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David THESMAR - Professor at MIT Sloan School of Management

PHD THESIS

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L'université n'entend ni approuver ni désapprouver les opinions particulières du candidat.

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General Introduction

Shiller, Fischer, and Friedman (1984), Shiller (2014) point out the volatility puzzle in stock prices. If prices equal the sum of the expected dividends discounted at a constant discount rate, how is it possible that prices are more volatile than the realized dividends themselves? The view that stock prices movements can be entirely explained by the variation in the expected dividends is implausible. It must be that price fluctuations reflect either the variation in the discount rates or both the variation in the discount rates and the one in the expected dividends. It turns out that discount rates do vary over time (see, for example, Shiller (1980), Campbell and Shiller (1988), Cochrane (1992)). This finding poses many questions regarding the procedures one uses in corporate finance, accounting, banking, and policy decisions. My thesis aims to address some of these questions.

This thesis consists of three articles I worked on during my Ph.D. program at the Toulouse School of Management. The three articles are of different topics and can be read in the separation of one another. They, however, speak to the common broader literature on return predictability and the application in portfolio allocation and corporate decisions. Specifically, the articles help shed light on several important questions regarding (i) the debates on return predictability ; (ii) how investors and managers form their expectation of returns; (iii) how such expectations would enter their decisions; and (iv) what could be the consequence of using a biased expectation of returns in corporate valuation. The below discussion gives a more detailed overview of each article.

In my first article, "Literature Review on Time-varying Expected Returns", I provide a literature review on the topic of returns predictability. Expected returns (discount rates) enter investment decisions in various ways: from portfolio allocation and corporate capital budgeting decisions to many accounting, banking, and policy procedures. For the last decades, many variables have been added to the pool of predictors of returns. In addition to the publicly available time series used in many empirical studies, there have been more data from surveys and experiments on how people form expectations of returns. This paper aims to shed light on the return predictability story and at the same time build a connection with the survey and experiment literature on expectation formation. The first part of this chapter focuses on the evidence of time-varying expected returns from the asset pricing literature. This part also covers the ongoing debates on return predictability which mainly concern the econometric methodologies and the external validity of the predictive variables. Finally, I also review some theories that help explain time-varying expected returns. The second part of this chapter covers the survey and experiment literature on expected returns. The question is that whether the expected returns observed in these studies are consistent with the representative agent asset pricing model in which prices are driven by the variation of the agent's expected returns (which is, in turn, driven by the change in economic risk or the agent's risk aversion, or both) as mentioned in the first part. The evidence suggests the answer is no. In general, people seem to extrapolate on past and current returns when forming expectations. At the same time, we also observe heterogeneity in expected returns, which suggests the potential of some heterogeneous agent models to explain time-varying expected returns. In the third part of this chapter, I revisit the theories that allow different types of investors to co-exist in the market. As a result, these models can accommodate both the evidence of extrapolative expectation while still explaining why the aggregate expected returns could be predicted as observed in the empirical studies in part 1.

My second paper, "Return Predictability, Expectations, and Investment: Experimental Evidence" is a joint work with Andries, Bianchi, and Pouget. 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. Return predictability may affect not only agents' expectations but potentially also investment decisions. We use an experiment to investigate how investors form their expected returns given the predictability of returns and how these expectations affect their investment decisions. Our question is how investors form expectations when they have access to other information such as a predictor on top of the history of returns. Our second question is how expectations, possibly influenced by the perception of return predictability, are incorporated into investment decisions. A controlled experiment would allow us to directly observe expectations and investment given different levels of access to information and abstract from frictions that may contribute to portfolio inertia. In each round of the experiment, subjects are provided with a visual graph of past simulated realizations of risky index returns and the past realizations of a predictor (called variable a), which in half of the rounds, helps to predict next-period returns. Subjects are asked to make forecasts of future returns, choose how much to allocate to the risky asset from a given wealth endowment, and state whether they view the information in variable a as useful or not. The risk index subjects are asked to forecast, and allocate wealth to, is simulated to mimic US equity returns five-year averages, and the signal provided via variable a has the same predictive power in our experiment as the US aggregate dividend-price ratio over the next five-year index returns. Our main finding is 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. 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 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 show that our model provides a good fit to the data, suggesting that our subjects are fairly sophisticated in dealing with those forms of uncertainty. In terms of investment, subjects are more prone to take risks in rounds perceived as predictable than in rounds perceived as iid. Moreover, their investments depend on their own forecasts, and this elasticity is significantly higher when subjects perceive predictability. At the same time, overall elasticities remain small, consistent with a number of recent studies. Moreover, we show that these elasticities are challenging to reconcile with relatively high levels of risky investment. These findings have important implications for asset pricing models studying how shocks to expectations translate into price volatility or other equilibrium outcomes.

In my third paper, "Managers' Expected Returns and Project Valuation", I show that managers' biased expectation of returns and their reliance on the CAPM model can lead to inefficient decisions. Practitioners have widely used the Capital Asset Pricing Model (CAPM) to estimate the cost of capital of their firms or projects. When doing so, managers have to form expectations on the market excess returns, i.e., the market risk premium. This component is known to vary hugely over time as it captures the fluctuations in investors' required returns which are possibly driven by the variation in their risk aversion or the risk in the economy. Survey forecasts on managers' expected returns suggest that managers may hold expected excess returns on the market portfolio different from the market. Examples of such divergence include extrapolation on past returns and the price level. It is also shown that survey forecasts of excess returns are negatively correlated with the expected returns on the market. I use forecasts from CFOs survey and the market reaction to M&A announcements to study the consequence of managers' misperception of expected excess returns on the market portfolio. I show that the difference in the expected returns between managers and the market has important implications on firms' capital budgeting decisions and how the market reacts to such decisions. During the period of time when managers are pessimistic relative to the market, i.e., managers' expected excess returns (on the market portfolio) are low realative to the ones perceived by the market, they may end up using a discount rate that is lower than the market. The consequence is that the valuation of projects by managers during these times tends to exceed their market valuation. Therefore, managers may want to undertake these projects at a cost that is too high in the view of the market. The news of acquiring these projects is less favorable, and therefore one should expect a worse market reaction. The reverse also holds for periods when managers are optimistic relative to the market, i.e., managers' expected excess returns are high relative to the ones perceived by the market, and ones should expect more exciting market reaction to news of projects taking place during such time. I show from the data that one percentage point difference between the managers' expected excess returns and the market's is associated with 0.2 to 1.1 percentage points higher in cumulative abnormal returns around the announcement of the deals, depending on the measure of the market's expected returns. My paper is built upon the literature on the real effect of the use of CAPM in corporate finance. My main contribution is to show that the biases in managers' expected excess returns and their reliance on the CAPM have a real consequence in their capital budgeting decisions. One implication from the finding is that managers can simply use the all-time historical average returns as their expected returns rather than just using certain rules of thumb.

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Chapter 1: Review on time-varying expected returns*

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Abstract

It has been evident that expected returns are time-varying. Yet, surveys and experiments document extrapolations in the way people form their expectations of returns, which is inconsistent with the empirical evidence on return predictability. This survey aims to shed light on these facts. First, it discusses the most prominent evidence of time-varying expected returns, including the ongoing debates and the theories that explain such evidence. It later discusses the evidence on the formation of expected returns from surveys and experiments. The paper concludes with the theories that can accommodate both the evidence of return predictability and the ones from surveys and experiments on how individuals form their expected returns.

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1 Introduction

Expected returns (discount rates) enter investment decisions in various ways. The classical Merton-Samuelson model suggests that allocation to risky assets should be a function of the agent's expected returns of the assets. In corporate decisions, expected return is an important component of the capital budgeting decisions which mainly rely on the net present value (NPV) or internal rate of returns (IRR) rule (Graham and Harvey (2001), Jacobs and Shivdasani (2012)). Expected returns also play essential roles in many accounting, banking, and policy procedures. The first evidence of return predictability dates back to Fama and French (1988b), showing that aggregate dividend yields can predict subsequent index returns. For the last decades, many variables have been added to the pool of predictors, from valuation ratios such as the dividend-price and the earnings-price ratio to macro variables such as the consumption wealth ratio. In addition to the publicly available time series used in many empirical studies, there have been more data from surveys and experiments on how people form expectations of returns. It is, therefore, necessary to place both the return predictability and the evidence from surveys and experiments on expected returns in the same picture. This survey aims to shed light on the return predictability story and at the same time build a connection with the survey and experiment literature on expectation formation.

This survey mainly focuses on the predictability of excess returns on an aggregate portfolio (market returns). Throughout the paper, I use the term *return predictability* and *time-varying expected return* interchangeably to mention the idea that the conditional expected return is not the same as the unconditional value as some information available at the current moment is useful in predicting future returns. Therefore, when returns are predictable, the expected returns also vary as a function of available information[1].

The structure of this survey differs from that of earlier review articles. First, this paper does not aim to provide an extensive literature review on expected returns. Instead, besides the evidence and intuition of return predictability, to give a broader picture, I also include some parts of the debates on the econometric methodologies and the external validity of the predictive regressions. Second, this paper contrasts the evidence of return

[1] Notice that reverse causality should be applied here. Assuming constant expected cash-flows, when the expected returns are high (low), prices are low (high) since prices are the expectation of future cash-flows discounted at the expected return. Therefore, by observing the variations in price (or price ratio) today, one may infer information about future returns.

predictability with the expectations elicited from surveys and experiments. The difference in expectations is worth noticing as it suggests that individuals hold biased expectations relative to the model-based aggregate expected returns. Finally, this survey also visits the literature that can explain time-varying expected returns yet still incorporate the evidence on how investors form expectations of returns.

I begin section 2 with a discussion on the most prominent evidence of time-varying expected returns. In the first part of this discussion, I visit the literature showing that today's variation in prices can be explained by the variation in expected returns rather than the one in expected cash-flows. I also discuss various variables that have been shown to predict future returns. The second part of this section also covers the ongoing debates on return predictability which mainly concern the econometric methodologies and the external validity of the predictive regressions. Finally, in the third part, I also revisit some theories that explain time-varying expected returns.

In section 3, I look into the evidence from surveys and experiments on how individuals form their expectations. For the last decades, many surveys that are conducted to elicit individuals' expectations of market returns. These can be a valuable source of data to explore in addition to time series of market returns and predictive variables. As mentioned in this part, data from different surveys are pretty consistent with each other, which suggests that this type of data is more than just meaningless noise. A clear pattern coming out of the survey data is that respondents seem to form their expectations in an extrapolative manner, i.e., their expected returns are high following high past returns and vice versa. This extrapolation tendency contrasts with the evidence of return predictability mentioned in section 2 under the representative agent assumption. In more detail, during times when the predictive variables predict high future returns, expectations from surveys suggest low future returns and vice versa. Subsequently, I discuss the evidence of the heterogeneity in expectation formation, which gives way to other theories that incorporate both return predictability and extrapolative expectations.

Section 4 visit the theories that allow for different types of investors to co-exist in a market. As a result, these models can accommodate both the evidence of extrapolative expectation while explaining why the aggregate expected returns could be predicted, as observed in the empirical studies in section 2.

Section 5 concludes with a summary of key findings from the literature and the future path of research.

There are some aspects of time-varying expected returns that I did not address in this paper. For example, the applications of time-varying expected returns can vary from portfolio allocation to corporate decision, accounting and regulations (see Cochrane (2008) for instance). This article does not cover cross-sectional return predictability as well as the related anomalies. On the other hand, I focus on the equity risk premium that changes over time and the forces behind such evolution.

2 Return predictability - Empirical Evidence and Intuition

2.1 Empirical Evidence

One of the first evidence[2] of time-varying expected excess returns using multivariate series perhaps dated back to Fama and French (1988). The dividend-price ratio (D_t/P_t) or sometimes dividend yield (D_t/P_{t-1}) was shown to be able to forecast returns in the same direction. The intuition is simple: high aggregate expected returns decrease price and drive up dividend-price ratio and vice versa. Therefore, the dividend-price ratio as observed today reveals information about expected returns. What is surprising in this study is not simply that dividend-price can forecast returns but rather the economic significance behind the forecasting regressions. Expected returns vary a lot across time: For the period 1927 - 1986, the standard deviation of expected returns on NYSE is more than 6%, almost as large as average excess returns, and is around two-third of the standard deviation of realized returns in the same period. R^2 also raises with return horizons: starting at around 7% for annual returns and reaching 13 - 50% for four-year returns, depending on the periods studied. The fact that the forecast power increases with horizons is, as emphasized by Fama and French (1988), due to the negative correlation between the shock to return and the one to the dividend-price ratio of the same period. Whenever the current realized return is low, the dividend-price ratio tends to be high (so is expected returns), and vice versa. As a result, unlike the unconditional variance, the conditional variance of returns increases less than linear with horizons, making return

[2]Including Shiller, Fischer, and Friedman (1984), Rozeff (1984), Flood, Hodrick, and Kaplan (1986), Fama and French (1988) and Campbell and Shiller (1988)

predictability more important for longer horizons.

Campbell and Shiller (1988), through their present value identity, has noted that today's change in price relative to dividend must be either from the change in expected returns, the change in expected dividend growth, or a "bubble" component:

$$dp_t \approx \sum_{j=1}^{k} \rho^{j-1} r_{t+j} - \sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j} + \rho^k dp_{t+k} \tag{1}$$

where ρ is the approximation constant. $dp_t = d_t - p_t$, $\Delta d_t = d_t - d_{t-1}$ and d_t, p_t, r_t are the log of dividend, log of price and log of gross returns at time t, respectively. The big question is which type of information that today's price tell us about the future? Which of the three elements, can be forecasted?

Using the Campbell and Shiller (1988) present value identity, Cochrane (2011) shows that one can decompose the variance of the contemporary dividend-price ratio into its covariance with long-term returns, long-term dividend growth, and a "rational bubble" component:

$$var(dp_t) \approx cov\left[dp_t, \sum_{j=1}^{k} \rho^{j-1} r_{t+j}\right] - cov\left[dp_t, \sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j}\right] + \rho^k cov(dp_t, dp_{t+k}) \tag{2}$$

The 15-year coefficients from the vector autoregression (VAR) using annual returns, dividend-price ratio, and dividend growth in Cochrane (2011) suggest that all the variation in the current dividend-price ratio can be attributed to the variation in expected returns. This is an important point to make as it states that the change in today's stock price reflects the shock to aggregate expected returns instead of the shock to aggregate expected dividend growth. This finding is contrary to what has been implied by various efficient-market models.

Campbell (1990), also based on the Campbell-Shiller present value identity, decomposes the variance of unexpected returns into the variation in expected returns and expected dividend growth.[3]

$$r_t - E_{t-1}(r_t) = (E_t - E_{t-1})\sum_{j=0}^{\infty}\rho^j \Delta d_{t+j} - (E_t - E_{t-1})\sum_{j=1}^{\infty}\rho^j r_{t+j} \tag{3}$$

where E_t and E_{t-1} are the expectation at time t and t-1, respectively. $E_t - E_{t-1} \equiv \Delta E_t$ denotes the difference between the expectation between time t and t-1. The above identity states that the innovation in today's returns (the unexpected returns) can be attributed to the change in expected dividend growth and the one in expected returns. Using the VAR approach and the value-weighted NYSE data, Campbell noted around one-third of the variation in today's unexpected returns could be attributed to the change in expected returns. Interestingly, he observed a negative correlation between the change in expected dividend growth and the change in expected returns: A bad news about future cash-flows ($\Delta E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j} < 0$) is likely to be accompanied by a bad news about expected returns ($E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1} r_{t+1+j} > 0$). As a result, this would amplify the variations in the contemporary realized returns. The result serves as additional evidence that information about expected returns is indeed incorporated in today's price/returns, and that is why forecasts of returns can be made using today's signals.

