[13] This is remarkable as the model behind (14) assumes a rather high level of sophistication on subjects. Moreover, in our predictions (14), we have not allowed ourselves any degree of freedom in picking parameter values which would accommodate possibly subjective perceptions. As mentioned, all values in (14) are derived by assuming fully rational expectations, so that

[13] The lowest p-value is always associated to the coefficient β_1, whose estimates are somewhat smaller than those predicted in (14). According to (10), this implies that the estimated $\overline{q}$ is somewhat larger than what assumed in (13), which may be interpreted as subjects overestimating their ability to detect when returns are not predictable.

the values of π, p, q correspond to those actually observed in the data.

We also observe that the model performs better, in that its predictions are closer to the estimated coefficients, in samples which we have described in Section 5 as closer to the theoretical benchmark in Equation (3). This is the case after some learning has taken place or for subjects which have higher detection ability. This confirms the view that the model proposed in (14) entails minimal departures from the omniscient model. In particular, it does not feature any systematic bias in the perception of ability and of correlations nor any departure from Bayesian reasoning nor any form of extrapolation from past returns.

6.2 Investments

To analyze our results on investment, we rely on a standard Merton-Samuelson portfolio choice model with power utility and log normal returns, whereby an agent with coefficient of relative risk aversion γ_i invests a fraction θ_i of her wealth into a risky asset with expected returns $E_i(r)$ and variance $\sigma_i^2(r)$ under the allocation rule:

$$\theta_i = \frac{1}{\gamma_i}\frac{\mathbb{E}_i(r)}{\sigma_i^2(r)}. \tag{15}$$

Denote with $\sigma^2(r)$ and with $\sigma^2(r^p)$ the variance in the i.i.d. and in the predictable case, respectively. Suppose that subjects correctly assess that $\sigma^2(r) > \sigma^2(r^p)$ and that they have some (even limited) ability to correctly perceive predictability. In the notation of Equations (7)-(8), suppose $\overline{p}_i > 0.5$ and $\overline{q}_i > 0.5$, which is indeed the case for respectively 91% and 77% of our subjects. The perceived variance is then lower when they perceive a as predictive. According to Equation (15), for a given forecast $\mathbb{E}_i(r)$, both the level of investment and the sensitivity of investment to forecast are larger in rounds perceived as predictable. This indeed what we have found in Section 3.2.

More generally, equation (15) predicts a tight link between the level of investment and its sensitivity to forecast, both of which can be observed in our data. This allows us to derive some estimates of subjects' risk aversion as implied by their choices.

Suppose that for investor i we observe different investment choices $\theta_{i,l}$ associated to different forecasts $F_{i,l}$ over a set Ω of rounds in which the investor perceives the same variance, $\sigma_{i,l}^2(r) = \sigma_i^2(r)$ for all $l \in \Omega$. Since risks are independent across rounds, Equation (15) gives

$$\frac{1}{\gamma_i\sigma_i^2} = \frac{1}{|\Omega|}\sum\nolimits_{l\in\Omega}\frac{\theta_{i,l}}{F_{i,l}}, \tag{16}$$

and

$$\frac{1}{\gamma_i\sigma_i^2} = \frac{\partial\theta_{i,l}}{\partial F_{i,l}}|_{l\in\Omega}. \tag{17}$$

These relations simply make explicit that, for a given variance of risk σ_i^2, both the average ratio of investment to forecast and the elasticity of investment to forecast are equal, and determined by the investor's risk aversion γ_i. To simplify the exposition, in what follows, we denote with $[\gamma_i\sigma_i^2]_A$ the estimated $\gamma_i\sigma_i^2$ obtained from Equation (16) and with $[\gamma_i\sigma_i^2]_E$ those obtained from Equation (17).

Our estimates of $[\gamma_i\sigma_i^2]_A$ and $[\gamma_i\sigma_i^2]_E$ are displayed in Table 9, where we assume that the perceived variance differs between rounds perceived as i.i.d. vs. rounds perceived as predictable (which is consistent with the results in Section 3.2), while being constant within each group of rounds.[14] In Panel A, the sample includes all rounds in which a is perceived as useful; in Panel B, the sample includes all rounds in which a is perceived as useless. For each panel, we report several statistics. First, we report the average $[\gamma_i\sigma_i^2]_A$ and $[\gamma_i\sigma_i^2]_E$, together with the 95% confidence intervals. Since these estimates feature a few outliers with very large values, we also report the median estimates.

Second, we perform a standard t-test of equality of the means. We report the difference between the average $[\gamma_i\sigma_i^2]_A$ and the average $[\gamma_i\sigma_i^2]_E$, the 95% confidence intervals of the difference, and the p-value of the t-test of equality of the means (denoted as p-value(D)).

Third, we take the stronger view that Equations (16) and (17) should give consistent estimates not only on average but also individual by individual. We report the fraction of individuals for which $[\gamma_i\sigma_i^2]_A$ falls within the 95% confidence intervals of $[\gamma_i\sigma_i^2]_E$, and we denote this fraction by $Pr(l, h)$. Similarly, $Pr(< l)$ (resp., $Pr(> h)$) is the fraction of individuals for which $[\gamma_i\sigma_i^2]_A$ falls below (resp., above) the 95% confidence intervals of $[\gamma_i\sigma_i^2]_E$. Finally, we report p-value(W), that is the p-value of the Wilcoxon signed-rank test that the estimates from Equations (16) and (17) are drawn from the same distribution.

We show first, that $[\gamma_i\sigma_i^2]_A$ are significantly lower than $[\gamma_i\sigma_i^2]_E$. The median is 0.106 vs. 0.311 for "perceived predictable" rounds and 0.139 vs. 0.354 for "perceived i.i.d." rounds. At the same time, the equality of mean cannot be rejected at conventional levels (p-values are respectively equal to 0.075 and 0.977).

Second, we notice that the fraction of individuals for which $[\gamma_i\sigma_i^2]_A$ falls within the 95% confidence intervals of $[\gamma_i\sigma_i^2]_E$ is equal to 65% for "perceived predictable" and to 72% for "perceived i.i.d." rounds. In most of the remaining cases, $[\gamma_i\sigma_i^2]_E$ is too large relative to $[\gamma_i\sigma_i^2]_A$. Third, the hypothesis that the estimates from Equations (16) and (17) are drawn from the same distribution can be rejected.