As the dividend-price ratio is prone to be affected by corporate policy, it is appealing

[3]Take expectation at time t and time t+1 of equation (1) and let $k = \infty$:

$$E_t(dp_t) = E_t\sum_{j=1}^{\infty}\rho^{j-1} r_{t+j} - E_t\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j}$$
$$E_{t+1}(dp_t) = E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1} r_{t+j} - E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j}$$

Denote $\Delta E_{t+1} = E_{t+1} - E_t$ the innovation (surprise) between period t and t+1:

$$\Delta E_{t+1}(dp_t) = \Delta E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1} r_{t+j} - \Delta E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j}$$
$$0 = \Delta E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1} r_{t+j} - \Delta E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j}$$
$$\Delta E_{t+1} r_{t+1} = \Delta E_{t+1}\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j} - \Delta E_{t+1}\sum_{j=2}^{\infty}\rho^{j-1} r_{t+j}$$

Shifting the equation to one period earlier:

$$\Delta E_t r_t = \Delta E_t\sum_{j=0}^{\infty}\rho^j \Delta d_{t+j} - \Delta E_t\sum_{j=1}^{\infty}\rho^j r_{t+j}$$

to search for other alternatives. Campbell and Shiller (1988), Campbell and Shiller (2001) use the long-run annual S&P500 data from 1871 till 2000 and show that besides the dividend-price ratio, the (accounting) earning-price ratio and the ten-year moving average smoothed earning-price ratio are good forecasters of ten-year subsequent returns with even better fit compared to dividend-price ratio. Kothari and Shanken (1997) show that the book-to-market ratio also dominates the dividend-price ratio for the equally-weighted and value-weighted CRSP index data (period 1926 - 1991). Since these ratios contain the price in the denominator, which is partly driven by the variation in expected returns, it should not be surprising that they can be used as predictive variables to forecast returns.

While valuation ratios have proved to be good forecasters for long-term excess returns, the consumption-wealth ratio (*cay*) introduced by Lettau and Ludvigson (2001) is a strong predictor for short to medium-term returns. In more detail, Lettau and Ludvigson (2001) look at the deviation of aggregate consumption, assets holdings, and labor income from their long-term common trends. They argue that throughout the business cycle, when expected returns are high and so are their expected wealth, investors who want to smooth out their dynamic consumption may increase consumption out of current wealth in this period. Alternatively, when expected returns are low, investors decrease their consumption relative to the wealth of the same period. As a result, current consumption tends to deviate from its shared trend with wealth (asset holdings and labor income), and the aggregate consumption-wealth ratio is, therefore, informative about expected returns on the market. Using data on S&P index (1952-1998) and CRSP value-weighted index (1953-1998), Lettau and Ludvigson (2001) show that the consumption-wealth ratio *cay* can explain 9% to 10% of the variation in next quarter real returns and excess returns. Interestingly, *cay* can forecast returns on top of the dividend-price ratio. However, as shown in Cochrane (2011), *cay* almost has no effect on forecasting long-run returns. Notice that long-run predictability comes from the ability of the predictive variable to forecast short-run returns and from its own persistence. As *cay* is a much faster moving process than dividend-price, a shock to *cay* should not be carried over to many years in the future. Therefore, when we consider long-horizon predictability, any shock to *cay* in the current period has already faded out.

Similar to Lettau and Ludvigson (2001), Fama and French (1989) argue that expected excess returns should vary with the fluctuation in business condition. Firstly, expected returns are related to term premium, which goes up and down according to the business cycle. They use the term spread, measured by the difference between the Aaa corporate bond yield and the one-month T-bill rate, as the variable that captures this term premium. Interestingly, the term spread, which is more well-known to track term premium in bonds, can also identify such premium in stocks. As one may presume, the sensitivity of expected returns to the term spread is similar for bonds to stock portfolios. This suggests that one should use this variable in combination with other predictive variables that track the longer-term aspect of business conditions. Secondly, expected returns are also related to the risk premium (or default premium), which is also driven by business conditions. Besides dividend yield, which is known to capture such premium, Fama and French (1989) also introduces the default spread, measured by the difference between the yield on the market portfolio of corporate bonds and the one on Aaa bonds, as a predictive variable. The main results suggest that using both default spread and term spread as predictive variables can produce a higher R^2 in medium-term forecasting regressions than the use of dividend yield and term spread.

2.2 The challenge to return predictability

Predictability seems great so far, but there are reasons that one should be skeptical or at least should be cautious when using these predictive variables to forecast returns. The first concern of return predictability is about the econometric properties of the predictive regressions, more specifically, the statistical significance of the predictors. The second one is related to the external validity of these predictive regressions.

Predictive regressions are prone to bias in t-statistic that is in favor of rejecting the null hypothesis of no relationship between returns and the predictors. Nelson and Kim (1993) and Stambaugh (1999) challenge the evidence of return predictability by showing that the coefficients from the predictive regressions tend to suffer from bias towards rejection of the null hypothesis of i.i.d. returns. This bias is due to the contemporary correlation between the predictors such as the dividend-price ratio and the return of the same period. In more detail, the predictive regression is often of the form:

$$r_t = b_r x_{t-1} + u_t \tag{4}$$

where $u \sim i.i.d.(0, \sigma_u^2)$ and x_t is the dividend-price ratio. The correlation between the shock to returns and the one to the dividend-price ratio in the same period is large and negative, i.e., when the price in period t is high, the return r_t tends to be high, and the price ratio x_t tends to be low. Therefore, $cov(u_t, x_t) \neq 0$ which means $E(u_t|x) \neq 0$ where x is the vector that contains the dividend-price series. This is a violation of the classic OLS assumption, and therefore the estimated coefficients are biased (upward biased as showed by Stambaugh (1999)). Goetzmann and Jorion (1993) uses bootstrapping to tabulate the sampling distribution of the estimated coefficients on the predictive variables under the null hypothesis. They show that the estimated OLS coefficients as observed in the data never exceed the 95% fractile of the sampling distribution of the coefficient. This suggests that the OLS t-statistics that one uses in the literature is biased toward rejecting the null.

Cochrane (2008) argue that the null hypothesis that returns are i.i.d. cannot be posed in isolation of the null hypothesis that the dividend-price ratio can predict dividend growth as in Goetzmann and Jorion (1993), Nelson and Kim (1993) and Stambaugh (1999). Specifically, one has to consider the joint sampling distribution of the coefficients of returns on dp_t and the one of Δd_t on dp_t. Letting k = 1, projecting both the LHS and the RHS of identity (1) on dp_t, we obtain:

$$1 = b_r - b_d + \rho\phi \tag{5}$$

where b_r is the coefficient of returns r_{t+1} on dp_t, b_d is the coefficient of returns Δd_{t+1} on dp_t and ϕ is the auto-regressive coefficient of dp_t on its first lag. Equation (5) puts a constraint on the null hypothesis of b_r and b_d. Cochrane (2008) approximates the sampling distribution using the VAR simulations under the null hypothesis. Although the result shows weak evidence of return predictability, it allows a strong rejection of the null hypothesis that dividend growth can be predicted. For a much longer horizon (which allows the bubble component ϕ to disappear), today's price volatility is either explained by the variation in long-term returns or the variation in long-term dividend growth. The sampling distribution of the coefficient b_r^{lr} of long-run returns $\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}$ on dp_t under the null hypothesis implies the joint distribution of b_r and the persistence ϕ. In other words, under the null, to observe a b_r^{lr} at least as high as the estimated value, we need not only b_r to be high but also ϕ to be persistent. This hardly occurs throughout their simulations under the null (p-value = 0.0%). Cochrane (2008) argues that the test of b_r^{lr} is more powerful than that of b_r because it is, in theory, harder to reject the null in the former.

Another skepticism is whether the predictive power found in those forecast regressions is still robust for an out-of-sample period. When a market-timing trader forms his expectation of returns, he only has access to the prevailing information up to period t, including past returns and the predictive variables. Usually, the out-of-sample fit is worse than the in-sample fit. However, suppose these variables are helpful in forecasting returns, the out-of-sample fit should be higher than the one of an empty model, i.e., when investors have expected returns that equal the historical average. This boils down to the question of how stable the parameters in these predictive regressions are.

Goyal and Welch (2003) document that dividend yield and dividend-price ratio have changed over time and become more and more non-stationary. Accordingly, identity (1), dividend ratio must have shifted from predicting subsequent returns (first term on the RHS) to predicting itself (the third term on the RHS). Using annual data on the CRSP value-weighted index, Goyal and Welch (2003) show that the magnitude of the coefficients on dividend yield has declined over time given the prevailing data and is almost zero towards the year 2000. Consequently, the out-of-sample root means squared errors of the dividend ratio model could not outperform the one using only the prevailing historical mean of returns. Welch and Goyal (2008) revisit the predictive power of the most predominant predictive variables in the literature and find little evidence of out-of-sample predictability for different horizons. In other words, a naïve trader who believes that stock returns will behave just like in the past and use the prevailing unconditional expected returns would do just as well as the sophisticated one who uses all prevailing predictive variables to form expected returns. Bossaerts and Hillion (1999), using different model selection criteria that take into account the over-fitting problem, come to confirm the presence of return predictability with international data. The selected models, however, provide only poor out-of-sample fit. These findings directly challenge the external validity of predictive regressions in the literature.

Cochrane (2008), argues that the poor out-of-sample R^2, however, does not provide a valid statistical rejection of return predictability but should instead be considered as a caution. Campbell and Thompson (2008) show that a regression estimated over a period of time as short as twenty years can generate results that are contradictory to what the theory suggests. They instead adopt a much longer time series from 1872 until 2005, which allows them to expand the out-of-sample period with respect to Welch and Goyal (2008)) and Bossaerts and Hillion (1999). They show that, under some sensible constraints (positive expected returns, theory-consistent slope, etc.), the predictive regressions of dividend-price, earning-price, and smoothed earning-price ratio for one-year horizon perform better than the prevailing unconditional mean.

Despite the ongoing debates, return predictability is still an important finding of the last decades. Its applications should go beyond portfolio theory (perhaps most criticisms are about the usefulness of return predictability in asset allocation). For example, capital budgeting decisions have a long tradition to rely on the NPV rules in which the future cash-flows are often discounted at a constant discount rate. This would lead to investment inefficiency due to the mis-valuation of projects[4].

2.3 Why are expected returns time-varying?

Given the evidence of time-varying expected returns, it is important to know why they vary. Time-varying equity risk premium can be explained by the risk that is time-varying (Gabaix (2012)) or how risk is evaluated through the agent's preference (Campbell and Cochrane (1999), Barberis, Huang, and Santos (2001), Ju and Miao (2012)) and their belief (Barberis, Greenwood, Jin, and Shleifer (2015)). Although return predictability could be achieved by introducing a DRRA preference, the models discussed below aim also to explain excess volatility in stock prices in addition to time-varying expected returns. The two puzzles are closely related and, therefore, should be jointly explained. Shiller (1980), Shiller (2014) points out the volatility puzzle in stock prices. The standard efficient market model states that price equals the sum of conditional expected dividends discounted by a constant discount rate:

$$P_t = E_t \sum_{k=0}^{\infty} \frac{D_{t+k}}{(1+r)^{k+1}} \tag{6}$$

[4]The third chapter of this thesis provide evidence of mis-valuations of projects due to the use of biased discount rate.

where r is constant. This implies that price volatility cannot exceed the volatility of subsequent realized dividends themselves. Therefore, the view that the variation in expected dividends can entirely explain stock price movements faces a contradiction. It must be that price changes reflect either the variation in the discount rate or both the variation in the discount rate and the one in expected dividends.

In the habit model of Campbell and Cochrane (1999), time-varying expected returns are driven by the surplus consumption, i.e., the relative amount of consumption that exceeds the agent's consumption habit $S_t \equiv \dfrac{C_t - X_t}{C_t}$. The agent's expected utility is:

$$E \sum_{t=0}^{\infty} \rho^t \frac{(C_t - X_t)^{1-\gamma}}{1-\gamma} \tag{7}$$

where ρ is the time discount factor, X_t is the level of consumption habit, C_t is the consumption and γ is the utility curvature parameter. In a particular period, the local relative risk aversion is:

$$-\frac{C_t u''(C_t)}{u'(C_t)} = \frac{C_t \gamma}{C_t - X_t} = \frac{\gamma}{S_t} \tag{8}$$

This utility function allows for relative risk aversion to increase when consumption declines towards habit and vice versa. In the model, habit responds to consumption and is a slow-moving process, i.e., as consumption changes, the habit slowly adapts to the new level of consumption. Expected cash-flows are also assumed to be constant in their model. The intuition for return predictability is as follows. During bad times, where consumption declines towards habit, people become more risk-averse and require a higher risk premium. Therefore, expected returns rise, and prices decrease. Although one may realize that it is a good opportunity to buy, they cannot afford the risk of having consumption that may go below habit. The same argument applies to good times, where consumption is high relative to habit. People are more willing to take risks, which decreases expected returns and increases prices. Therefore, returns in their model can be predicted by looking at today's dividend-price ratio. They also show that the large variation in the dividend-price ratio can be explained by the time-varying risk premium while also taking into accounts the "excess volatility" of stock prices.

The long-run risk model of Bansal and Yaron (2004) has uncertainty in the cash-flow dynamic as the main driver of time-varying expected returns. In this model, the agent's risk aversion is constant, but the volatility of dividend growth varies across business cycles (and so does the volatility of consumption growth). During times when the uncertainty about dividend growth is high, investors require a higher risk premium to compensate for the risk they have to bear. Similar to Bansal and Yaron (2004), the rare disaster model of Gabaix (2012) also has time-varying expected returns driven by time-varying risk. Specifically, the value loss suffered by assets during a disaster event changes throughout the business cycles. In this model, each asset i at time t has an "expected resilience" H_{it}, i.e., how well the asset will do in a disaster:

$$H_{it} = p_t E_t[B_{t+1}^{-\gamma} F_{i,t+1} - 1 | \text{there is a disaster at t+1}]$$

where γ is the risk aversion constant over time, and p_t is the probability of the disaster. H_{it} is determined by both the resilience of the economy B_{t+1} and the one of the specific asset $F_{i,t+1}$. Gabaix lets the resilience H_{it} evolve over time, i.e., the value destruction that a disaster causes to an asset is time-varying. The market risk premium and the stock price are therefore functions of the resilience H_{it}. As the resilience is volatile, the dividend-price ratio is also volatile. During times when the economy's resilience is high (when dividend-price is low), the risk premium investors require to hold risky assets is lower, and the analogous argument applies when the economy's resilience is low. In contrast with the habit model of Campbell and Cochrane (1999), agents' risk aversion does not vary in this model. Still, the risk in the economy itself changes over time, which causes volatility in the expected returns.

Apart from traditional models, preference-based behavioral models can also account for time-varying expected returns and excess volatility. Analogous to Campbell and Cochrane (1999), in Barberis, Huang, and Santos (2001), time-varying expected returns are also driven by the dynamic of investors' risk aversion. The model incorporates two well-known concepts in psychology: prospect theory (Kahneman and Tversky (2013)) and the evidence that prior investment outcomes have impacts on the agent's risk aversion (Thaler and Johnson (1990)). In addition to utility from consumption, the agent also derives utility from the fluctuation in his financial wealth from year to year (feelings such as regrets, prides, etc., unrelated to consumption). As in the prospect theory model, the agent is loss-averse over this wealth fluctuation. To allow for a time-varying risk aversion, a variable z_t capturing the past investment performance is introduced, i.e., $z_t = \frac{Z_t}{W_t}$ where Z_t is a historical benchmark and S_t is the current financial wealth. When $W_t > Z_t$ (after a prior gain), a subsequent loss is less painful because it (or part of it) can be cushioned by the agent's prior gains. This reduces the agent's risk aversion. Alternatively, when $W_t < Z_t$ (after a prior loss), the subsequent loss is more painful, and therefore, the agent becomes more risk-averse. The agent in this model chooses (C_t, S_t) to maximize:

$$E\left[\sum_{t=0}^{\infty}(\rho^t \frac{C_t^{1-\gamma}}{1-\gamma} + b_t \rho^{t+1} W_t v(R_{t+1}, z_t))\right] \tag{9}$$

where b_t is a scaling term. The $v(.)$ utility inherits the kink from the prospect utility while its specific shape depends on the past outcome z_t. Particularly, when z_t is low (after prior gain), the kink shifts to the left, and so does the gain domain. Small losses are not penalized as heavily as when the agent has no memory about past outcomes or when $z_t = 1$. This corresponds to the time when the agent is less risk-averse and more willing to hold risky assets. When z_t is high (after prior loss), any loss is penalized heavily, which captures the idea that losses on top of other past losses are more painful. Although time-varying risk aversion also plays the main role in the variation of expected returns, this model is different from Campbell and Cochrane (1999) in what causes risk aversion to vary over time. In Campbell and Cochrane (1999), the variation in risk-aversion is due to the change in consumption relative to habit, while in Barberis, Huang, and Santos (2001) it is due to the evolution of the agent's past financial performance. Related to Barberis, Huang, and Santos (2001), Andries (2019) also has the reference point as a function of current and past expectation of utility from consumption. She shows that the history-dependent reference point can cause expected excess returns to vary over time.