[14] We have repeated our estimates also distinguishing between early and late rounds (early rounds are from 1 to 10 and late rounds are from 11 to 20) and found similar results.

Overall, these results point to the fact that the elasticity of investment to forecast appears too small relative to the average investment level. It is difficult for a standard model in Equation (15) to make sense of both magnitudes at the same time.

To explore this observation further, in Panels C and D of Table 9, we compute the relative risk aversion coefficient implied by the estimates of $\gamma_i \sigma_i^2$ obtained from Equations (16) and (17). Consistently with the forecast model in Section 6.1, we assume that the perceived variance coincides with the true average variance, conditional on the perceived predictability. That is, the variance when a is perceived as useful is

$$\sigma^2 \mid_{a \text{ useful}} = \frac{p\sigma^2(r^p) + (1-q)\sigma^2(r)}{p + (1-q)},$$

where p is the probability that a predictable graph is perceived as such and $(1-q)$ is the probability that an i.i.d. graph is perceived as predictable, and $\sigma^2(r^p)$, $\sigma^2(r)$ are the variance of returns in predictable and in i.i.d. rounds, respectively. Similarly, the variance when a is perceived as useless is

$$\sigma^2 \mid_{a \text{ useless}} = \frac{q\sigma^2(r) + (1-p)\sigma^2(r^p)}{q + (1-p)}.$$

Substituting the actual values of $p = 0.8064$, $q = 0.7043$, $\sigma^2(r^p) = 0.548\%$ and $\sigma^2(r) = 0.814\%$, we get

$$\sigma^2 \mid_{a \text{ useful}} = 0.62\%, \text{ and } \sigma^2 \mid_{a \text{ useless}} = 0.76\%. \tag{18}$$

We obtain our estimates of γ_i in Panel C and D by substituting the values in (18) into the median estimates of $\gamma_i \sigma_i^2$ from Panels A and B.[15] The median estimate of γ_i from Equation (16) is equal to 17.11 when a is considered useful and to 18.37 when a is considered useless. These are large but not too far from other estimates provided in asset pricing models.

At the same time, the median estimates of γ_i from Equation (17) are respectively 50.21 and 46.79, which are almost 3 times larger than those from Equation (16) (comparing the means would give even larger differences). While low elasticities have been shown in a number of recent studies (see e.g. Ameriks, Kézdi, Lee and Shapiro (2019) and Giglio et al. (2019)), it is remarkable to observe them also in our experimental setting, which allows to precisely estimate investments and to abstract from several constraints conductive to inertia such as transaction costs, inattention, investment constraints.

These sets of results make salient a crucial, and new, investment puzzle:

[15] As mentioned, we view median estimates as more informative as our average estimates tend to be inflated by some outliers. Our results would be even stronger if we were to use average estimates.

even absent these constraints, the variations in risk allocations with respect to variations in forecasts are too small, when compared to the average risk taking decisions subjects choose to make.

7 Conclusion

The experiment we designed allows us to analyze how investors form their expectations and how they choose to allocate their wealth to a risky asset under different market conditions.

Our results indicate that when they are provided with a simple predictability model, our subjects utilize the relevant information and form rational forecasts. On the other hand, when no such "easy" model is given, subjects default to irrational extrapolative expectations, similar to those documented in previous studies. We have interpreted our findings with a simple model of expectation formation which accommodates subjects' uncertainty on whether they are facing predictable returns and, if so, on how to apply predictability. This model provides a good fit to the data without having to introduce extrapolative tendencies or other biased perceptions.

We also find that subjects do use their own forecasts to choose their wealth allocations, and both the level of risky investments and the elasticity of investments to forecasts are larger when they perceive predictability, again pointing at an important effect of predictability on investments.

Nonetheless, portfolios display a form of "inertia": variations in risk positions around their mean are small relative to the changes in expectations. This result obtains even though each round of our experiment corresponds to a new simulated risk and to a new portfolio to invest; investment is precisely measured; and transaction costs, inattention or investment constraints do not play any role.

These small elasticities could be explained by our subjects being highly risk averse. This is however inconsistent with the relatively large average wealth allocations into the risky asset – a key new puzzle. We note this "puzzle" holds true even when subjects behave rationally in their forecast formations and it indicates that variations in investors' expectations may be of limited help to justify large variations in market prices and to rationalize equilibrium outcomes.

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8 Tables

Table 1: Descriptive Statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
Round	1,880	10.5	10.5	5.768	1	20
a useful	1,880	0.5	0.5	0.5	0	1
Forecast	1,880	5.283	5	7.086	-16	50
Invest	1,880	44.99	40	36.24	0	100
Perceive	1,880	0.551	1	0.498	0	1
a(t)	1,880	6.035	5.484	3.236	2.064	12.17
r(t)	1,880	3.192	2.95	8.603	-11.79	19.25
Change Forecast	1,786	-0.0651	0	10.03	-35	43
Change Invest	1,786	0.935	0	39.52	-100	100
Delay	1,880	82.74	61	78.71	11	1,180
Pr(a useful | predictable)	1,880	8.064	1	1.804	2	10
Pr(a useless | i.i.d.)	1,880	7.043	1	2.164	1	10
Detect	1,880	15.11	15	2.417	10	20
Forecast Distance	1,880	8.771	7.1	7.518	0.072	56.6
			Perceive=1			
Forecast	1,036	5.739	6	7.052	-15	40
Invest	1,036	48.58	50	36.96	0	100
a(t)	1,036	6.223	6.22	3.27	2.064	12.17
r(t)	1,036	3.783	3.37	8.148	-11.79	19.25
Forecast Distance	1,036	7.714	6.314	5.982	0.09	39.31
			Perceive=0			
Forecast	844	4.724	5	7.092	-16	50
Invest	844	40.58	30	34.86	0	100
a(t)	844	5.805	4.749	3.182	2.064	12.17
r(t)	844	2.467	-1.12	9.083	-11.79	19.25
Forecast Distance	844	10.07	7.723	8.887	0.072	56.6
			Other Treatments			
Forecast(5)	1,160	6.705	6	7.462	-15	100
Invest(5)	1,160	52.36	50	33.79	0	100
Change Forecast(5)	1,102	-0.124	0	9.562	-92	98
Change Investment(5)	1,102	0.923	0	32.07	-100	100

NOTE: This table reports descriptive statistics of our variables.