The ambiguity aversion model of Ju and Miao (2012) has state belief that drives changes in dividend-price ratio and expected returns. In this model, the distribution of consumption is determined by the state of nature. This state is unobservable by the agent. Each period, the agent observes aggregate consumption growth and updates his state belief for the next period. In addition to having a time-varying belief, the agent is also averse to the consumption growth uncertainty since the distribution of this growth depends on the state. The ambiguity aversion model of Ju and Miao (2012) has the equity risk premium that is a non-monotonic function of state beliefs. Consider a little bad news occurrence in good times (the prior that the future state is good is near 1). First, the expected future consumption growth is updated downward. Equivalently, the expected continuation value decreases, and prices fall. Second, the posterior is pulled toward 0.5, and thus the uncertainty of the state increases. Since the agent is ambiguity averse, he requires a higher risk premium for a higher level of ambiguity. Therefore, the reduction in prices is more than the one in expected consumption due to agents' pessimism. On the contrary, consider a piece of good news during bad times (the prior that the future state is good is near 0). On the one hand, the expected continuation value increases. On the other hand, an increase in the ambiguity level (since the posterior is getting closer to 0.5) would make agents more reluctant to take risks and require a higher risk premium. As a result, prices, in this case, will increase less than the increase in expected consumption due to agents' aversion to ambiguity.

Belief-based behavioral models[5] which have investors who are extrapolating on past price/returns can also explain both return predictability and excess volatility. Additionally, these models are built on the survey evidence that investors tend to extrapolate on past returns, i.e., expect future returns to be high when recent returns are high and vice versa. Chapter 4 discusses how these models can accommodate both the empirical facts of return predictability and the survey evidence of return extrapolation.

To sum up, except for the belief-based behavioral models, time-varying expected returns are mainly driven by either the change in the representative agent's risk aversion over time or the perceived risk itself that changes over time. The common thing in these models is the connection between the economic condition and the expected returns. If time-varying expected return is driven by risk aversion, a good time is depicted as a period where agents are more willing to hold risky assets and therefore require less risk premium. If time-varying expected return is driven by the perceived risk by the agent, a good time is seen as a period of lower uncertainty, which rewards investors with lower returns for holding risky assets.

[5]See Cutler, Poterba, and Summers (1988), Barberis and Shleifer (2003), Barberis, Greenwood, Jin, and Shleifer (2015), De Long, Shleifer, Summers, and Waldmann (1990), Hong and Stein (1999)

3 Expectation of Returns - What do we get from surveys and experiments?

The availability of survey data on return forecasts covering the last several decades can be a valuable source of information to study how individuals form their expectations of returns.

It has been widely observed in surveys that investors tend to extrapolate on current stock returns when forming their expectations of future returns (see De Bondt (1993), Fisher and Statman (2000), Vissing-Jorgensen (2003), for example). Greenwood and Shleifer (2014) is one of the first to contrast the expectations from surveys and the evidence of return predictability. They use data from six different surveys to study how investors/professional forecasters form their beliefs about future returns. They differentiate between *expectations of returns* - the survey responses and *expected returns* - the asset pricing model-based forecasts. The survey data covered in this study are quite diversified in terms of respondents: from individual investors (Gallup survey, American Association of Individual Investors, Shiller's Investor Survey, and the Survey of the University of Michigan) to professional forecasters (Investor's Intelligence Newsletter) and managers (Chief Financial Officers survey of Graham and Harvey). Hence, return forecasts elicited from these surveys can reflect a widely shared belief about the risk premium required on the market portfolio. In these surveys, the respondents' forecasts of returns are for the US stock market and are between six-month to three-year horizon [6]. Greenwood and Shleifer (2014) found that expectations of returns from the six surveys are highly positively correlated despite different survey methods. This suggests that these responses are likely to contain useful information on the shared belief of the stock market's future performance. What is more striking is that expectations of returns are negatively correlated with the model-based expected returns constructed using the dividend-price and consumption wealth ratio. Specifically, it is documented that the forecasts of future returns from surveys are extrapolative, i.e., if current realized returns are high, they also tend to be high and vice versa. Additionally, high survey forecasts of returns coincide with higher mutual funds inflows and vice versa, suggesting a connection between expectations and

[6] In the surveys of Gallup, American Association, Investor's Intelligence, and Shiller, respondents were not directly asked for their forecasts, but instead put their expectation about future market returns into categories such as "bullish", "bearish", etc.

real investment decisions. This raises a puzzle. If survey forecasts reflect investors' belief about future returns, what do the model expected returns (expected returns constructed using the predictors) really reflect?

Similarly, Amromin and Sharpe (2014), using data from Gallup/UBS and Michigan survey, found that investors form their expectation of future returns in an extrapolative way. Specifically, investors' expectations are positively correlated with different measures of economic conditions. In good times, when unemployment is low, and the current business condition is bright, investors are more optimistic and forecast higher returns in the next 12 months, and the opposite holds in bad times. Therefore, investors, on average, make positive forecast errors in good times and negative forecast errors during bad times. As in Greenwood and Shleifer (2014), the survey-based expectations in Amromin and Sharpe (2014) are negatively correlated with the well-known predictors such as the dividend-price ratio and cay. However, Amromin and Sharpe (2014) show that portfolio equity shares of investors are quite insensitive to their own expectations compared to the level of sensitivity implied by the classic portfolio choice model of Samuelson (1975).

Given the survey evidence, a relevant question is whether extrapolation on past or current returns is a robust phenomenon. Suppose either there is only a subset of extrapolative investors or investors are extrapolative only under some conditions. In that case, these survey expectations do not necessarily contradict the previous empirical evidence on return predictability. We may have different groups of investors in the economy where at least one of them is rational and holds expectation as observed in previous empirical studies. In session 4, I discuss the literature that aims to fit the expectations of returns from surveys to the big picture of return predictability. Some surveys and experiments may help shed light on the robustness of extrapolation. Amromin and Sharpe (2014) using data from Michigan survey at the household level to show that investors with higher financial wealth tend to (positively) rely more on current returns when making forecasts of returns. Dominitz and Manski (2011) using data from the Survey of Economic Expectations and the Michigan survey to show that individuals are pretty consistent in the process that they use to form expectations of returns. However, there is considerable heterogeneity across individuals. Specifically, they propose to think of the population as a composition of three types of investors. The *random walk type* are the ones who believe that stock returns are i.i.d.; the *persistence type* are those who extrapolate on past and current returns, and the *mean reversion type* is the one who believes that stock returns are mean revert. Interestingly, the percentage of each type in their sample is 27%, 41%, and 32%, respectively. This is strong evidence against the robustness of extrapolative expectation, as observed in many surveys. Dominitz and Manski (2011) argue that the cause of the difference in the formation of expectation may come from the way each individual interprets the questions, the amount of private information they have, or the way they use the available information. Malmendier and Nagel (2011), using data from the Survey of Consumer Finances, shows that individuals are different in the levels of risk-taking depending on their life experience. Individuals who experience high market returns in their life are more willing to participate in the stock markets and, conditional on their participation, invest more in stocks. Additionally, they found evidence supporting the channel that experience alters ones' belief, although not ruling out the possibility that it may also affect ones' preference. Specifically, they found that individuals tend to hold high expected returns if they experience high past returns and vice versa. Since the market at any point in time consists of investors with different life experiences, it makes sense to consider the heterogeneity in expected returns.

More recently, Andries, Bianchi, Huynh, and Pouget (2020) study how expectations of returns are formed in controlled experiments. In some of the rounds, subjects are given a series of predictive variables in addition to the realization of past returns and are asked to make their forecasts of future returns. They found that the same subjects can be both rational and extrapolative depending on whether they have access to the predictive variable when making forecasts. Notably, subjects incorporate past returns into their forecasts only when they do not observe the predictive variable. On subjects' heterogeneity, women are significantly more extrapolative when forming their forecasts of returns. Similar to Amromin and Sharpe (2014), they found that subjects' investments do not respond much to their own expectations even when there is no friction in their setting. Interestingly, subjects' risky investments are significantly more sensitive to their expectations when the predictive variable is available. This finding is important as it suggests that extrapolation may not matter much in the equilibrium as investors' portfolios may not reflect much of their expectations. Dahlquist and Ibert (2021) look at long-term returns expectations from the capital market assumptions of prominent asset managers and find that these expectations are in line with the expected returns constructed using asset pricing models. Specifically, when valuation ratios such as the price-earnings ratio are high, asset managers tend to have low expectations and vice versa. This suggests that, unlike individuals, the most sophisticated investors in the market are rational.

Overall, the survey and experiment data show that although extrapolation is an important phenomenon in expectation formation, it may not be robust across investors in the market. The next chapter will discuss the literature that aims to accommodate both the empirical evidence of return predictability and the survey/experiment evidence of extrapolative expectations.

4 Models that accommodate both return predictability and extrapolative expectations

The evidence that investors hold extrapolative expected returns challenges the well-known view that aggregate expected returns reflect an equilibrium where investors are compensated for holding risky equity. One of the first reactions is to ask whether responses from surveys really reflect expectations of returns. Survey methodology is known to be sensitive to the use of words. For example, Cochrane (2017) argues that in surveys where researchers asked people questions such as "What do you expect the next year return on S&P 500 to be?", ones cannot know whether the given response is under true probability measure or under risk-neutral probability. The risk-neutral probability of an asset is the hypothetical probability such that investors are indifferent between putting one dollar in this asset and putting one dollar in a risk-free asset. Equivalently speaking, this measure is risk-adjusted. Since prices are the risk-neutral expectations of the payoffs discounted at the risk-free rate, if respondents report high expected returns after a period of high prices, it may be the case that they are using the risk-neutral measure instead of the true one to form their expectations. However, questions to elicit investors' expectations have been asked in many different ways. For example, in the UBS/Gallup survey, they were asked, "what overall rate of return do you think the stock market will provide investors during the coming twelve months?" which does not explicitly use the word "expectation". In other surveys, such as the one of the American Association, investors are asked to categorize the future performance of the stock market into different market conditions of either *bullish*, *neutral* or *bearish*. In the experiment of Andries, Bianchi, Huynh, and

Pouget (2020), subjects were directly asked to give their forecast of the next period return. Given the various ways of posing the questions, we still observe a clear extrapolation structure, which suggests respondents are not too confused about the questions and their reported expectations are more than just noises. Perhaps a more plausible explanation is that there are several types of investors in the market holding different beliefs about the returns process.

De Long, Shleifer, Summers, and Waldmann (1990) categorize investors into three different types: the speculators, the extrapolators (referred to as positive feedback traders in their model), and the passive investors. The speculators are rational and are informed of the fundamentals ahead of the market. The extrapolators holds extrapolative expectation. They buy after an appreciation in prices and sell after a decline in prices. The passive investors are the ones whose demands only depend on the price relative to fundamentals. De Long, Shleifer, Summers, and Waldmann (1990) depicts a strategy of the speculators which may destabilize prices. Suppose the speculators observe a good but noisy signal about the fundamentals. Instead of buying just enough to bring the price close to its fundamentals, the speculator, in anticipating the action of the extrapolators will buy today and push prices to even higher than the expected fundamentals. Subsequently, the speculators sell the asset short when the extrapolators' demand increases due to the appreciation in the past price. Later, when the fundamentals are fully reviewed, the price goes back to its fair value, producing low returns. The analogous rationale applies when the speculators observe a negative signal of the fundamentals. In this model, although the speculators' strategy is not crucial in creating return predictability, it helps explain the high volatility in prices. Time-varying expected returns are driven by two forces. First, the presence of the extrapolators causes over-reaction to news, and prices later revert to their fundamentals. Second, the speculators also participate in amplifying the mispricing for a short period. They, however, later trade to correct this mispricing. Hong and Stein (1999), on the other hand, introduce two types of investors, who, under their definitions, are both rationally bounded. The first type is the speculators (referred to as news watchers), who cannot observe the new information all at the same time, i.e., information is only slowly incorporated into prices after several periods. The second type is the extrapolators (referred to in the paper as the momentum traders). They assume that these extrapolators will maintain their position for j periods, and there is a new generation of extrapolators entering the market every period. They are both rationally bounded as their trades are only based on news about fundamentals in the case of the speculators and are based on the past price change in the case of the extrapolators. Suppose a piece of good news arrives on the market, some speculators start to buy and push the price up. Extrapolators' demand increases after innovation in the price. Through time, information is gradually incorporated, and the price is getting closer to its fundamentals. Extrapolators in expectation of high future returns buy more aggressively and drive the price further from the fundamentals. After the peak, the price eventually reverts to its fair value. This mispricing and correction pattern suggests that a period when prices are high (so price ratio such as dividend-price is low) is often followed by a period of low returns. The analogous argument applies to the period of low prices (high dividend-price ratio).

Barberis, Greenwood, Jin, and Shleifer (2015) and Greenwood and Shleifer (2014) incorporate extrapolative expectations in a the traditional consumption-based asset pricing model. Similar to the models discussed above, they also have two types of investors: The extrapolators whose demands react positively to the recent change in price and the rational investors who form correct beliefs of the returns process and also know the extrapolators' beliefs. Suppose there is a piece of good news so that price increases to its new fair value. Extrapolators who hold optimistic expectations and maximize their lifetime utility start to buy to push the price higher than its fundamentals. The rational investors who also maximize their lifetime utility from consumption absorb the extrapolators' demands. Since the sentiment due to past evolution in the price eventually dies out, the mispricing created by the extrapolators is gradually corrected. Therefore, high prices due to the presence of extrapolators would be followed by low future returns. Unlike other asset pricing consumption-based models, this model does not have either the risk aversion or the risk itself that varies over time. By simply introducing a group of investors who are extrapolative on past returns as in De Long, Shleifer, Summers, and Waldmann (1990) and Hong and Stein (1999), the mispricing-correction patterns are the element that drives expected returns to vary over time.

To sum up, the common feature of the models above is that they have several groups of investors, and one of them is extrapolative on past returns. In these models, expected returns are time-varying in an analogous fashion. Since the extrapolators hold expectations that are positively correlated with past price changes, their trade would amplify the movement in price and push price away from the fundamentals. Due to the dying-out sentiment and the presence of rational investors in the market, the mispricing is eventually corrected. In these models, time-varying expected returns are not driven by the aggregate risk or the representative agent's risk aversion that varies over time. Expected returns still reflect the required returns by the marginal trader. However, prices at the equilibrium may be far from rational (Greenwood and Shleifer (2014)). Although the mechanism is simple, these behavioral models can accommodate both return predictability and extrapolative expectations.

5 Conclusion

Returns predictability has been an important phenomenon in asset pricing for the past decades. Yet, it also faces many challenges on the econometric methodologies and particularly its external validity. This paper first aims to provide a comprehensive survey on the evidence of return predictability together with its intuitions and a touch of the ongoing debate. Next, this paper discusses the survey and experimental evidence of individuals' expected returns and shows a common extrapolation pattern in their expectations. These results are inconsistent with the time-varying expected return evidence. Finally, it visits the literature that allows for return predictability while still incorporating the survey evidence.

The heterogeneity models, as discussed in section 4, have expected returns to be driven by the cycle of mispricing and subsequent correction. Such mispricing is in turn caused by extrapolative expectations (and sometimes also driven by speculative strategy). This suggests that the idea of using sentiment-based variables to predict returns is quite justifiable. We have seen this in the behavioral literature. For example, the close-end fund discount (Bathia and Bredin (2013); Doukas and Milonas (2004)), IPO-related variables (Brown and Cliff (2004); Baker and Wurgler (2006)), share of equity issues (Baker and Wurgler (2000)) and dividend premium (Baker and Wurgler (2007), Baker and Wurgler (2004)) are potentially sentiment-driven. Baker and Wurgler (2006), based on these sentiment variables, introduce an index of sentiments and show that such sentiments have different cross-sectional predictability capacities.

There are many potential applications of time-varying expected returns besides portfolio theory that deserve dedicated future research. Procedures varying from capital budgeting decisions, firm valuation to decisions of capital structures have expected returns play an important role in them. The evidence that expected returns are time-varying may suggest that some procedures are inefficient and need to be modified.

Further research also needs to be done to understand why some individuals are extrapolative when forming expectations of returns. In general, being able to provide evidence and explain the heterogeneity in ex-post expectations can be very useful. It has been widely accepted in asset pricing that agents should hold homogeneous ex-post expectations. Such evidence would give way to the class of models that enable heterogeneous agents.

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Table 1: Summary of models that explain time-varying expected returns

Paper	Main drivers	Summary	
Traditional models with representative agent	Campbell and Cochrane 1999	Time-varying risk aversion	When the current consumption falls short (exceeds by a large amount) with respect to the slowly moving level of habit, the agent becomes more (less risk-averse) and requires more (less) risk premium to hold the risky asset.
	Bansal and Yaron 2004	Time-varying aggregate risk	The volatility of dividend/consumption growth evolves over time, and the agent requires a different amount of risk premium even with constant risk aversion.
	Gabaix 2012	Time-varying aggregate risk	The resilience of an economy changes over time. This makes the value destruction by a disaster vary, and so does the risk premium required by the agent.
Behavioral models with representative agent	Barberis et al. 2001, Andries 2020	Time-varying risk aversion	The reference point of the gain-loss asymmetric utility function depends on past wealth. This makes the shape of the utility function time-varying. Therefore, the risk premium required by the agent to hold the risky asset also changes over time.
	Ju and Miao 2012	Time-varying state belief	The belief in the distribution of future states of nature changes as a function of today's consumption. Different data generating processes for consumption growth are switched on in different states. The agent is also ambiguity averse to the uncertainty of the consumption growth data generating process. Time-varying state belief and ambiguity aversion simultaneously drive expected returns.

Behavioral models with heterogenenous agents	De Long et al. 1990	Mis-pricing - Correction	The extrapolators have demand depending on past returns. The rational traders, who are rational and informed, anticipate the future price trajectory created by the extrapolators' demand, trade to push the price further from the fair value. Price eventually comes back to its fundamentals. The mispricing and correction patterns drive expected returns to vary over time.
	Barberis et al. 2015, Greenwood and Shleifer 2014, Barberis et al. 2015	Mis-pricing - Correction	After observing a change in price, the extrapolators trade and push prices further from the fundamentals. The rational traders later trade to correct the mispricing. The mispricing and correction patterns drive expected returns to vary over time.

Chapter 2: Return Predictability, Expectations, and Investment: Experimental Evidence*

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Abstract

We design a controlled experiment where we vary the information available to form returns expectations and choose risk allocations: in addition to the graphical display of the past returns of a risky index, we provide a separate signal that helps, in some rounds, predict future returns. We derive three novel results. First, subjects follow a dual forecast model: fully rational when the provided signal is deemed informative; extrapolative from past returns otherwise. Second, whether they perceive the signal as useful or not affects subjects' portfolios: their risk-taking depends significantly more on beliefs informed by the predictive signal than on their "uninformed" extrapolative forecasts; a difference in magnitude inconsistent with the classical investment model. Third, *all* the subjects of our experiment behave according to the two rules above, even when accounting for individual characteristics (e.g.,, financial literacy, risk appetite, gender).

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1 Introduction

How do investors form their expectations about risk and returns? How does it affect their investment decisions? We investigate these two key questions in a controlled experiment in which subjects have access to information that varies, across treatments, in how useful it is to forecast the returns of a market index.

We build on a rich literature studying how market participants form their beliefs, showing that investors put greater weight on the most recent past realizations of macroeconomic and financial indicators to forecast future outcomes: they have extrapolative expectations.[1] In particular, when equity index prices have been going up (down) over the past year, surveys of investors indicate they expect them to go up (down) again in the following year Greenwood and Shleifer (2014). But how set are they in forming such beliefs? And how much does it matter for equilibrium outcomes? Two questions naturally arise because, in the data, annual equity index returns follow a random walk, a well-known result at the basis of the efficient market hypothesis (Fama (1970)); so it seems irrational for investors to extrapolate. Our experiment is designed to provide some answers to these questions. Specifically: 1) how robust are extrapolative beliefs to changes in the information investors have access to or pay attention to? And, in turn, 2) how does it affect their risk decisions?

In successive rounds, the subjects of our experiment are shown graphical displays of the past realizations of a risky asset, "Index Return", and those of another variable, "Variable A". They are told that "Variable A" can, in some rounds, be useful to predict returns; which they must visually infer from the graphs. Each round, our subjects observe new, independent, simulations of "Index Return" and "Variable A"; receive an endowment to invest; and are asked i) to state whether they perceive the "Variable A" signal as predictive; ii) to provide their next-period return forecasts; and iii) to allocate their endowment between the risky asset and cash holdings. Before moving on to the next round, they receive feedback on all three: whether or not "Variable A" was informative, how "Index Return" realized, and how well their portfolio performed.

[1] See our survey of the literature below.

To mimic, as best as possible, investors' real risk decisions, we simulate "Index Return" to statistically match the US equity market 5-year average returns — a reasonable buy-and-hold investment horizon, given the low trade frequencies observed in the data (Alvarez, Guiso, and Lippi (2012); Sicherman, Loewenstein, Seppi, and Utkus (2016)). "Variable A" is simulated to match the dynamics of the US equity dividend-price ratio. In rounds where "Variable A" provides useful information, its predictive power for "Index Return" replicates that of dividend-price ratios for the following 5-year returns in the data (Fama and French (1988); Campbell and Shiller (1988)). In all other rounds, the simulated time series of "Index Return" and "Variable A" are uncorrelated.

The subjects of our experiment thus forecast and invest in risks similar to those of real market participants; and are provided useful signals, in some rounds, that are readily available in the data, i.e.,, can easily be given to investors. We further note that the predictability of equity index returns at mid-to-long term horizons has been extensively documented and studied in asset pricing theory (Campbell and Cochrane (1999); Bansal, Kiku, and Yaron (2009)), so the experiment design we propose does not built on obscure, or dubious, information treatments. We obtain three main results, each one a new, and we believe important, contribution to the literature.

First, extrapolative expectations are not robust to variations in the information agents observe. Our subjects form forecasts that extrapolate from the most recent return realizations, with similar weights as in previous experimental work (Landier, Ma, and Thesmar (2019)), but *only* in rounds where they perceive the information in "Variable A" as useless to predict returns. In rounds where they perceive the "Variable A" signal as useful, which they correctly identify more than 80% of the time, they use it exclusively in their forecasts, and no longer display any extrapolative biases. This result is quite remarkable because "Variable A"'s predictive power, replicating that of US equity dividend-price ratios in the data, is far from immediately obvious in the graphical displays that subjects observe.[2]

Second, how much agents rely on their own forecasts to choose their risk allocations depends on how informed they are. Our subjects' investments do vary in steps with their stated beliefs, but how much so differs across rounds. When subjects perceive "Variable A" as useless, the pass-through from beliefs to portfolio decisions is small;

[2]Examples of the simulated time series displays can be found in Appendix B.

considerably smaller than for beliefs informed by the “Variable A” signal, in rounds where it is perceived as predictive. Though our results can be partly explained by differences in risks between the informed and the uninformed rounds, their magnitudes are inconsistent with the classical investment model, as we discuss further below. As such, extrapolative expectations appear to have a statistically significant but puzzlingly low impact on risk decisions.

Third, *all* subjects display remarkably similar behaviors in the two dimensions above: to form their beliefs, they all use the information in “Variable A” when perceived as predictive, and extrapolate from past returns otherwise; they all use their own forecasts to make their risk decisions, but with considerably lower elasticities in rounds where they find the “Variable A” signals uninformative. These broad results hold whether individual fixed effects are included or not, and when we separate our subjects in groups of distinct characteristics: risk appetite, gender, financial literacy, time spent on each round, and ability to identify when “Variable A” is useful or not.

Having established these three sets of results — the main empirical contributions of our paper — we analyze them, and formalize their implications, via stylized forecast and investment models.

First, we posit a model of expectation formation where agents have extrapolative beliefs as their default forecasts when the only information they observe is the time series of past risk returns; but fully rational expectations when they receive useful, predictive, signals. Under our experimental design, subjects trying to form their beliefs according to this proposed model face two sources of uncertainty: one, they do not know for certain in which rounds the “Variable A” signals are predictive; and two, they are not told how to form rational expectations in such rounds — they know that “Variable A” can sometimes be useful, but not how. We test the stylized forecast model above under the restrictive conditions that subjects: 1) correctly assess their abilities to perceive correlations, i.e., their probabilities of identifying when “Variable A” is predictive or not; and 2) are, on average, unbiased in how to use the “Variable A” signal across predictive rounds. Even though these two assumptions suppose a high degree of sophistication in subjects’ dealings with uncertainty, we find they nonetheless allow our proposed “dual expectation model” to provide an excellent fit to the experimental data.

Naturally, even under less stringent rationality conditions, this stylized forecast model can only realistically apply to cases where agents can somewhat easily assess which signals are informative *and* how to interpret them. In an annex treatment, we ask our subjects to form forecasts and make risk allocations on long-horizon returns. Whether the "Variable A" signals are predictive or not is no harder to visually infer, but how to use their information is considerably more difficult to grasp. We find our subjects display extrapolative long-term beliefs in *all* rounds; they never use "Variable A" to form their long-horizon forecasts even when they perceive it as predictive.[3] The subjects of our experiment thus appear incapable of applying our proposed dual expectation model in this annex treatment.

Our forecast results thus suggests that equity market investors may all rationally use predictive information, e.g., price-dividend ratios, if provided in salient and easily interpretable signals; and all resort to extrapolative beliefs as the default, uninformed, option.

Turning to investment choices, second, we analyze our subjects' allocations via the prism of the classical Merton-Samuelson investment model, a natural framework for their static, one-period, risk decisions, repeated each round. In both types of rounds, with and without predictive information, we find that the elasticities of investments with respect to forecasts correspond to high levels of risk aversions ($\gamma \approx 50$); inconsistent with those implied by our subjects' average risk positions ($\gamma \approx 20$). In contrast to similar results observed in the data, (e.g., in Giglio, Maggiori, Stroebel, and Utkus (2019)), our experimental setting allows us to rule out the usual explanations for such a "portfolio inertia", as driven by frictions such as transaction costs, trading constraints, limited attention, measurement errors in investments, or anchoring on past decisions.

Refining our analysis to focus on the precise role information may play in shaping the investment "model" agents rely on to choose their allocations, we measure the impact of variations in beliefs deriving directly from variations in the signals that subjects use to form their forecasts — "Variable A" in rounds perceived as informative, the past "Index Return" otherwise — on their risk positions. The elasticity of investments to "informed" forecasts remains unchanged, and puzzlingly low, in rounds where "Variable A" is perceived as uninformative, i.e., when subjects form extrapolative beliefs. In contrast, when the provided signal is viewed as predictive, the pass-through from "informed" forecasts

[3]Their long-term investment strategies are the same in all rounds.

to risk allocations increases significantly, so much so that it no longer rejects the classical model. The corresponding risk aversion $\gamma \approx 25$ is not statistically different from that implied by our subjects' average risk positions in such rounds.

The divergence in risk allocation dynamics between rounds with and without information, i.e., between rounds where the "Variable A" signal is perceived as predictive or not, suggests that our subjects are self aware that their own forecasts should not be quite "trusted", particularly so when they derive from extrapolative beliefs. This form of model uncertainty, though intuitively close, does not appear to correspond to a standard min-max ambiguity aversion framework: our experimental evidence does not show any asymmetry in the impact of pessimistic versus optimistic forecasts, as such a model would predict Chen, Ju, and Miao (2014).

The analysis of the forecast and investment models, as described above, highlights the implications of our experimental results for various fields in finance. First, our information treatments confirm the role financial intermediaries may play, not as portfolio advisors but as information providers Andries and Haddad (see also 2020); Bender, Choi, Dyson, and Robertson (see also 2020). We note that, in our experiment, subjects increase their average risk investments by 20% in rounds where they perceive the "Variable A" signal as useful, and their "market timing" allocation variations reduce the variance of their portfolio returns by 23%; hinting at a potentially large impact on investors' wealth. Second, the limited pass-through from forecasts to risk positions that we observe in our study, combined with the role information appears to play beyond that implied by the classical investment model, suggests we need to proceed with caution when inferring equilibrium asset prices from survey evidence, particularly so in the case of extrapolative beliefs.

More generally, our results speak to any setting where agents must make forecasts and choose how to act accordingly. On how beliefs are formed, our data is inconsistent with the notion that agents always differ, as rational versus irrational individuals; and suggests instead they may *all* be sophisticated Bayesian or *all* prone to biases, depending on the information framework they face. On how decisions are made, our analysis invites us to allow for an agent's "trust" in her own forecasts to play a role; without necessarily introducing the min-max asymmetry specific to models with robustness or ambiguity aversion.[4]

After a brief review of the literature, we present our experimental design in Section 2. In Section 3, we describe how our subjects appear to assess the risk distributions they face. Section 4 analyses their next-period return forecasts; and Section 5 their risk allocations. Sections 6 and 7 provide, to the interested reader, additional results on the information subjects use to form their forecasts, and on subjects' heterogeneity.

Survey of the Literature Our paper builds on the literature analyzing expectations in surveys and in experimental settings, most of which document various forms of extrapolation: see e.g., Shiller (2000); Dominitz and Manski (2011); Greenwood and Shleifer (2014); Assenza, Bao, Hommes, Massaro, et al. (2014); Manski (2018); Landier, Ma, and Thesmar (2019); Afrouzi, Kwon, Landier, Ma, and Thesmar (2020); Bordalo, Gennaioli, Ma, and Shleifer (2020a). Our key innovations are 1) to introduce information treatments so markets *are* predictable in some rounds; and 2) to analyze both forecasts *and* risk decisions in a controlled experiment, over a series of independent rounds. These allow us to show, first, that, however well documented they are, extrapolative extrapolations may not be robust to the type of information investors observe, even in the case of easily available predictive signals such as price-dividend ratios for the US equity index; and, second, to analyze the pass-through from extrapolative beliefs to investment decisions.

Previous work using portfolio data shows extrapolative beliefs may influence investment decisions, and thus investors' welfare and market dynamics. Benartzi (2001); Greenwood and Nagel (2009); Bianchi (2018), though Giglio, Maggiori, Stroebel, and Utkus (2019) find such an influence to be very limited in magnitude in the data. How much their result derives from well known sources of inertia, e.g., inattention, transaction costs, anchoring on prior decisions etc., is difficult to estimate. In contrast, our experimental set-up allows us to consider this key question in a controlled environment where all exogenous constraints to dynamic portfolio reallocations are absent. Our results establish that variations in forecasts do indeed incur only small variations in risk positions; and reveal, further, that information environments matter more than implied by the classical investment model. The subjects of our experiment follow different risk decision rules depending on whether or not they perceive market returns as predictable by the provided

[4]See e.g., Chen, Ju, and Miao (2014), or Epstein and Schneider (2010) and Hansen and Sargent (2008) for reviews.

signal, such that how much they "trust" their own forecasts appears to play an important role.

Inferring from survey evidence, several models derive equilibrium asset prices under the assumption investors have extrapolative expectations, e.g., Barberis, Greenwood, Jin, and Shleifer (2015, 2018); Bordalo, Gennaioli, Porta, and Shleifer (2020b). Our results suggest such models may need to feature agents who rely on expectation models and forecast-to-investment elasticities that vary with the information they have access to, but are otherwise homogeneous in their extrapolative biases. We acknowledge however that the subjects of our experiment may have similar forecast behaviors solely because they have a common type — as students in the Masters in Finance at Toulouse School of Economics (even though they do display variations in individual characteristics and in their abilities to understand the experimental framework). Additional experiments, using different, more diverse, pools of subjects, are needed to confirm, or infirm, the striking homogeneity result we derive, an endeavor left for future work.

Finally, we point out that our experiment is not designed to explain why extrapolative beliefs are pervasive in the data. To rationalize the evidence, Gabaix (2019) argues that extrapolating from recent past realizations is a valid, to a rational inattentive agent, "one-size fits all" AR(1) forecast model of macroeconomic variables. An orthogonal justification relies instead on psychological studies that reveal our innate desire to perceive patterns (Chapman (1967); Tversky and Kahneman (1973); Whitson and Galinsky (2008)). The results of our experiment are consistent with either explanations: we force our subjects to be attentive to useful information, other than past returns, in rounds where "Variable A" is predictive; while at the same time providing them with a nice "ready made" pattern to follow.