Table 2: Forecast and Predictability

Dep Variable	Forecast				
	(1)	(2)	(3)	(4)	(5)
Perceive*a(t)	0.343***	0.387***	0.396***		
	(0.101)	(0.0982)	(0.0813)		
a(t)	-0.0118	-0.0376	-0.0422	0.359***	-0.0424
	(0.0763)	(0.0741)	(0.0705)	(0.0562)	(0.0782)
Perceive	-1.114*	-1.273*	-1.282**		
	(0.670)	(0.645)	(0.563)		
Individual FE	No	Yes		Yes	
Round FE	No	No		Yes	
Sample		All		Perceive	No Perceive
Number of Obs	1,880	1,880	1,880	1,036	843
Number of Clusters	94	94	94/20		93/20
R-squared	0.018	0.100	0.109	0.153	0.160

NOTE: This table reports the results of OLS regressions. The dependent variable is the forecast of next period returns in percentage points. The variable a(t) denotes the current value of variable a. Perceive is a dummy equal to one if the subject declares that the variable a is useful to predict returns. Perceive*a(t) is the interaction between Perceive and a(t). In column 4, the sample is restricted to observations in which subjects declare that that variable a is useful to predict returns. In column 5, the sample is restricted to observations in which subjects declare that that variable a is not useful to predict returns. Standard errors are in parenthesis, they are clustered at the individual level in columns 1 and 2, at the individual and round level in columns 3-5. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 3: Extrapolation and Predictability

Dep Variable	Forecast				
	(1)	(2)	(3)	(4)	(5)
Perceive*a(t)			0.348***		
			(0.0699)		
Perceive*r(t)		-0.158***	-0.101*		
		(0.0536)	(0.0562)		
a(t)			0.0928	0.445***	0.0959
			(0.0611)	(0.0537)	(0.0646)
r(t)	0.118***	0.192***	0.199***	0.0943**	0.198***
	(0.0292)	(0.0452)	(0.0448)	(0.0387)	(0.0414)
Perceive		1.483***	-0.959		
		(0.367)	(0.576)		
Sample		All		Perceive	No Perceive
Number of Obs	1,880	1,880	1,880	1,036	843
Number of Clusters	94/20				93/20
R-squared	0.109	0.122	0.142	0.163	0.217

NOTE: This table reports the results of OLS regressions. All regressions include individual and round fixed effects. The dependent variable is the forecast of next period returns in percentage points. The variable a(t) denotes the current value of variable a. The variable r(t) denotes the latest realized returns. Perceive is a dummy equal to one if the subject declares that the variable a is useful to predict returns. Perceive*a(t) is the interaction between Perceive and a(t). Perceive*r(t) is the interaction between Perceive and r(t). In column 4, the sample is restricted to observations in which subjects declare that that variable a is useful to predict returns. In column 5, the sample is restricted to observations in which subjects declare that that variable a is not useful to predict returns. Standard errors are in parenthesis, they are clustered at the individual and round level. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 4: Investment and Predictability

Dep Variable	Investment			Change Inv	Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast	2.225***	2.195***	2.053***			1.779***
	(0.194)	(0.194)	(0.216)			(0.253)
Change Forecast				2.194***		
				(0.0949)		
Perceive					6.871***	2.751*
					(2.292)	(1.441)
Forecast*Perceive						0.488**
						(0.225)
Individual FE	No	Yes	Yes	No	Yes	
Round FE	No	No	Yes	Yes	Yes	
Number of Obs	1,880	1,880	1,880	1,786	1,880	1,880
Number of Clusters	94		94/20	19	94/20	
R-squared	0.189	0.565	0.602	0.361	0.482	0.607

NOTE: This table reports the results of OLS regressions. In columns 1-3 and 5-6, the dependent variable is the fraction of the endowment invested in the risky asset, in percentage points. In column 4, the dependent variable is the difference between the current investment and the investment in the previous round. Forecast is the forecast of next period returns in percentage points. Change forecast is the difference between the current forecast and the forecast in the previous round. Perceive is a dummy equal to one if the subject declares that the variable a is useful to predict returns. Perceive*Forecast is the interaction between Perceive and Forecast. Standard errors are in parenthesis, they are clustered at the individual level in columns 1-2, and at the individual and round level in columns 3,5,6 and at the round level in column 4. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 5: Forecast and Investment over a Longer Horizon

Dep Variable	Forecast(5)		Invest(5)	Change Inv(5)	Invest(5)	
	(1)	(2)	(3)	(4)	(5)	(6)
Perceive*a(t)	0.0951	0.0654				
	(0.0779)	(0.0842)				
Perceive*r(t)		-0.0455				
		(0.0586)				
a(t)	-0.0737	-0.0188				
	(0.0823)	(0.0679)				
r(t)		0.0770**				
		(0.0320)				
Perceive	0.683	0.912			1.682	6.739
	(0.450)	(0.779)			(3.123)	(4.395)
Forecast(5)			0.711**			1.375**
			(0.296)			(0.490)
Change Forecast(5)				0.914***		
				(0.231)		
Forecast(5)*Perceive						-0.855
						(0.590)
Number of Obs	1,160	1,160	1,160	1,102	1,160	1,160
Number of Clusters	58/20					
R-squared	0.152	0.156	0.545	0.089	0.525	0.525

NOTE: This table reports the results of OLS regressions. All regressions include individual and round fixed effects. In columns 1-2, the dependent variable is the forecast of the average returns over the next five periods, in percentage points. In columns 3, 5 and 6, the dependent variable is the fraction of the endowment invested in the risky asset for the next five periods, in percentage points. In column 4, the dependent variable is the difference between the current five-periods investment and five-periods investment in the previous round. The variable a(t) denotes the current value of variable a. The variable r(t) denotes the latest realized returns. Perceive is a dummy equal to one if the subject declares that the variable a is useful to predict returns. Perceive*a(t) is the interaction between Perceive and a(t). Perceive*r(t) is the interaction between Perceive and r(t). Change Forecast(5) is the difference between the current five-periods forecast and the five-periods forecast in the previous round. Forecast(5)*Perceive is the interaction between Forecast(5) and Perceive. Standard errors are in parenthesis, they are clustered at the individual and round level. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 6: Revealing Predictability