2 Experiment

2.1 Design

The purpose of our experiment is to analyze how investors form their forecasts and risk taking decisions; and whether they depend on receiving, or not, information that helps predict market returns.

To do so, we ask subjects to observe, in successive independent rounds, graphic displays of the past realizations of an "Index Return" —in bold red; and of a "Variable A" — in dotted blue; where a salient yellow dot marks the last realization of "Variable A".

We tell subjects the value of the average "Index Return", i.e., its unconditional expectation. In addition, and crucial to our experimental design, subjects are explicitly told that "Variable A" helps predict returns in some rounds, but is useless in others; and that all rounds are independent.

Subjects are then asked, each round: 1) whether or not they believe "Variable A" is useful, this round, to predict returns; 2) what their forecast is for the next-period "Index Return"; and 3) how much they want to invest, out of a 100 ECU (Experimental Currency Unit) endowment, renewed each round, in the risky "Index Return".[5]

Once a round is played, subjects are told if "Variable A" was useful to predict returns this time (in bold characters); what the next-period "Index Return" turned out to be and whether their forecast had been precise, i.e., within one percentage point of the return realization; and finally how much their risk ECU investment portfolio made, this round. The graphical time series display is updated to add the final "Index Return" realization — with a salient yellow dot, similar to that of "Variable A".

These three questions/answers constitute the core of our baseline treatment, in addition to which we asked, in different experimental implementations, subjects to provide 80% confidence intervals around their own forecasts, as well as longer-horizon forecasts and investments.

The instruction sheet, as well as examples of the graphical displays of rounds with either predictive or un-predictive "Variable A", and of the feedback information subjects receive, can be found in Appendix B.

To make the experiment relevant with respect to investors' real decisions, it is designed so the "Index Return" and "Variable A" time series simulations mimic the US equity returns averaged over 5-year periods, and the US equity dividend-price ratios, at a 5-year frequency, respectively. In rounds where "Variable A" provides useful information, it replicates the predictive power of dividend-price ratios for the following 5-year returns (Fama and French (1988); Campbell and Shiller (1988)). We use the parameters of the return-dividend yield VAR model estimated by Cochrane (2009) on US equity returns

[5] Subjects provide their answers in "boxes" that are made blank at the beginning of each round: past answers do not appear one round to the next, and neither do indicative numbers, e.g., a 50% risk investment, so as not to influence the outcomes of the experiment.

(CRSP data, period 1927-1998).[6]

Across *all* rounds: the "Index Return" time series is simulated to have the same average return, the same average volatility, and, crucially, no serial autocorrelation in returns; the "Variable A" time series is simulated to have the same average value, equal to the mean "Index Return", the same average volatility, and to follow an AR(1) process with same persistence. Their unconditional distributions are statistically indistinguishable between rounds.[7]

The co-movements between "Index Return" and "Variable A", on the other hand, differ across rounds; the key to our experimental treatment.

In rounds where "Variable A" has no predictive power, the process r_t of "Index Return" is simulated according to the random walk:

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

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

In rounds where "Variable A" is predictive, the process r_t of "Index Return" is simulated according to:

$$r^p_{t+1} = a_t + \epsilon^p_{t+1}, \tag{2}$$

where a_t is the realization at time t of the "Variable A" and $\{\epsilon^p_t\}$ are normally distributed shocks $\epsilon^p_t \sim \mathcal{N}(0, \sigma^2_p)$, serially independent but correlated with the "Variable A" shocks.[8] The predictive power in "Variable A" is measured by: $Corr(r^p_{t+1}, a_t) = 57\%$ and $\sigma^2_p = 0.67\sigma^2$.

For convenience purpose, we refer to process (1) as the "i.i.d." case and to process (2) as the "predictable" case.[9]

At any time t, the best forecast for next-period "Index Return" is constant equal to μ in the i.i.d. case; whereas, in the predictable case, it is the time-varying a_t, which last realization is saliently displayed in the experiment (see Figure 3 in Appendix B).

[6]Our simulation method is described in details in Appendix A.

[7]Kolmogorov–Smirnov tests for distributions on arbitrary pairs of the displayed simulated returns drawn from the two types of rounds have average p-value 0.497.

[8]To obtain that the "Index Return" simulated from process (2) remain serially uncorrelated, even though "Variable A" is predictive *and* persistent, the shocks to r^p_t and to a_t must co-move: $Corr(\epsilon^a_t, \epsilon^p_t) = -0.2$. The AR(1) process for "Variable A" is given in Appendix A.

[9]The processes' parameters are $\mu = 6.07\%$, $\sigma = 9.02\%$, and, for "Variable A", volatility $\sigma_a = 3.98\%$ and persistence $\rho_a = 0.66$.

Subjects are not told this simple forecast rule, however. They are not given any information about processes (1) and (2) other than "Variable A" is predictive in some rounds, and that the "Index Return" average value is $\mu = 6.07\%$. They must therefore infer from the visualization of the simulated time series how to use the available information: whether returns are persistent, whether they are subject to e.g., regime shifts, how volatile they are, how to interpret "Variable A" when they believe if is useful to form forecasts, and how it affects market risks. Since they play the same game over many rounds, and know, at the end of each one, how well they did and whether "Variable A" was predictive, subjects can learn about processes (1) and (2) over time.

To limit the risk they may irrationally anchor their choices on past forecasts and investments, or design cross-rounds hedging strategies, we tell them explicitly that the simulated time series are independent across rounds, but not the ratio of predictable to unpredictable rounds. Resetting the ECU endowments each round and forcing subjects to actively decide on their risk investments, thus limiting the scope for inattention, as well as the absence of any transaction costs, is aimed at eliminating sources of portfolio inertia exogenous to our experimental treatment.

2.2 Implementation

We conducted the experiment in two waves. In the first wave (January 2019), we recruited 58 participants, students in the Master of Finance at Toulouse School of Management (TSM). The second wave (January 2020) included 36 students from the same Master. The experiment took place in Toulouse School of Economics (TSE) computer lab on an application we built using the Otree framework (Chen, Schonger, and Wickens (2016)). After logging in, subjects saw detailed instructions, including a description of the tasks and of the payment rules (see Figure 4 in Appendix B).[10]

In the baseline treatment, common to both waves, we let subjects play for 20 rounds, half i.i.d. and half predictable. The order of the graphs was randomized across subjects.

In the first wave, we asked subjects to also make 5-period ahead forecasts and investments; and in the second wave, subjects provided their 80% confidence intervals around their own forecasts, and played for another 20 rounds, in which they were told, before they made their forecasts and investments, when "Variable A" was useful and when it

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

was not. These additional treatments are presented separately in Section 6.

As compensation for participating in the experiment, subjects received 5 ECU for every correct answer regarding whether "Variable A" was predictive and 10 ECU for every "precise" forecast in a $(-1\%, +1\%)$ percentage points interval of the return realization. In addition, they received their full portfolio ECU value from a randomly drawn round of the experiment. The final payoff, in Euros, was the total ECU received, divided by twenty.

This compensation scheme was designed to incentivize subjects to provide truthful answers on their view of "Variable A", on their best forecasts, and to optimize their risk investments. Because the likelihood of "precise" forecasts was low — under processes (1) and (2), the realized next-period returns have an average 11% chance of being in the $(-1\%$ point, $+1\%$ point) interval around the rational conditional expectation — the risk that subjects might choose to "hedge" between their forecast answers and their investment decisions was limited. Finally, because the portfolio compensation derived from one single round randomly chosen at the end of the experiment, the scope for an increasingly important wealth impact on risk taking decisions in later rounds appeared limited.

We verified that the simulated data correctly represented 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 previous realized returns $\{r_{t-1}\}$ (see Table 19 in Appendix B). The regression coefficients of r_t on a_{t-1} are all close to 1 with R^2 close to that of process (2) ($R^2 = 0.33$) in the predictable case and around 0 (and not significant) in the i.i.d. case. The regression coefficients of r_t on r_{t-1} are close to 0 in all rounds. In two outlier i.i.d simulations, r_t has a small but significant *negative* loading on r_{t-1} (p-value ≈ 0.05), though we found it did not affect the subjects' extrapolative biases described in Section 4.1.

Finally, even though $Corr(r_t, a_t) = 0$ under both processes (1) and (2), the last realizations of "Variable A" and of "Index Return" in the 20 rounds of the experiment, i.e., the 20 finals draws for "Index Return" and the 20 final draws for "Variable A", are statistically correlated, with correlation -25%, in our simulated data. For this reason, we interpret the results obtained when regressing on r_t and a_t separately, rather than simultaneously, in the rest of the paper (both sets of results are provided in the tables).

3 Assessing Return Distributions

Table 1 shows descriptive statistics on how subjects assess the "Index Return" risk distributions.

Subjects have a good ability to detect whether "Variable A" is predictive, i.e., to observe its correlation with "Index Return" on the graphical displays. Conditional on being in a predictable round simulated from process (2), subjects' answers about the usefulness of "Variable A" are correct 80.6% of the time.[11] Conditional on being in an i.i.d. round simulated from process (1), subjects correctly view "Variable A" as useless 70.4% of the time. Both results are significantly greater than 50%, as would be implied by random guesses (p-value = 0.00). We find these results notable: as the reader can observe in the examples provided in Appendix B, the difference between the correlated and uncorrelated rounds is far from visually obvious.[12]

The difference in correctly identifying round "types", predictable or not, is significant (p-value = 0.00): subjects overestimate the proportion of predictable rounds at 55.1%, as opposed to the true proportion 50%. This result appears consistent with previous work showing people have an innate desire to perceive patterns, making it harder to identify randomness and the absence of correlations (Chapman (1967); Tversky and Kahneman (1973); Whitson and Galinsky (2008)).

The average next-period return forecast in rounds in which "Variable A" is perceived as useless is 4.72%, significantly below the true mean of 6.07% (p-value = 0.00). That agents tend to make pessimistic forecasts, on average below the true statistical mean, is a common feature of survey data; and our result is in line with evidence in e.g., Dominitz and Manski (2007), Hurd and Rohwedder (2012), Giglio, Maggiori, Stroebel, and Utkus (2019). Quite striking however, when subjects perceive returns as predictable by "Variable A", their average forecast increases significantly (p-value = 0.00) to 5.74%, i.e., to a level no longer significantly different from the true mean of 6.07% (p-value = 0.13).

In a similar pattern, the average forecast confidence interval (CI) is significantly different from the true statistical one in rounds perceived as unpredictable ($CI = 21.01\%$

[11] The slight variations in how correlated "Variable A" is to "Index Return" in the predictable rounds simulations (see Table 19) have no incidence on the ability to detect "Variable A" as useful.

[12] Subjects' abilities to visually infer correlations are also studied in Wunderlich, Symmonds, Bossaerts, and Dolan (2011); Ungeheuer and Weber (2020); Chinco, Hartzmark, and Sussman (2020).

significantly below the true 23.1% interval, p-value = 0.00); but not in rounds perceived as predictable (CI = 19.93% versus the true 18.9%, p-value = 0.14). The difference in confidence intervals across rounds is not significant (p-value = 0.31).

These results jointly show our subjects have a good ability to identify when the information in "Variable A" is useful to predict returns, and to, then, correctly assess their risk distribution: their first two moments estimates are indistinguishable from the truth, a remarkable result. On the other hand, subjects are more likely to make mistakes in identifying when "Variable A" is uncorrelated to the market returns, and they do, then, make significant errors in their risk distribution assessments.

Forecasts are more accurate in rounds where "Variable A" is perceived as useful, as measured by the distance between subjects' forecasts and the next-period returns realizations (*Forecast Distance*). On average, the distance is 7.71% in rounds perceived as predictable and 10.07% otherwise (the difference is significant with p-value = 0.00). Because the 2.36 percentage point difference in *Forecast Distance* across perceived round types is only partly explained by the 1.02 percentage point difference in average forecasts, it must be the case that subjects not only understand how to use the information contained in "Variable A" to assess the distribution of risk returns in rounds perceived as predictable, but also exploit it for their forecast variations one round to the next. Section 4 explores this question in details.

Finally, subjects choose greater risk allocations when they perceive "Variable A" as useful, with an average investment of 48.58 ECU; significantly higher (p-value = 0.00) than the 40.58 ECU average investment when they perceive "Variable A" as useless. These results, and their interpretation, are treated in Section 5.

4 Forecasts

4.1 Results

As noted in Section 2, subjects are not told how to make rational forecasts in either round type; they can make mistakes in assessing whether "Variable A" is useful or not, and in how to use it; and they may incorrectly extrapolate from the past realizations of market returns to form their forecasts. To study these questions, we run the following regression:

$$F_{i,k} = \alpha_1 + \alpha_2 \text{Predict}_{i,k} + \beta_1 a_{t,k} + \beta_2 a_{t,k} \times \text{Predict}_{i,k} \qquad (3)$$
$$+ \gamma_1 r_{t,k} + \gamma_2 r_{t,k} \times \text{Predict}_{i,k} + \epsilon_{i,k},$$

where $F_{i,k}$ is the forecast of subject i for next-period returns in round k; $\text{Predict}_{i,k}$ is a dummy taking value 1 if subject i perceives "Variable A" is useful to predict returns in round k and taking value 0 otherwise; and $a_{t,k}$ and $r_{t,k}$ are the last realizations of "Variable A" and "Index Return" in round k.[13] The results are presented in Table 2.

We observe, first, that subjects correctly use the last realization of "Variable A" to form their forecasts only when they perceive it as useful. The loading on $a_t \times$ Predict is 0.40 and significant at the 1% threshold; the loading on a_t alone is not significantly different from zero, controlling for individual and round fixed effects (column (3) in Table 2). Subjects thus exploit the information in "Variable A" consistently with the true forecast model in *both* types of rounds, i.e., significantly when it is useful and not at all when it is useless.

Second, subjects do extrapolate, i.e., use the last realization of "Index Return" to form their next-period forecasts, but only when they perceive the information in "Variable A" as useless. The loading on r_t when Predict $= 0$ is 0.19 and significant at the 1% threshold; the loading on r_t when Predict $= 1$ is $0.19 - 0.16 = 0.03$, not significantly different from zero (p-value=0.33), controlling for individual and round fixed effects (column (6) in Table 2).

When they do not view the signal in "Variable A" as useful information, our subjects form forecasts consistent with those observed in previous work, i.e., extrapolative from past returns, and with a similar magnitude: the loading on $r_t = 0.19$ is close to the 0.32 coefficient estimated in Landier, Ma, and Thesmar (2019). When, on the other hand, they perceive "Variable A" as useful, our subjects stop extrapolating altogether, indicating they view the information in "Variable A" as "better".

Crucially, these two opposite forecast models — extrapolative when "Variable A" is viewed as useless versus rationally loading on the provided signal when it is viewed as useful — coexist within subjects (our results are robust with and without individual fixed

[13]We later extend our forecast analysis to include other realizations of "Variable A" and "Index Return" in round k, i.e., $\{a_{t-1,k}, a_{t-2,k}, \dots\}$ and $\{r_{t-1,k}, r_{t-2,k}, \dots\}$, in Section 6.

effects). The *same* subjects have extrapolative forecasts in rounds they perceive as non predictable by "Variable A"; and forecasts consistent with rational expectations in rounds they perceive as predictable by "Variable A". Our results dispute an heterogeneous bias assumption, whereby some agents are rational throughout and others extrapolators throughout.

4.2 Interpretation – forecast model

The results of Table 2 suggest that agents have differing forecast rules, rational when provided with useful information, extrapolative otherwise. We formalize and test such an expectation model

Our subjects face two sources of uncertainty, when forming their forecasts. First, they know they may be wrong when assessing "Variable A" is useful or useless. Second, conditional on perceiving that "Variable A" is useful, they do not know for sure how to use the information it contains, since they are not told that $\mathbb{E}_t(r_{t+1}) = a_t$ in predictable rounds; and, conditional on perceiving that "Variable A" is useless, they do not know whether to use the information in "Index Return", since they are not told that $\mathbb{E}_t(r_{t+1}) = \mu$ in unpredictable rounds.

We incorporate these two dimensions of uncertainty in the following forecast model.

First, suppose that subjects have an expectation model $\mathbb{E}^u(r_{t+1})$ when they view "Variable A" as useless, and an expectation model $\mathbb{E}^p(r_{t+1})$ when they view "Variable A" as predictive. Their forecast conditional on their perception about "Variable A" can be written as:

$$\begin{cases} \mathbb{E}\left(r_{t+1} \,|_{A \text{ p. useless}}\right) & = \pi_u \mathbb{E}^u(r_{t+1}) + (1-\pi_u)\mathbb{E}^p(r_{t+1}) \\ \mathbb{E}\left(r_{t+1} \,|_{A \text{ p. predictive}}\right) & = \pi_p \mathbb{E}^p(r_{t+1}) + (1-\pi_p)\mathbb{E}^u(r_{t+1}) \end{cases}, \tag{4}$$

where the weights π_u and π_p correspond to the probabilities that a given subject assigns to the fact that "Variable A" is indeed useless or predictive, conditional on the fact that she perceives it as such.

In testing Equation (4) below, we assume π_u, π_p are the true posterior probabilities: $\pi_p = \Pr\left(\textit{predictable} \mid \textit{A perceived predictive}\right)$ and $\pi_u = \Pr\left(\textit{i.i.d} \mid \textit{A perceived useless}\right)$, which subjects can learn in the experiment via the feedbacks they receive each round.

To model forecasts when "Variable A" is perceived as useless, the evidence in Table 2 encourages us to opt for an extrapolative expectation model; we choose the forward looking model $F_t = \mathbb{E}_t(r_{t+1}) + \lambda(r_t - \mathbb{E}_{t-1}(r_t))$, where $\mathbb{E}_t$ is the rational conditional expectation operator at any time t, as in Landier, Ma, and Thesmar (2019); Afrouzi, Kwon, Landier, Ma, and Thesmar (2020):

$$\mathbb{E}^u_t(r_{t+1}) = \lambda_u r_t + (1-\lambda_u)\mu, \tag{5}$$

where r_t is the last realization of "Index Return" and μ is the unconditional average. Landier, Ma, and Thesmar (2019) estimate $\lambda_u \approx 0.32$ from experimental evidence; the true rational expectation model would yield $\lambda_u = 0$ in our framework.

We assume a model of the same form when "Variable A" is perceived as predictive:

$$\mathbb{E}^p_t(r_{t+1}) = \lambda_p a_t + (1-\lambda_p)\mu. \tag{6}$$

where a_t is the last realization of "Variable A".[14]

Inspired by the evidence in Table 2, we choose to model the agents as Bayesian rational in how they use information when they perceive "Variable A" as predictive, and thus in their valuation of λ_p. First, given some priors λ^p_p and λ^u_p for the loadings of $\{r_t\}$ on $\{a_{t-1}\}$ in rounds perceived as predictable and as useless, their posterior value for λ_p is:

$$\lambda_p = \frac{\pi_p \lambda^p_p + (1-\pi_u)\lambda^u_p}{\pi_p + (1-\pi_u)},$$

with π_u, π_p the true posterior probabilities, as above.

Second, we assume that agents have no average bias in estimating the loadings of $\{r_t\}$ on $\{a_{t-1}\}$ throughout the experiment, so that, given the mistakes they make in assigning the simulated graphs to the correct predictable or i.i.d categories, we obtain priors:

$$\lambda^p_p = \frac{\bar{\pi}_p \times 1 + (1-\bar{\pi}_u) \times 0}{\bar{\pi}_p + (1-\bar{\pi}_u)},$$

[14] Our test of the model of Equations (4), (5) and (6) in Table 3 below would not reject the alternative $\mathbb{E}^u_t(r_{t+1}) = \lambda_u r_t + (1-\lambda_u)\widetilde{\mathbb{E}}^u_t(r_{t+1})$ and $\mathbb{E}^p_t(r_{t+1}) = \lambda_p a_t + (1-\lambda_p)\widetilde{\mathbb{E}}^p_t(r_{t+1})$, as long as $\widetilde{\mathbb{E}}^u_t(r_{t+1})$ and $\widetilde{\mathbb{E}}^p_t(r_{t+1})$ use information orthogonal to a_t and r_t. Such models are considered in Section 6.

$$\lambda_p^u = \frac{\bar{\pi}_u \times 0 + (1-\bar{\pi}_p) \times 1}{\bar{\pi}_u + (1-\bar{\pi}_p)},$$

where $\bar{\pi}_p = Pr(A \textit{ perceived predictive} \mid \textit{predictable})$ is the true fraction of predictable graphs perceived as such and $\bar{\pi}_u = Pr(A \textit{ perceived useless} \mid \textit{i.i.d})$ is the true fraction of i.i.d. graphs perceived as such.[15]

A simple derivation yields:

$$\lambda_p = \frac{\pi_p^2 + (1-\pi_u)^2}{\pi_p + (1-\pi_u)}. \tag{7}$$

Equation (7) corresponds to a model where subjects have an imperfect ability to detect predictability and imperfect knowledge of the return processes, but are 1) *sophisticated* in being aware of these limitations; 2) *rational* in estimating their probabilities of being right or wrong about "Variable A"; and 3) unbiased, on average, in assessing the loading of $\{r_t\}$ on $\{a_{t-1}\}$ in the simulated graphs.[16]

In Table 3, we test how well the expectation model of Equations (4), (5), (6) and (7), whereby agents have extrapolative expectations as a "default" fall-back rule but switch to sophisticated rational forecasts when given useful information about returns, fares in our experimental data. We find that the model's predicted loadings on the last realized values of "Index Return" and "Variable A", r_t and a_t, across rounds, cannot be rejected, at conventional levels.

We believe this result is remarkable given the high level of sophistication and "rationality" we assume for how subjects interpret the information contained in "Variable A", and use it, when they view it as predictive; while at the same time preserving extrapolative expectations strictly consistent with previous evidence, both qualitatively and quantitatively, otherwise.

5 Investments

Having studied how our subjects form their returns forecasts, we now turn to their risk investment decisions. To guide our analysis, we can start from a standard Merton-

[15] $\bar{\pi}_p$ and $\bar{\pi}_u$ are related to π_p and π_u via: $\pi_p = \frac{\bar{\pi}_p}{\bar{\pi}_p+(1-\bar{\pi}_u)}$ and $\pi_u = \frac{\bar{\pi}_u}{\bar{\pi}_u+(1-\bar{\pi}_p)}$. From Table 1, $\bar{\pi}_p = 80.6\%$ and $\bar{\pi}_u = 70.4\%$.

[16] While this is a strong assumption, it should not be ruled out: subjects do observe full 40-periods time series in the graphical displays they are provided each round.

Samuelson portfolio choice model, with power utility: in a one-period world, an agent with risk aversion γ_i has optimal risk investment

$$\theta_i = \frac{1}{\gamma_i}\frac{\mathbb{E}_i(r)}{\sigma_i^2(r)}, \tag{8}$$

given her expectation $E_i(r)$ and her estimated variance $\sigma_i^2(r)$ of market returns.

Under the investment rule (8), individual subjects' risk taking decisions should vary *only* with their forecasts, corresponding to $E_i(r)$, and with their stated confidence intervals, corresponding to $\sigma_i^2(r)$, in any given round. We study the influence of both measures below. However, at the core of our experiment is another key question of interest: whether the information that subjects receive affect their risk decisions *beyond* whatever impact it may have on their stated beliefs $E_i(r)$ and $\sigma_i^2(r)$; a potential rejection of the classical model of Equation (8).

5.1 Results

5.1.1 Forecasts: expected returns and investment

In Table 4, we report the results of the regression:

$$\theta_{i,k} = \alpha_1 + \alpha_2 \text{Predict}_{i,k} + \beta_1 F_{i,k} + \beta_2 F_{i,k} \times \text{Predict}_{i,k} + \epsilon_{i,k}, \tag{9}$$

where $\theta_{i,k}$ is subject i's investment into the risky fund (out of her 100 ECU endowment) in round k; $F_{i,k}$ is subject i's forecast of next period return, and $\text{Predict}_{i,k}$ is the "perceived predictable" dummy, as above.

We observe, first, that stated beliefs about expected returns have a significant impact on risk taking, consistent with the model of Equation (8). The estimated elasticity of investments to forecasts is stable across specifications, with and without individual and rounds fixed effects: an increase of one percentage point in the next-period return forecast translates into an increased risk investment of 2.2 ECU (see columns (1)-(3) of Table 4).

Second, subjects rely on their own forecasts more when they perceive returns as predictable: the loading on $F_{i,k} \times \text{Predict}_{i,k}$ in columns (4)-(6) of Table 4 is significantly greater than zero. Accounting for individual and round fixed effects, an increase of one percentage point in the next-period return forecast results in an additional 1.80 ECU in risk investment in rounds where "Variable A" is perceived as useless versus an additional $1.80 + 0.66 = 2.46$ ECU in rounds it is perceived as informative, i.e., a 36% greater pass-through from forecasts to investments.

Importantly, these results are true both between and within subjects. Those with significantly higher average forecasts have significantly greater risk investments; and any given subject has a significantly higher risk investment in rounds where her next-period return forecast is above her own average. Both effects are amplified in rounds when "Variable A" is perceived as informative.

We note that the greater pass-through from forecasts to investments in rounds where "Variable A" is viewed as useful has important welfare implications in our experiment: it explains a difference of 5.62 ECU in average investments across rounds, corresponding to an additional portfolio expected annual return of 0.34 percentage points — a 14% increase relative to the average expected portfolio returns of 2.73 percentage points in rounds where "Variable A" is viewed as useless.[17]

5.1.2 Confidence intervals: risk and investment

In Table 5, we report the results of the regression:

$$\theta_{i,k} = \alpha_1 + \alpha_2 HighCI_{i,k} + \beta_1 F_{i,k} + \beta_2 F_{i,k} \times HighCI_{i,k} + \epsilon_{i,k}, \tag{10}$$

where $\theta_{i,k}$ is subject i's investment into the risky fund (out of her 100 ECU endowment) in round k, $F_{i,k}$ is subject i's forecast of next period return, and $HighCI_{i,k}$ is a dummy variable that takes value of 1 if subject i's confidence interval in round k is above her median confidence interval for rounds of same type as k, perceived as predictable or not by "Variable A". The results are derived separately for rounds perceived as predictable or not by "Variable A".

Consistent with Equation (8), in rounds where "Variable A" is not perceived as predictive, we observe a lower pass-through from forecasts to investments when the risky asset is viewed as more volatile than usual: the loading on $F_{i,k} \times HighCI_{i,k}$ in rounds s.t. $\text{Predict}_{i,k} = 0$, is negative and significant (at the 10% level, with and without individual

[17] The average expected annual return is derived using the average next-period returns forecast of 5.74% in rounds perceived as predictable versus 4.72% otherwise (see Table 1), controlling for individual and round fixed effects.

fixed effects).

However, when "Variable A" is perceived as predictive, the reported beliefs on the asset's volatility no longer impact the pass-through from forecasts to investments: the loading on $F_{i,k} \times HighCI_{i,k}$ in rounds s.t. $\text{Predict}_{i,k} = 1$ is essentially 0 (p-value = 0.01).

We observe that, in all types of rounds, the coefficient on $HighCI_{i,k}$ in regression (10) is not significantly different from zero, suggesting the reported confidence intervals may represent how much subjects trust their own forecasts, which, in turns, affects their investments in rounds where "Variable A" is perceived as useless (more on that below), more so than their variance beliefs.

5.1.3 Information: predictability and investments

The results of Sections 5.1.1 and 5.1.2 suggest that our subjects' risk taking model differs across information treatments, i.e., whether "Variable A" is perceived as useful or not, inconsistent with the classical Merton-Samuelson model of Equation (8).

To analyze the information-to-investment mechanism at play, we verify, first, if the signal contained in the last realizations of "Variable A" and of "Index Return" affect risk decisions, *outside of* their observed impact on forecasts (described in Section 4.1), via the regression:

$$\begin{aligned}\theta_{i,k} = \alpha_1 + \alpha_2 \text{Predict}_{i,k} + \beta_1 F_{i,k} + \beta_2 F_{i,k} \times \text{Predict}_{i,k} \\ + \gamma_1 a_{t,k} + \gamma_2 r_{t,k} + \epsilon_{i,k},\end{aligned} \tag{11}$$

where $\theta_{i,k}$ is subject i's investment into the risky fund (out of her 100 ECU endowment) in round k, $F_{i,k}$ is subject i's forecast of next period return, $\text{Predict}_{i,k}$ is the "perceived predictable" dummy, and $a_{t,k}$ and $r_{t,k}$ are the last realizations of "Variable A" and "Index Return" in round k, as above.

The results are reported in Table 6. We find the loading on the "Variable A" signal a_t is overall not significantly different from 0 in rounds perceived as informative; same as that on the extrapolative signal r_t in rounds perceived as non-informative by "Variable A", with and without individual fixed effects. The pass-through from the signals perceived as informative to risk investment decisions occurs mostly via changes in beliefs in our experiment.[18]

We study next the information-to-investment channel *inside of* forecasts, i.e., the impact on risk decisions of the changes in beliefs that derive directly from the signals perceived as informative: from a_t in rounds perceived as informative, and from r_t otherwise, consistent with the forecast model of Section 4.2. To do so, we first extract the "informed" beliefs:

$$\begin{cases} F_{i,k} = \alpha_u + \underbrace{\beta_u r_{t,k}}_{\tilde{F}_{i,k}} + \epsilon_{u,i,k} \quad |_{A \text{ p. useless}} \\ F_{i,k} = \alpha_p + \underbrace{\beta_p a_{t,k}}_{\tilde{F}_{i,k}} + \epsilon_{p,i,k} \quad |_{A \text{ p. predictive}} \end{cases},$$

and compare, separately across round types:

$$\begin{cases} \theta_{i,k} = \alpha + \beta F_{i,k} + \epsilon_{i,k} \\ \text{vs.} \\ \theta_{i,k} = \tilde{\alpha} + \tilde{\beta} \tilde{F}_{i,k} + \tilde{\epsilon}_{i,k} \end{cases}, \tag{12}$$

where $\theta_{i,k}$, $F_{i,k}$, $a_{t,k}$ and $r_{t,k}$ are as above.

The results of regression (12) in this two-step analysis are presented in Table 7. The "informed beliefs" thus extracted from our subjects' forecasts have a vastly different impact on risk investment decisions depending on whether the "Variable A" signal is perceived as predictive or not. When "Variable A" is viewed as useless, the pass-through from forecast to investment is unchanged whether beliefs are "informed" or not ($\beta \approx \tilde{\beta}$ in columns (5) and (6) of Table 7). In contrast, in rounds where "Variable A" is perceived as predictive, the risk investment loading on beliefs jumps from $\beta = 2.46$, when using subjects' forecast $F_{i,k}$, to $\tilde{\beta} = 3.82$ when using their "informed" forecasts $\tilde{F}_{i,k}$, i.e., the belief variations deriving directly from changes in the provided signal a_t.

This result is a clear departure from the classical Merton-Samuelson model: investment decisions appear to depend not just on subjective expectations, as according to Equation (8), but also on how "trustworthy" or "informed" these expectations are. This

[18] We do find significant loadings on the signal a_t at the 10% threshold when round fixed effects are added, including for rounds perceived as unpredictable by "Variable A".

observation warrants exploring further the modeling implications of our subjects' risk taking decisions, as we do next.

5.2 Interpretation — investment model

Various work in the macroeconomics and finance literature infer general equilibrium pricing implications from investors' beliefs obtained via surveys of expectations; assuming, implicitly, that investors adjust their risk decisions perfectly in line with their own expectations.

The results described in Section 5.1 show our subjects do make investment decisions consistent with their own forecasts; a key result, and an important contribution of our experiment.

However, Sections 5.1.1 and 5.1.2 also reveal the pass-through from beliefs to risk is 1) dependent on information conditions; and 2) limited in magnitude: in rounds where "Variable A" is perceived as non informative, a forecast increase of one percentage point — corresponding to a 21.2% increase relative to the 4.72% average forecast – translates into an increase of 1.80 ECU, corresponding to only 4.4% greater risk taking relative to the 40.58 ECU investment average, and even less so when the risk asset is viewed as more volatile or the forecast less reliable i.e., when the reported confidence intervals are above the median; in rounds where "Variable A" is perceived as predictive, a forecast increase of one percentage point — corresponding to a 17.4% increase relative to the 5.74% average forecast – translates into an increase of 2.46 ECU, corresponding to 5.1% greater risk taking relative to the 48.58 ECU investment average, irrespective of the reported confidence intervals.