Dep Variable	Forecast		Invest	
	(1)	(2)	(3)	(4)
a(t)	0.313***	0.311***		
	(0.0475)	(0.0486)		
r(t)	0.152***	0.152***		
	(0.0292)	(0.0293)		
Predictive	1.388*		10.16***	
	(0.730)		(3.501)	
Predict*a(t)	-0.00519			
	(0.0440)			
Predict*r(t)	-0.212***			
	(0.0568)			
Not Predictive		0.969		10.11***
		(0.993)		(3.062)
Not Predict*a(t)		-0.0532		
		(0.126)		
Not Predict*r(t)		0.0458		
		(0.0474)		
Forecast			2.181***	2.176***
			(0.200)	(0.198)
Predict*Forecast			0.705*	
			(0.352)	
Not Predict*Forecast				0.162
				(0.325)
Number of Obs	2,240	2,240	2,240	2,240
Number of Clusters	94/20			
R-squared	0.117	0.134	0.579	0.580

NOTE: This table reports the results of OLS regressions. All regressions include individual and round fixed effects. In columns 1-2, the dependent variable is the forecast of next period returns in percentage points. In columns 3-4, the dependent variable is the fraction of the endowment invested in the risky asset, in percentage points. Predictive is a dummy equal to one if the subject is told that the variable a is useful to predict returns and equal to zero if the subject is not told whether the variable a is useful. Not Predictive is a dummy equal to one if the subject is told that the variable a is not useful to predict returns and equal to zero if the subject is not told whether the variable a is useful. The variable a(t) denotes the current value of variable a. The variable r(t) denotes the latest realized returns. Predict*a(t), Predict*r(t), Not Predict*a(t), Not Predict*r(t), Predict*Forecast, Not Predict*Forecast are the interactions between each dummy Predictive and Not Predictive and each variable a(t), r(t), Forecast. Standard errors are in parenthesis, they are clustered at the individual and round level. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 7: Heterogeneous Behaviors

Dummy (D)	Late Rounds		Fast Replies		High Ability	
Dep Variable	Forecast	Invest	Forecast	Invest	Forecast	Invest
	(1)	(2)	(3)	(4)	(5)	(6)
Perceive*a(t)*D	0.420***		0.460***		0.333***	
	(0.142)		(0.136)		(0.102)	
Perceive*a(t)*(1-D)	0.303***		0.194		0.356**	
	(0.0960)		(0.131)		(0.147)	
Perceive*r(t)*D	-0.109*		-0.184**		-0.123*	
	(0.0628)		(0.0733)		(0.0614)	
Perceive*r(t)*(1-D)	-0.103		-0.0382		-0.0850	
	(0.0822)		(0.0655)		(0.0989)	
a(t)*D	0.0812		0.0708		0.0856	
	(0.100)		(0.142)		(0.0581)	
a(t)*(1-D)	0.0869		0.120		0.108	
	(0.0956)		(0.112)		(0.128)	
r(t)*D	0.162***		0.250***		0.183***	
	(0.0480)		(0.0645)		(0.0459)	
r(t)*(1-D)	0.230***		0.152***		0.230**	
	(0.0637)		(0.0483)		(0.0870)	
Forecast*Perceive*D		0.793*		0.872**		0.580*
		(0.470)		(0.415)		(0.290)
Forecast*Perceive*(1-D)		0.553**		0.412		0.789
		(0.229)		(0.252)		(0.494)
Forecast*D		1.845***		1.828***		1.910***
		(0.441)		(0.409)		(0.320)
Forecast*(1-D)		1.743***		1.755***		1.640***
		(0.231)		(0.240)		(0.429)
Number of Obs	1,880	1,880	1,880	1,880	1,880	1,880
Number of Clusters			94/20			
R-squared	0.146	0.596	0.150	0.597	0.144	0.596

Note: This table reports the results of OLS regressions. All regressions include individual and round fixed effects. In columns 1,3,5, the dependent variable is the forecast of next period returns in percentage points. In columns 2,4,6, the dependent variable is the fraction of the endowment invested in the risky asset, in percentage points. In columns 1-2, D refers to the dummy Late Rounds, which is equal to 1 for Rounds 11-20 and equal to zero for Rounds 1-10. In columns 3-4, D refers to the dummy Fast Replies, which is equal to 1 if the number of seconds the subject takes for submitting the answers in each "Question Page" is below the sample median (equal to 61). In columns 5-6, D refers to the dummy High Ability, which is equal to 1 if the subject's correct answers to whether the variable a is useful to predict returns is above the sample median (equal to 15 out of 20). The variable a(t) denotes the current value of variable a. The variable r(t) denotes the latest realized returns. Perceive is a dummy equal to one if the subject declares that the variable a is useful to predict returns. For each variable a(t), r(t), Perceive and Forecast, *D indicates the interaction with the dummy D and *(1-D) indicates the interaction with the dummy (1-D), taking value 1 when D=0 and value 0 when D=1. All regressions include also the variables Perceive*D and Perceive*(1-D). In columns 3-5, the dummy Fast Replies is also included. Standard errors are in parenthesis, they are clustered at the individual and round level. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 8: Forecast Model

Dep Variable	Forecast			
	(1)	(2)	(3)	(4)
β_2	0.343 [0.149 - 0.537]	0.441 [0.162 - 0.719]	0.472 [0.181 - 0.762]	0.346 [0.0610 - 0.631]
β_1	-0.0118 [-0.158 - 0.135]	-0.0255 [-0.242 - 0.191]	-0.0502 [-0.281 - 0.180]	0.0393 [-0.168 - 0.247]
α_2	-1.114 [-2.498 - 0.271]	-1.112 [-3.089 - 0.864]	-0.939 [-3.094 - 1.217]	-1.376 [-3.409 - 0.658]
α_1	4.792 [3.767 - 5.818]	4.524 [3.033 - 6.015]	4.728 [3.029 - 6.427]	5.177 [3.747 - 6.607]
Sample	All	Late	Fast	Detect
p(α_1=5.2658)	0.365	0.329	0.535	0.903
p(α_2=-2.1198)	0.154	0.317	0.283	0.473
p(β_1=0.1325)	0.0533	0.153	0.120	0.378
p(β_2=0.3169)	0.793	0.383	0.296	0.840
Number of Obs	1,880	940	945	740
R-squared	0.018	0.030	0.039	0.021

NOTE: The top part of the table reports the OLS estimates of Equation (11) $F_{i,l} = \alpha_1 + \alpha_2 P_{i,l} + \beta_1 a_g + \beta_2 a_g P_{i,l} + \epsilon_{i,l}$. 95% confidence intervals are in brackets. In the bottom panel, we report the p-values of the t-tests that each estimated coefficient is equal to the values in Equation (14). In column 1, we report estimates on the full sample; in column 2, we restrict rounds between 11 and 20; in column 3, we restrict to decisions submitted with a delay below the sample median (equal to 61 seconds); in column 4, we restrict to subjects with correct answers on whether variable a has predictive power above the sample median (equal to 15).