Section 5.1.3 further reveals that our subjects' risk decision model requires to account not only for beliefs, as in the classical Merton-Samuelson framework, but also for the type of information influencing beliefs. Variations in forecasts attributable to the predictive signal "Variable A" have an impact on risk decisions more than twice that of variations incurred from extrapolative expectations, the apparent default forecast framework when "Variable A" is perceived as useless.

To provide a measure for the implications of our results with respect to the classical risk investment model, we note that, under Merton-Samuelson, the average ratio of investment to forecast and the elasticity of investment to forecast are equal, determined by the investor's risk aversion γ_i. From Equation (8), we derive, over any set of rounds Ω in which subject i perceives the same variance, i.e., over rounds k s.t. $\sigma^2_{i,k} = \sigma^2_i \mid_\Omega, \forall k \in \Omega$:

$$\frac{1}{\gamma_i} = \sigma^2_i \mid_\Omega \times \frac{1}{|\Omega|} \sum_{k \in \Omega} \frac{\theta_{i,k}}{F_{i,k}} \quad \text{and} \quad \frac{1}{\gamma_i} = \sigma^2_i \mid_\Omega \times \frac{\partial \theta_{i,k}}{\partial F_{i,k}} |_{k \in \Omega}. \tag{13}$$

Departures from the equalities of Equation (13) — how much the implicit risk aversions we obtain from our subjects average risk investments vary from those obtained via sensitivities of investments to forecasts — allow us to quantify the "failure" of the classical investment model in our experimental dataset.

We derive measures for our subjects' risk aversions when "Variable A" is perceived as predictable and when it is perceived as useless; using either the elasticity with respect to the forecasts $F_{i,k}$ or with respect to the "informed forecasts" $\tilde{F}_{i,k}$ of Section 5.1.3; using the true variance levels from processes (1) and (2) for σ^2_i weighted by the true mistake probabilities, as in the forecast model of Section 4.2. All the results are obtained under the assumption the perceived returns variances are constant, for each subject, within round types.[19]

The resulting distributions of risk aversion γ across individuals are represented in Figure 1 and in Figure 2.

We observe, first, a large degree of heterogeneity in the estimated risk aversion coefficients across individuals.[20]

Second, we find a clear departure from the classical model when comparing the estimates of γ_i obtained from average investment levels to those, roughly twice higher, obtained from investment elasticities to forecasts — a median risk aversion of 20.4 versus 49.2 in rounds where "Variable A" is perceived useless and 20.6 versus 48.8 when it is perceived as predictive.

The average risk investments we observe in our experiment, corresponding to $\gamma \approx 20$, are consistent with previous evidence in asset pricing Hansen, Heaton, and Li (see e.g., 2008); Malloy, Moskowitz, and Vissing-Jørgensen (see e.g., 2009). In contrast, the higher implicit risk aversion levels $\gamma \approx 50$ obtained via the elasticities of investment-to-forecasts

[19] We use variances $\sigma^2 \mid_{p.predictive} = \pi_p \sigma^2_p + (1 - \pi_p)\sigma^2$ and $\sigma^2 \mid_{p.useless} = \pi_u \sigma^2 + (1 - \pi_u)\sigma^2_p$, where σ^2 and σ^2_p are the true conditional variances of processes (1) and (2) and π_u, π_p are the true posterior probabilities: $\pi_p = \Pr(\textit{predictable} \mid \textit{A perceived predictive})$ and $\pi_u = \Pr(\textit{i.i.d} \mid \textit{A perceived useless})$.

[20] For clarity of exposition, we only include estimates of γ_i between 0 and 100 in Figure 1. The full distribution features a few outliers with very large estimates, see Figure 7 in Appendix C.

constitute a clear puzzle: our subjects' variations in risk allocations in response to variations in forecasts are *too limited*. It should be emphasized that this result is obtained in an experimental framework explicitly designed to eliminate well-known sources of portfolio inertia, such as inattention, transaction costs or anchoring on past decisions, making it all the more intriguing.

Third, and final, our results make salient the specific set of measures where the classical investment model may no longer be rejected: in rounds where the provided "Variable A" signal is perceived as useful, using the elasticities of investments to "informed beliefs" — with implicit median risk aversion $\gamma = 26.1$, close to $\gamma = 20.6$ obtained via the average investment levels.[21]

Taken together, these observations suggest that our subjects are well aware that 1) their forecast model is more "reliable" in rounds where their beliefs derive from an exogenously given signal, "Variable A", than in rounds where they rely on their default extrapolative forecast model; and 2) that their forecasts may be "noisy". As a consequence, they treat variations in beliefs stemming from the "trustworthy" forecast model, i.e., those deriving directly from changes in the last realizations of "Variable A" in rounds it is perceived as informative, in line with (or close to) the classical Samuelson-Merton model of Equation (8) for their risk decisions; but not so for variations in beliefs that cannot be fully "trusted". Hence the results obtained in Figure 1 for rounds where "Variable A" is perceived as useless or for variations in forecasts orthogonal to the provided signal when it is perceived as useful; as well as the results of Section 5.1.2 under the interpretation of wider confidence intervals as a representation of lesser "trust" in their own extrapolative forecasts.

6 Role of Information — Additional Results

In this section, we explore how subjects use the information they receive throughout the experiment, beyond that provided by the last realizations of "Variable A" and "Index Return", analyzed above. The results we obtain support our main interpretation of

[21]For subjects in the second wave of experiment, we can also derive risk aversion measures implied by the confidence intervals; however, the results remain largely unchanged: the reported intervals are not significantly different from those under the variances of footnote 19 (p-value=0.45 for rounds perceived predictable, p-value=0.20 otherwise).

subjects' behaviors, derived in Sections 4 and 5; they provide a more in depth description of subjects' beliefs and choices to the interested reader.

6.1 Additional information treatments

In the first replication of our experiment (January 2019), we added a "long-horizon" treatment in which we asked subjects to provide their forecasts and risk investments at a long, five-period, horizons. In the second replication (January 2020), we added a "reveal" treatment in which subjects were told explicitly when "Variable A" was useful to predict returns, before they made their forecasts and investment decisions.

The answers statistics corresponding to these two additional information treatments are provided in Table 1. As in the baseline treatment, subjects have more optimistic forecasts and greater investments in rounds perceived, or declared, as predictable by "Variable A". They also have higher forecasts and investments for 5-period average returns than for the next period, consistent with recent evidence in Cassella, Golez, Gulen, and Kelly (2021) that investors have greater optimistic biases at the long-horizon.

A broad observation, from the results we describe below, is that when the information provided in "Variable A" is harder (easier) to use, subjects revert more (less) to extrapolation; and use their own belief variations less (more) to make their risk decisions. This finding confirms our interpretations of the results of Sections 4 and 5.

6.1.1 Long horizon forecasts and investments

A fully informed rational forecaster would derive, under the simulations of processes (1) and (2):

$$\begin{cases} \mathbb{E}_t\left(\overline{r}_{t+1,t+5}\ |_{\text{i.i.d.}}\right) & = \mu \\ \mathbb{E}_t\left(\overline{r}_{t+1,t+5}\ |_{\text{predictable}}\right) & = \kappa a_t + (1-\kappa)\mu \end{cases},$$

where $\overline{r}_{t+1,t+5}$ is the average return over five periods starting at $t+1$; a_t is the realization of "Variable A" at time t; and $\kappa < 1$ depends on the persistence of "Variable A".[22]

Under the parametrization of Cochrane (2009), the variance of the unexplained returns $\overline{r}_{t+1,t+5} - \mathbb{E}_t\left(\overline{r}_{t+1,t+5}\right)$ is lower, in the predictable rounds of simulation (2), than for next-

[22]Given $\rho < 1$ the persistence parameter in the AR(1) process of variable $\{a_t - \mu\}$, $\kappa = \frac{1}{5}\frac{1-\rho^5}{1-\rho}$.

period returns, so predictability should have a larger impact on forecasts and investments in the long horizon treatment.

However, the rational forecast rule for 5-period average returns appears considerably more difficult to evaluate from the time series displays we provide. In contrast to the one period forecast, for which it is necessary and *sufficient* to identify a_t as the best forecast for r_{t+1} when "Variable A" is predictive, the long-horizon average forecast requires to also estimate the dynamics of the "Variable A" process, for which no information whatsoever is explicitly given in the experiment.

To analyze which channel has a greater influence on our subjects' forecasts and investments over longer horizons, we follow an analysis similar to Sections 4.1 and 5.1.1, and report our results in Table 8.

We find that subjects do not use the information in the last realization of "Variable A" to make their long-horizon forecasts, even when they view it as predictive; and extrapolate from past returns instead, significantly, in *all* rounds. As for the one-period forecasts, these results are true with and without subjects' fixed effects.

We observe further that the sensitivity of investments to forecasts remains positive and significant, but, first, it has a much lower magnitude than in the one-period case – a change in beliefs of one percentage point results in an average 0.7 ECU change in investment, versus 2.2 ECU for the one-period horizon; and, second, the pass-through from forecasts to investments is not significantly different in rounds where "Variable A" is perceived as predictive. These results are in stark contrast to the same subjects' one-period forecast model (Section 4) and one-period risk taking decisions (Section 5).

6.1.2 Revealing predictability

In the second information treatment, we show our subjects, after they've played the baseline treatment, ten simulations of the i.i.d process (1) where we tell them explicitly that "Variable A" is not useful to predict returns; and ten simulation of the predictive process (2) where we tell them explicitly that "Variable A" is useful to predict returns. Which comes first, the ten "Predictive" or the ten "Not Predictive" rounds, is randomized across subjects. Under this treatment, subjects know whether "Variable A" is predictive or not *before* forming their forecasts and risk decisions. They remain uninformed about the exact processes (1) and (2), and may thus make "mistakes" in their forecasts.

We analyze our subjects' forecasts and investments under this information treatment similarly to Sections 4.1 and 5.1.1, and report our results in Table 9.

The results we obtain have surprisingly similar magnitudes to those of Tables 2 and 4, for the baseline treatment: subjects form their forecasts using the signal a_t with loading 0.39 in rounds revealed as predictable by "Variable A", and using the extrapolative signal r_t with loading 0.18 otherwise (compared to loadings 0.40 and 0.19 in the baseline); the pass-through from forecasts to investments is 0.63 ECU greater in rounds revealed as predictable by "Variable A" (compared to loadings 0.66 ECU in the baseline).

This finding is indicative that subjects are aware, in the baseline treatment, that they are quite good at spotting when "Variable A" is predictive or not; so that revealing explicitly when it is the case and when not has a limited impact on their decisions.

6.2 Using additional information, current round

In the analysis of Section 4, we study how subjects' forecasts may be influenced, across round types, by the signals in the last available realizations of "Variable A" and "Index Return". Subjects, however, observe additional information each round: a full graphical display of 40-period long times series of these two variables, which they may rely on to form their forecasts.

To verify whether the forecast variations depend on signals in the time series other than the last realizations $\{a_t, r_t\}$, we regress:

$$\begin{cases} F_{i,k} = \alpha_u + \beta_u r_t + \beta_{u,1} r_{t-1,k} + \beta_{u,2} r_{t-2,k} + \beta_{u,3}\overline{r_k} + \epsilon_{u,i,k} & |_{A \text{ p. useless}} \\ F_{i,k} = \alpha_p + \beta_p a_t + \beta_{1,p} a_{t-1,k} + \beta_{2,p} a_{t-2,k} + \beta_{3,p}\overline{a_k} + \epsilon_{p,i,k} & |_{A \text{ p. predictive}} \end{cases}, \tag{14}$$

where $F_{i,k}$ is the forecast of subject i for next-period return r_{t+1} in round k; $\{a_{t,k}, a_{t-1,k}, a_{t-2,k}\}$ and $\{r_{t,k}, r_{t-1,k}, r_{t-2,k}\}$ are the last three realizations of "Variable A" and "Index Return" in round k; and $\overline{a_k}$ and $\overline{r_k}$ are the average realizations of "Variable A" and "Index Return" in the full time series in round k.

Table 10 displays the results of regression (14). We find our subjects extrapolate solely from the last return realization r_t in rounds where they perceive the signal "Variable A" as useless, and not from the previous realizations $\{r_{t-1}, r_{t-2}\}$; though they do appear to also make statistical inferences from the average realized return in the time series (the coefficient $\beta_{u,3}$ on $\overline{r_k}$ is positive and significant). In contrast, when they do perceive it as useful, subjects use not only the last realization a_t of "Variable A", but also how it evolved relative to the previous $\{a_{t-1}, a_{t-2}\}$: the loadings $\beta_{1,p}$ and $\beta_{2,p}$ are both negative and significant, indicating subjects use not only a_t but also $a_t - a_{t-1}$, and to a lesser extent $a_t - a_{t-2}$. Such a result, whereby beliefs are formed not only from rational expectations but also from changes in rational expectations over time — the rational forecast for the next-period returns r_{t+1} is determined by a_t at time t, by a_{t-1} at time $t-1$, by a_{t-1} at time $t-2$ etc. — appear consistent with diagnostic expectation models Bordalo, Gennaioli, Porta, and Shleifer (see e.g., 2019), though it is obtained in a non-dynamic context in our case.

We note these results do not contradict the interpretation we derived above: subjects do use the signals $\{a_t, r_t\}$ consistent with the forecast model of Section 4.2.

6.3 Using additional information, past rounds

As we discuss in previous sections, our subjects are given no specific information about the risk process they are asked to forecast and invest on, beyond that "Variable A" can sometimes help predict its returns.

Each round they play provides useful feedback information about 1) when "Variable A" is predictive or not; and 2) how well their forecast model performs. Subjects may thus learn gradually as the experiment unfolds, and they accumulate more experience, a rational use of past information.

Subjects may also use past information irrationally: even though they are explicitly told that all rounds are independent, they may be influenced by the returns realizations and profits they made in previous rounds, or anchor on their own past forecasts and risk decisions.

These two questions are explored next.

6.3.1 Learning

So as to uncover the possible effects of learning, we analyze whether subjects display different behaviors in early vs. late rounds. Table 11 displays comparative results in forecasts and risk decisions between the first half of the baseline treatment, i.e rounds 1 to 10, versus the second half, i.e., rounds 11 to 20.

Our results are indicative that our subjects gain in understanding and confidence in the course of the experiment. Their forecasts load on the signal a_t only in rounds where they perceive it is useful in both the first and the second half of the baseline treatment, but with a significantly greater weight, 0.52 versus 0.30, in the second half, closer to that of a fully informed rational forecaster; their average risk investments are significantly higher, by 4.93 ECU, in the later rounds, and the pass-through from forecasts to risk positions increases (though not significantly, at the 10% threshold).

6.3.2 Extrapolating from previous rounds

To form their next-period forecasts, our subjects use the information in the "Variable A" signal when they perceive it as useful, and extrapolate from the last realization of "Index Return" otherwise (Section 4) — both in the information set of the round they are currently playing. They may also be influenced by information from the rounds they previously played (which order is randomized across subjects), i.e., by the past "Index Return" and "Variable A" realizations.

Table 12 displays the results we obtain when regressing forecasts on the previous rounds' next-period returns realizations $\{r_{t+1}\}$ and signals $\{a_t\}$.

We find that the past realizations of $\{r_{t+1}\}$ and $\{a_t\}$ in prior rounds affect how our subjects form their forecasts in only one very specific way, and *only* for rounds where "Variable A" is perceived as non-informative: the average next-period realized return from the start of the experiment has a significant positive influence on their expectations in the current round.

If this result were true in all rounds, it could be interpreted as subjects learning over the experiment about the true next-period return average, as possibly different from the 6.07% figure they were initially given. However, because they use the average next-period realizations from the previous rounds only when they perceive "Variable A" as non-informative, we believe the results of Table 12 comfort our interpretation of Section 4.2, whereby the same subjects, with fully rational forecasts when they receive useful information, display the usual biases otherwise — reminiscent of an experience effect in this case, in the spirit of Malmendier and Nagel (2011, 2016); Laudenbach, Malmendier, and Niessen-Ruenzi (2019).