Table 9: Implicit Risk

	(1)	(2)	(3)	(4)
Panel A		Sample: Perceive=1		
	Average	Median	CI[95%]	
$\gamma\sigma^2$ from Equation (16)	0.181	0.106	0.109	0.265
$\gamma\sigma^2$ from Equation (17)	0.972	0.311	0.105	1.840
	Difference	CI[95%]		p-value(D)
N=91	-0.785	-1.652	0.081	0.075
	Pr(<l)	Pr(l,h)	Pr(>h)	p-value(W)
	34.04	64.89	1.06	0.000
Panel B		Sample: Perceive=0		
	Average	Median	CI[95%]	
$\gamma\sigma^2$ from Equation (16)	0.238	0.139	0.142	0.346
$\gamma\sigma^2$ from Equation (17)	0.258	0.354	-0.658	1.173
	Difference	CI[95%]		p-value(D)
N=90	-0.014	-0.941	0.914	0.977
	Pr(<l)	Pr(l,h)	Pr(>h)	p-value(W)
	26.88	72.04	1.08	0.000
Panel C		Sample: Perceive=1		
	Variance: $\overline{p}\sigma^2(r_t^p) + (1-\overline{p})\sigma^2(r_t)$=0.62%			
Median γ from Equation (16)		17.11		
Median γ from Equation (17)		50.21		
Panel D		Sample: Perceive=0		
	Variance: $\overline{q}\sigma^2(r_t) + (1-\overline{q})\sigma^2(r_t^p)$=0.76%			
Median γ from Equation (16)		18.37		
Median γ from Equation (17)		46.79		

NOTE: In Panels A and B, we report the estimates of $\gamma\sigma^2$ from Equations (16) and (17). For each equation, we report the mean and median estimates together with the 95% confidence intervals. Difference reports the difference in the average estimates obtained from Equation (16) and Equation (17), and the 95% confidence intervals of this difference. P-value(D) is the p-value of the t-test of equality of the means. Pr(l,h) is the fraction of estimates from Equation (16) which fall within the 95% confidence interval of the estimates from Equation(17). Pr(<l) (resp., Pr(>h)) is the fraction of estimates which fall below (resp., above) the 95% confidence interval. p-value(W) is the p-value of the Wilcoxon signed-rank test that the estimates from Equations (16) and (17) are drawn from the same distribution. In Panels C and D, we report the estimates of the relative risk aversion coefficient γ implied by the median estimates of $\gamma\sigma^2$ from Panels A and B, assuming that the variance in Panel A is equal to 0.62% and in Panel B is equal to 0.76%, as derived in Equation (18). In Panel A and C, the sample includes rounds in which a is perceived as useful; In Panel B and D, the sample includes rounds in which a is perceived as useless. N refers to the number of observations used in each panel.

9 Appendix

9.1 Return Process

Case with Predictable Returns. We simulate predictable annual returns according to the VAR process:

$$\begin{aligned} r^p_{1,t+1} &= \alpha x_{1,t} + \varepsilon_{1,t+1}, \\ x_{1,t+1} &= \beta x_{1,t} + \delta_{1,t+1}, \end{aligned} \tag{19}$$

where $r_{1,t}$ is the demeaned annual excess log return and $x_{1,t}$ is a state variable, estimated from the demeaned annual log dividend yield. The two shocks ε_1 and δ_1 follow normal distributions with mean 0 and standard deviation $\sigma(\varepsilon_1)$ and $\sigma(\delta_1)$ respectively, and have correlation $\rho_{e,\delta}$. We use the estimated parameters from Cochrane (2009) on US equity (CRSP, 1927-1998): $\alpha = 0.16$, $\beta = 0.92$, $\sigma(\delta_1) = 15.2\%$, $\sigma(\varepsilon_1) = 19.2\%$, $\rho_{e^p,\delta} = -0.72$.

The returns in the predictable process (2) displayed to subjects in the experiment correspond to a compounded 5-year average of returns simulated from annual process (19) above. For any simulated series from process (19) of length $5 \times T$: $\{x_{1,1}, x_{1,2}...x_{1,5\times T}\}$ and $\{r_{1,2}, r_{1,3}...r_{1,5\times T+1}\}$, we extract the returns $\{r^p_2, r^p_3, ..., r^p_{T+1}\}$ where $r^p_2 = \mu + \frac{r_{1,2}+r_{1,3}+r_{1,4}+r_{1,5}+r_{1,6}}{5}$; $r^p_3 = \mu + \frac{r_{1,7}+r_{1,8}+r_{1,9}+r_{1,10}+r_{1,11}}{5}$;...; $r^p_{T+1} = \mu + \frac{r_{1,5T-4}+r_{1,5T-2}+r_{1,5T-1}+r_{1,5T}+r_{1,5T+1}}{5}$, where $\mu = 6.07\%$ (again from Cochrane (2009)). Iterating from $r_{1,t+1}$, we obtain

$$\begin{aligned} r^p_{t+1} &= \underbrace{\mu + \frac{1}{5}\alpha\frac{1-\beta^5}{1-\beta}x_{1,t}}_{\text{expected return } a_t} \\ &\quad \underbrace{+\frac{1}{5}\left[\alpha\frac{1-\beta^{5-1}}{1-\beta}\delta_{1,t+1} + \alpha\frac{1-\beta^{5-2}}{1-\beta}\delta_{1,t+2} + .. + \alpha\delta_{1,t+5-1} + \sum_{i=1}^{5}\varepsilon_{1,t+1}\right]}_{\text{shock } \epsilon^p_{t+1}}, \end{aligned}$$

corresponding to the predictable returns process (2).

From a simulated series from process (19): $\{r_{1,2}, r_{1,3}...r_{1,5\times T+1}\}$ and $\{x_{1,1}, x_{1,2}...x_{1,5\times T}\}$, we also extract the conditional expectations $\{a_1, a_2...a_T\}$ for the predictable returns $\{r^p_2, r^p_3...r^p_{T+1}\}$ where $a_1 = \mu + \frac{1}{5}\alpha\frac{1-\beta^5}{1-\beta}x_{1,1}$; $a_2 = \mu + \frac{1}{5}\alpha\frac{1-\beta^5}{1-\beta}x_{1,6}$;...; $a_T = \mu + \frac{1}{5}\alpha\frac{1-\beta^5}{1-\beta}x_{1,5T-4}$, where $\mu = 6.07\%$ as above. The predictive variable a thus constructed is such that $(a - \mu)$ follows an AR(1) process with persistence β^5.

Case with i.i.d. returns. We simulate i.i.d. annual returns according to process:

$$r_{1,t+1} = \mu + e_{1,t+1}, \tag{20}$$

where $\mu = 6.07\%$ as in (19) and $e_1 \sim N(0, \sigma^2(e_1))$. We set $\sigma(e_1) = 20.18\%$ so that the unconditional variance is the same as for $r^p_{1,t+1}$ in (19). The returns in i.i.d. process (1), displayed to subjects in the experiment, correspond to a compounded 5-year average of returns simulated from annual process (20).

Conditional Variance of Returns. Let $r_{N,t}$ be the N-year demeaned average return in the i.i.d. case

$$r_{N,t} = \frac{r_{1,t} + r_{1,t+1} + ... + r_{1,t+N}}{N}.$$

The conditional variance (equal to the unconditional variance) of $Nr_{N,t}$ is

$$Var_t(Nr_{N,t+1}) = N\sigma^2(e_1). \tag{21}$$

Let $r^p_{N,t}$ be the N-year demeaned average return in the predictable case:

$$r^p_{N,t} = \frac{r^p_{1,t} + r^p_{1,t+1} + ... + r^p_{1,t+N}}{N},$$

such that:

$$Nr^p_{N,t+1} = \underbrace{\alpha\frac{1-\beta^N}{1-\beta}x_{1,t}}_{\text{expected return } Nx_{N,t}} + \underbrace{(\alpha\sum_{i=1}^{N-1}\frac{1-\beta^i}{1-\beta}\delta_{1,t+i} + \sum_{i=1}^{N}\varepsilon_{1,t+i})}_{\text{shock } N\varepsilon^P_{t+1}},$$

with conditional variance:

$$\begin{aligned} Var_t(Nr^p_{N,t+1}) &= N\sigma^2(\varepsilon_1) + \alpha^2\sigma^2(\delta_1)\sum_{i=1}^{N-1}(\frac{1-\beta^i}{1-\beta})^2 \\ &\quad +2\alpha\rho_{\varepsilon,\delta}\sigma(\varepsilon_1)\sigma(\delta_1)\sum_{i=1}^{N-1}\frac{1-\beta^i}{1-\beta}. \end{aligned}$$

Given our estimated parameters, the negative term in $\rho_{e,\delta}$ dominates the positive term in α^2, so that $Var_t(r^p_{N,t+1}) < Var_t(r_{N,t+1})$, for N sufficiently low. For our experiment, we are interested in $N = 5$ for the one-period returns and $N = 25$ for the five-period averages, for which we have $Var_t(r^p_{5,t+1}) = 0.67Var_t(r_{5,t+1})$; $Var_t(r^p_{25,t+1}) = 0.61Var_t(r_{25,t+1})$.

9.2 Experimental Protocol

The experiment starts with the instruction page (as in Figure 2), followed by 20 rounds of Question Page / Result Page (as in Figures 3 and 4). Each round corresponds to a new simulation of returns, 10 rounds for the i.i.d. process (1) and 10 rounds for the predictable process (2).

For the predictable rounds, we obtain the simulated returns of process (2) via a simulation of length 225 of the VAR process (19), averaged over 5-year periods to obtain 45 points for the expected return process r^p_{t+1} and 45 points for the conditional expectations a_t. We repeat this procedure to get 1,000 simulations, among which we choose the 10 simulations that have a statistical correlation between the simulated returns r^p_{t+1} and the conditional expectations a_t closest to 0.6, the theoretical correlation between the returns process and the predictive variable a.

For the i.i.d. rounds, we obtain the simulated returns of process (1) via a simulation of length 225 of the annual i.i.d. process (20), averaged over 5-year periods to obtain 45 points for the expected return process r_{t+1}. In addition, and independently, we add a simulation of length 225 of the state variable $x_{1,t}$ from VAR process (19) to obtain 45 points with same distribution as the variable a_t in the predictable rounds. We repeat this procedure to get 1,000 simulations, among which we choose the 10 simulations that have a statistical correlation between the simulated returns r_{t+1} and the variable a_t closest to 0, the theoretical correlation between the returns process and the variable a in the i.i.d. case.

We verify for each of the 20 rounds displayed to our subjects, the statistical regressions of the returns r_t on the variable a_{t-1}, and on past returns r_{t-1}. The results are displayed in Table 10 below. In all rounds, the graph displayed in the Question page shows the first 40 points for the returns r_t, from $t = -40$ to $t = -1$ in red, and the first 41 points for variable a_{t-1}, from $t = -40$ to $t = 0$ in blue (shifted so that r_t and a_{t-1} are one above the other); with a_{-1}, the best predictor for next-period returns r_0 displayed as a fat yellow dot at $t = 0$.

Figure 1: Simulations: i.i.d. case (top panel) and predictable case (bottom panel)

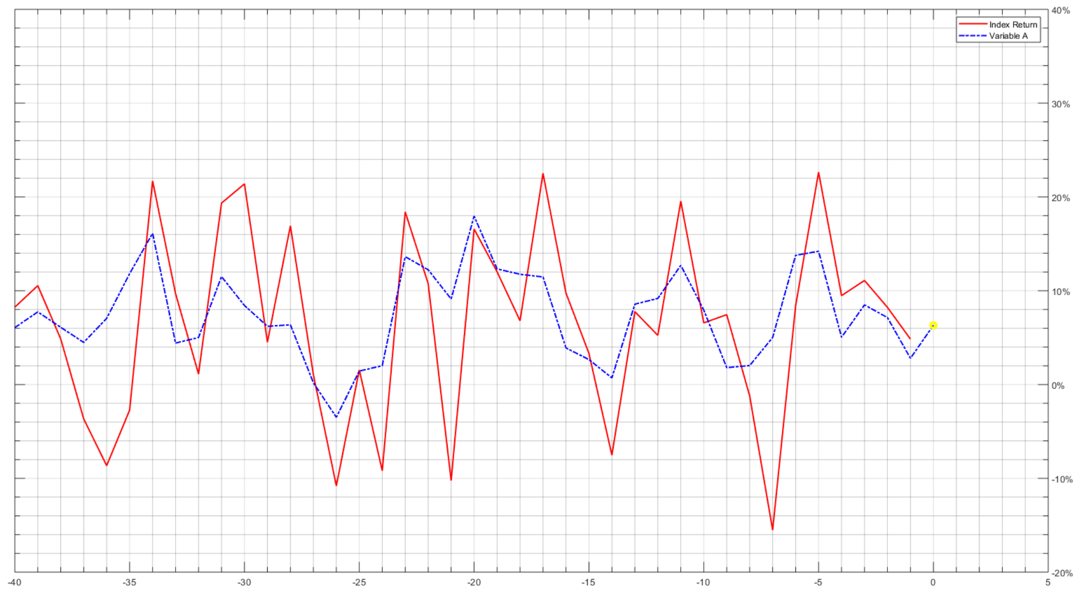
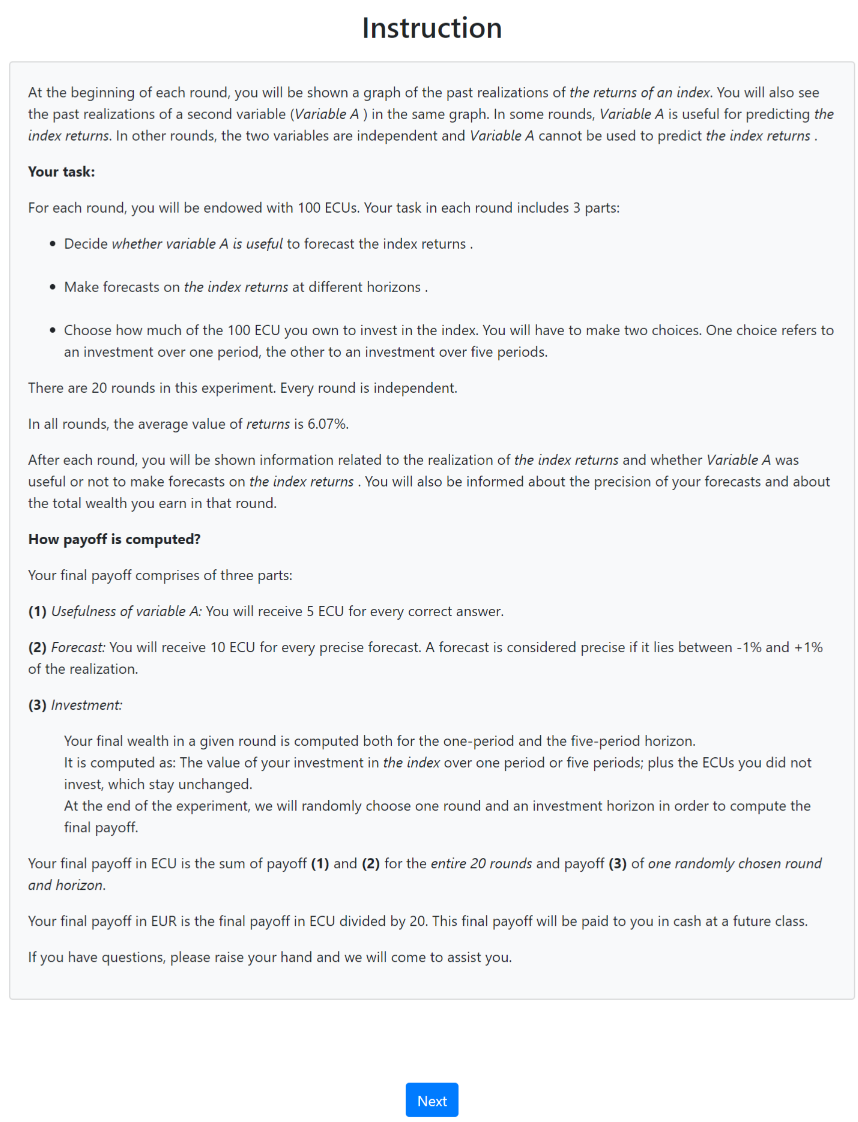


Figure 2: Instruction page



Instruction

At the beginning of each round, you will be shown a graph of the past realizations of *the returns of an index*. You will also see the past realizations of a second variable (*Variable A*) in the same graph. In some rounds, *Variable A* is useful for predicting *the index returns*. In other rounds, the two variables are independent and *Variable A* cannot be used to predict *the index returns* .

Your task:

For each round, you will be endowed with 100 ECUs. Your task in each round includes 3 parts:

- Decide *whether variable A is useful* to forecast the index returns .
- Make forecasts on *the index returns* at different horizons .
- Choose how much of the 100 ECU you own to invest in the index. You will have to make two choices. One choice refers to an investment over one period, the other to an investment over five periods.

There are 20 rounds in this experiment. Every round is independent.

In all rounds, the average value of *returns* is 6.07%.

After each round, you will be shown information related to the realization of *the index returns* and whether *Variable A* was useful or not to make forecasts on *the index returns* . You will also be informed about the precision of your forecasts and about the total wealth you earn in that round.

How payoff is computed?

Your final payoff comprises of three parts:

(1) *Usefulness of variable A:* You will receive 5 ECU for every correct answer.

(2) *Forecast:* You will receive 10 ECU for every precise forecast. A forecast is considered precise if it lies between -1% and +1% of the realization.

(3) *Investment:*

> Your final wealth in a given round is computed both for the one-period and the five-period horizon.
> It is computed as: The value of your investment in *the index* over one period or five periods; plus the ECUs you did not invest, which stay unchanged.
> At the end of the experiment, we will randomly choose one round and an investment horizon in order to compute the final payoff.

Your final payoff in ECU is the sum of payoff **(1)** and **(2)** for the *entire 20 rounds* and payoff **(3)** of *one randomly chosen round and horizon.*

Your final payoff in EUR is the final payoff in ECU divided by 20. This final payoff will be paid to you in cash at a future class.

If you have questions, please raise your hand and we will come to assist you.

Next

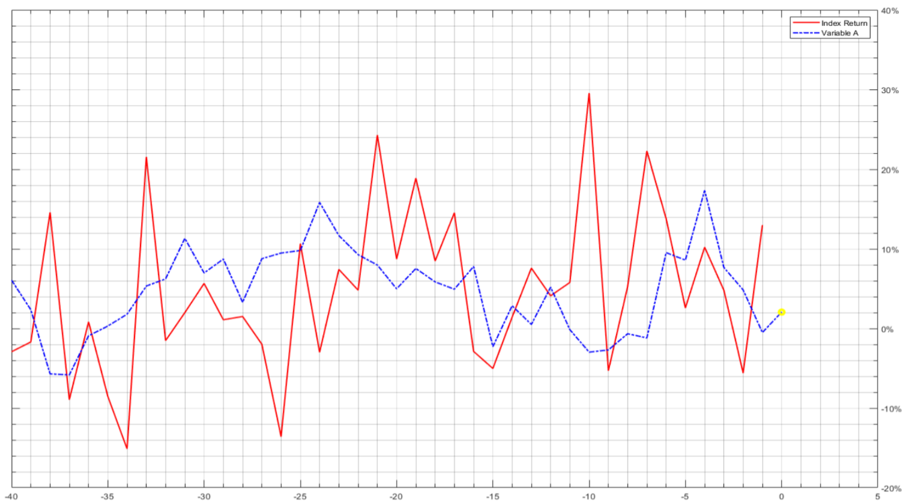
Figure 3: Question page

See General Instruction

See Examples

Round 1: Forecasting and Investing

Below is the realization of *the index returns* and *Variable A* for the last 40 periods. You are at date 0, today.



You are endowed with 100 ECUs.

What is your forecast of *the index return* over the next period?

Your forecast (in percentage):

If your investment is for 1 period, how many of your 100 ECU do you want to invest in *the stock index?*

Investment amount (in ECU):

What is your forecast of the average 1-period returns over the next 5 periods?

Your forecast (in percentage):

If your investment is for 5 periods, how many of your 100 ECU do you want to invest in *the index?*

Investment amount (in ECU):

In this graph, do you think *Variable A* (blue line) is useful to predict *the index returns* (red line)?

Yes

No

Next

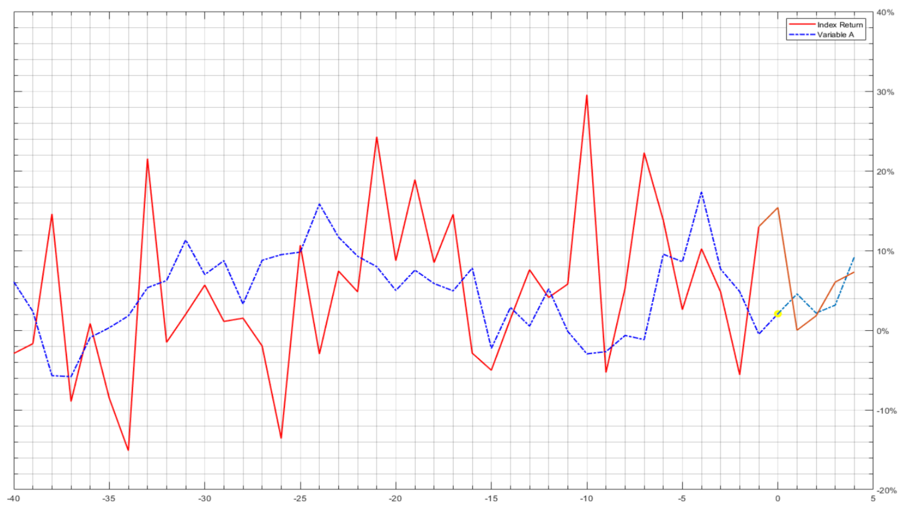
Figure 4: Answer page

See General Instruction

See Examples

Round 1: Realization

The graph below shows the realizations of *the index returns* for the next 5 periods.
In this round, *Variable A* was **not useful** to predict *the index returns* .



Forecasting and investment result

HORIZON: 1 PERIOD

Description	Index Return (Next period)	Forecast result	Value before realization	Value after realization
Investment in *the index*	15.39 %	imprecise	50	58.32
Total Wealth	---	---	100	108.32

HORIZON: 5 PERIODS

Description	Index Return (average over 5 periods)	Forecast result	Value before realization	Value after realization
Investment in *the index*	6.11 %	precise	50	67.86
Total Wealth	---	---	100	117.86

Click the "Next Button" to go to the next round.

Next

Table 10: Regression Coefficients of r_t on a_{t-1} and r_{t-1}.

Graph no.	Predictability	a(t-1)	p-value	R2	r(t-1)	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	No	0.07	0.79	0	-0.13	0.45
2	No	-0.05	0.88	0	-0.01	0.96
3	No	0.09	0.78	0	0.16	0.34
4	No	-0.02	0.95	0	0.02	0.89
5	No	-0.27	0.4	0.02	0.13	0.44
6	No	-0.12	0.58	0.01	0.58	0.6
7	No	-0.02	0.94	0	-0.1	0.52
8	No	-0.05	0.91	0	-0.3	0.06
9	No	0.01	0.96	0	-0.34	0.04
10	No	-0.01	0.98	0	-0.04	0.81
11	Yes	1.17	0	0.34	0.21	0.21
12	Yes	1.53	0	0.38	-0.07	0.67
13	Yes	1.19	0	0.38	0	0.99
14	Yes	1	0	0.36	0.03	0.87
15	Yes	0.96	0	0.33	0.07	0.64
16	Yes	0.99	0	0.32	0.04	0.79
17	Yes	1.11	0	0.4	0	0.99
18	Yes	1.09	0	0.35	0.14	0.4
19	Yes	1.06	0	0.35	-0.11	0.5
20	Yes	0.85	0	0.32	-0.14	0.39

NOTE: This table reports the results of OLS regressions. The dependent variable is the returns r_t either for the i.i.d process (1) or the predictable process (2). Columns (3), (4) and (5) report the coefficient, p-value and R^2 of the regression on a_{t-1}. Column (6) and (7) report the coefficient and p-value of the regression on r_{t-1}.