6.3.3 Anchoring on previous rounds

We verify next whether previous rounds' decisions, as well as the specific outcomes of these decisions, may influence the forecasts and investments that follow. Our subjects 1) must enter each new round's forecast and risk investment in empty boxes; 2) have 100 ECU endowments renewed each round; and 3) are explicitetly told each round is independent. "Anchoring" on previous choices should therefore be limited in our experiment, compared to the evidence in the empirical literature.

Table 13 displays the results we obtain when regressing forecasts and investment decisions in a given round on the choices, forecasts and risk investments, and on the outcomes, forecast errors and portfolio profits, in the immediately preceding round.

Our subjects appear to fully understand that all rounds are independent: when considering round types separately, none of their previous rounds' answers or outcomes are significant at the 5% threshold, with and without individual fixed-effects.

7 Heterogeneous Behaviors

A crucial finding in the analysis of Sections 4, 5 and 6 is that the results we obtain are equally valid *across* and *within* subjects, suggesting they have homogenous behaviors: all subjects have extrapolative forecasts when they find the information in "Variable A" useless or too hard to exploit, all use the "Variable A" signal rationally otherwise; all subjects use their own forecasts to make their risk decisions, but more so their forecast variations stemming from useful "Variable A" information.

In this section, we invite the interested reader to explore in details which subjects' heterogeneity can be observed, and whether it affects their behaviors. The results we obtain show how robust is the key, and maybe surprising, result above — that our subjects have remarkably similar forecast and risk decision models.

7.1 Heterogeneity in average forecasts and investments

To understand better how our subjects may differ, we start by analyzing whether they display heterogeneous average beliefs and/or investments.

We find, first, that the average forecasts are quite homogenous in our experiment: only 8% of all forecast variations can be explained by individual fixed effects. This result contrasts considerably from survey evidence in the data, e.g., Giglio, Maggiori, Stroebel, and Utkus (2019) find that 40% to 60% of all panel variations in beliefs are explained by individual fixed effects.

One key difference between our experimental set-up and that of market returns surveys is that each of the rounds our subjects play corresponds to a *completely new* time series simulation, whereas real world investors vary their forecasts overtime given new data points on the *same, unique,* time series of Index Returns actual past realizations. The homogeneous average forecasts that our subjects make therefore indicate that the belief persistence observed in survey data derives mostly from anchoring biases rather than from optimistic versus pessimistic personalities. We confirm this finding by noting that only 3 out of our 94 subjects have pessimistic forecasts – below the reported average for a given round – 80% of the time; only 4 out of 94 subjects have optimistic forecasts – above the reported average for a given round – 80% of the time. These numbers fall to 0/94 and 1/94 (0/94) when looking for subjects who display pessimistic or optimistic beliefs 90% of the time (100%) of the time.

We turn, second, to our subjects average risk investments; and find a much greater dispersion: 40% of all ECU risk positions are explained by individual fixed effects. 19 out of 94 subjects have high risk investments — above the average for a given round — 80% of the time; 28 out of 94 subjects have prudent investments — below the average for a given round — 80% of the time. These numbers remain at 9/94 (4/94) and 14/94 (8/94) when looking for subjects who display risky or prudent investments 90% of the time (100%) of the time. These results reflect important variations in risk appetites across subjects, as also evidenced by their implicit risk aversions, displayed in Figure 1, obtained from both their average investments *and* from their elasticities of investments to forecasts (Section 5).

While their average reported beliefs indicate our subjects do not differ as optimists versus pessimists, their risk taking decisions reveal variations in their appetite for risk; suggesting subjects' characteristics do impact their answers in the experiment. We explore this question in the next section.

7.2 Heterogeneous subjects' characteristics

As described above, our subjects vary considerably in risk aversions. Two other criteria, standard to the household finance literature, are easily obtained: their gender and their financial literacy — as proxied by their average grades in the Masters' program they attend.[23] In addition, influenced by the results of Section 6 which show that the impact of "Variable A" signals on both beliefs and investments varies depending on how easy it is to use the information they sometimes contain, we analyze whether differences in their ability to "understand" the experimental framework may affect our subjects' answers. To do so, we consider two different metrics: first, subjects' response time, each round, a possible proxy for how difficult they find it to complete their tasks; second, their ability to detect correlations, as measured by the number of their correct answers when identifying "Variable A" as predictive or not.

We explore below whether these different sources of variations in our subjects' characteristics may result in heterogeneous behaviors with respect to 1) how their beliefs are formed given the information they receive; and 2) how their beliefs and information impact, in turns, their risk investments.[24]

7.2.1 High and low risk taking

As discussed above, our subjects vary in their willingness to take risk, with important individual fixed effects in their ECU investments in "Index Return". Accordingly, we split our subjects in two equal groups, with dummy "High θ" equal to one for subject i if her average risk investment, in all rounds, is above the median of 40 ECU (Table 1).

In Table 14, we display the results obtained when we compare the forecasts and risk decisions across these two groups. We find that subjects with a greater appetite for risk differ from the others only in that they use the "Variable A" information significantly more to form their forecasts, when they perceive it as predictive. The two groups of subjects otherwise behave the same.

We note the greater average risk investment for the "High θ" group does correspond to lower risk aversions, and not from lesser risk estimates: this group has significantly

[23]Other commonly studied characteristics are either unknown, e.g., our subjects' wealth, or not disperse enough in our sample, e.g., their age group.

[24]There are some commonalities across characteristics, e.g., high grades subjects are slightly more likely to be women; the correlations between the personality characteristics we analyze are provided in Table 21 in Appendix C.

larger confidence intervals on average (22.21% versus 19.09%, p-value=0.01).

7.2.2 Fast and slow responses

We turn to how much time subjects take when answering the required questions, which we record for each subject in each round. We split them in two equal groups, with dummy "Fast" equal to 1 for subject i if she is, on average across rounds, faster to submit her answers than the group's median "speed" of 61 seconds per round.

In Table 15, we display the results obtained when we compare the forecasts and risk decisions across these two groups.

We find both groups have forecast behaviors consistent with those of Section 4: they use the signal a_t in rounds where they perceive it as useful, and extrapolate from r_t otherwise. However, the faster subjects exploit the useful signal a_t twice as much, in rounds perceived as predictable by "Variable A", indicating a better understanding of the risk environment.

All subjects use their own forecasts to make their risk investment decisions, with a higher forecast-to-investment pass-through in the rounds perceived as predictable by "Variable A", but significantly more so for the faster subjects, with a loading of 2.99 ECU in rounds perceived predictable versus 1.57 ECU otherwise.

Both sets of results show that, even though all subjects have similar forecast and investment behaviors, the "Fast" ones have answers closer to the fully informed rational forecast model and to the classical investment rule of Equation (8); a finding consistent with notion that the faster subjects understand the experimental framework better.

The investment results obtained in Table 15 may partly derive from the difference in risk beliefs across the two groups, as measured by the reported confidence intervals: the "Fast" group has significantly lower confidence intervals on average (18.95% versus 21.83%, p-value=0.00); with significantly lower intervals in rounds perceived as predictable by "Variable A" than in rounds where it is perceived useless (17.96% versus 20.29%, p-value=0.08), which is not the case for the "Slow" group.[25]

Finally, to study further how slow or fast answers impact beliefs and investment decisions, we replicate our analysis but, this time, by splitting, for each subject, the

[25] The reported confidence intervals are significantly above the true statistics for the "Slow" group in rounds where "Variable A" is predictive (p-value=0.01); and significantly below the true statistics for the "Fast" group in rounds where "Variable A" is not predictive (p-value=0.01).

rounds in which she is faster versus slower than her usual speed (per round type). We find remarkably similar results: the same subject uses the signal a_t, when she perceives it as useful, significantly more in rounds she answers fast; she also uses her own forecasts more in these rounds.[26]

7.2.3 Detection ability

Next, we split our subjects in two equal groups, depending on their ability to correctly identify when "Variable A" is useful or not. Over the 20 rounds they play in the baseline treatment, subjects are correct in their assessment of "Variable A" a median 15 times. We consequently set the "High Ability" dummy to one for subjects with more than 15 correct answers, and analyze, as reported in Table 16, whether it affects their forecasts and investments.

We find, once again, that both groups appear to follow the same forecast and investment model: they all extrapolate on past returns in rounds they perceive as unpredictable by "Variable A", and on the useful signal a_t otherwise; they all use their own forecasts to choose their risk investments but significantly more so in rounds perceived as informative.

The only significant difference between the two sets of subjects is that the "Low Ability" group retains some extrapolative behaviors even in rounds where "Variable A" is perceived as predictive, with a 0.10 loading versus 0.18 in the other rounds. This result does not refute the forecast model we sketched in Section 4: a "Low Ability" subject, aware she is quite likely to make mistakes in identifying "Variable A" as useful or not, should have lesser differences in forecasts between round types, and may thus retain extrapolative behaviors throughout (see Equation (4)).

In both groups, subjects report tighter confidence intervals in rounds they perceive as predictable by "Variable A", though not significantly so. The "High Ability" group has on average wider confidence intervals, but not significantly so. That both groups have similar risk beliefs is consistent with the investment decisions results of Table 16.

7.2.4 Grades / financial literacy

We now split our subjects in two equal groups, depending on the average grades they received in their Masters' program during the year they participated in the experiment.

[26]The results of our analysis are reported in Table 22 in Appendix C.

We set a "High Grades" dummy to one for subjects in the top 50% of their class; and analyze, as reported in Table 17, whether the grades they receive — a realistic proxy for their financial literacy — affect our subjects' forecasts and investments.

We find that the "High Grades" subjects differ from the others only in that they use their own forecasts significantly more, in all rounds, to choose their investments — resulting in a 50% greater pass-through from forecasts to risk allocations. In light of the analysis of Section 5.2, this result suggests that the "High Grades" subjects have greater confidence in their own forecast model.

In both groups, subjects report similar confidence intervals in rounds they perceive as predictable or not by "Variable A". However, the "High Grades" group has wider, significantly so, average confidence intervals (23.55% versus 17.23%, p-value=0.00).[27] Their reported risk beliefs do not appear to affect the average risk investments, as seen in the results of Table 17.

7.2.5 Gender

Finally, we split our subjects in two groups, depending on their gender (46 women versus 47 men); and analyze, as reported in Table 18, whether it affects how they form their forecasts and choose their investments.

Once more all subjects display behaviors consistent with the analysis of Sections 4 and 5. The women in our subject pool significantly differ from the men in only one dimension: they extrapolate more, i.e., use the last realized return signal more to form their forecasts, in rounds perceived as unpredictable by "Variable A".

All subjects report similar confidence intervals in rounds they perceive as predictable or not by "Variable A". However, the women have wider, significantly so, average confidence intervals (21.76% versus 19.41%, p-value=0.02). Their reported risk beliefs may explain why women use their own forecast slightly less to make their risk decisions, though not significantly so across rounds, as seen in column (6) of Table 18.

We note that the women in our subjects group tend to have significantly higher grades than the men (p-value=0.02); they are better at correctly identifying when "Variable A" is useful (the correlation between the "Female" and "High Ability" dummies is 19%, see Table 21); so some of the analyses above may overlap.

[27] These reported confidence intervals are significantly different from the true statistics, except for "High grade" students in round perceived as not predictable by "Variable A".

8 Conclusion

We design an experiment that allows us to analyze how investors form their returns expectations, and choose their risk allocations, depending on the information they receive.

While we find important dispersions in forecasts and risk allocations each round, *all* subjects seem to behave according to the following two rules, with little to no evidence of heterogeneous biases.

First, when they are provided with a relatively simple predictive signal, subjects utilize the relevant information exclusively and form rational forecasts under Bayes law. When no such useful information is given, subjects default to extrapolative expectations, with magnitudes similar to those documented in previous studies.

Second, our subjects do use their own forecasts to choose their risk allocations. However, their portfolios display a form of "inertia": variations in risk positions around their mean are small relative to variations in expectations. This is particularly true for forecast variations stemming from extrapolative expectations; forecast dynamics deriving directly from the predictive signal subjects receive in some rounds have a more than twice greater impact on risk decisions.

Our sets of results have direct implications to the field of finance, notably concerning the role financial intermediaries can play as information providers, as well as the equilibrium asset pricing impact of investors' expectation dynamics, whether extrapolative or not.

However, we believe our analysis relates more broadly to these core questions: how do we form our beliefs, and which information do we use to do so? how much do we "trust" and use our own beliefs to make our economic decisions?

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Tables and Figures

Table 1: Descriptive Statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
$Pr(A \text{ perceived predictive} \mid \text{ predictable})$	1,880	0.806	0.9	0.395	0.2	1
$Pr(A \text{ perceived useless} \mid \text{ i.i.d})$	1,880	0.704	0.7	0.457	0.1	1
Predict	1,880	0.551	0.550	0.498	0	1
Forecast (in %)	1,880	5.28	5	7.09	-16	50
Forecast Distance (in %)	1,880	8.77	7.10	7.52	0.07	56.60
Invest (in ECU)	1,880	44.99	40	36.24	0	100
5-year Forecast (in %)	1,160	6.71	6	7.46	-15	100
5-year Invest (in ECU)	1,160	52.36	50	33.79	0	100
Predict=1						
Forecast (in %)	1,036	5.74	6	7.05	-15	40
Confidence Interval (in %)	414	19.93	20	14.30	1	88
Forecast Distance (in %)	1,036	7.71	6.31	5.98	0.09	39.31
Invest (in ECU)	1,036	48.58	50	36.96	0	100
5-year Forecast (in %)	662	7.22	6	8.56	-15	100
5-year Invest (in ECU)	662	54.01	50	34.41	0	100
Predict=0						
Forecast (in %)	844	4.72	5	7.09	-16	50
Confidence Interval (in %)	306	21.01	20	13.78	1	82
Forecast Distance (in %)	844	10.07	7.72	8.89	0.07	56.60
Invest (in ECU)	844	40.58	40	34.86	0	100
5-year Forecast (in %)	538	6.11	6	5.90	-14	80
5-year Invest (in ECU)	538	50.45	50	32.99	0	100
"Variable A" is revealed predictive						
Forecast (in %)	360	5.87	6.5	6.39	-15	28
Invest (in ECU)	360	54.03	50	38.79	0	100
"Variable A" is revealed not predictive						
Forecast (in %)	360	5.76	6	6.83	-15	27
Invest (in ECU)	360	50.54	50	38.74	0	100

NOTE: "Predict" is a dummy equal to one if the subject perceives "Variable A" is useful to predict returns. ""Variable A" is revealed predictive" and "Variable A" is revealed not predictive" correspond to treatments where subjects are told explicitly if "Variable A" is useful or not.

Table 2: Forecast and Predictability

Dep Variable	Forecast						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a(t)	-0.01	-0.04	-0.04				0.09
	(0.08)	(0.07)	(0.07)				(0.06)
a(t)*Predict	0.34***	0.39***	0.40***				0.35***
	(0.10)	(0.10)	(0.08)				(0.07)
r(t)				0.18***	0.19***	0.19***	0.20***
				(0.04)	(0.039)	(0.04)	(0.04)
r(t)*Predict				-0.13***	-0.16***	-0.16***	-0.10**
				(-2.83)	(0.05)	(0.05)	(0.06)
Predict	-1.11*	-1.27**	-1.28**	1.28***	1.45***	1.48***	-0.96
	(0.67)	(0.64)	(0.57)	(0.36)	(0.38)	(0.35)	(0.58)
Individual FE	No	Yes	Yes	No	Yes	Yes	Yes
Round FE	No	No	Yes	No	No	Yes	Yes
Number of Obs	1,880	1,880	1,880	1,880	1,880	1,880	1,880
Number of Clusters	94	94	94/20	94	94	94/20	94/20
R-squared	0.02	0.10	0.11	0.03	0.11	0.12	0.14

NOTE: This table reports the results of OLS regressions. The dependent variable is the forecast of next period returns in percentage points. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. a(t) denotes the last realization of "Variable A". r(t) denotes the last realization of "Index Return". Standard errors are in parenthesis. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Table 3: Forecast Model

	Model	Data	Difference	p-value
	(1)	(2)	(3)	(4)
β_1	0.12	0.02	0.10	0.92
	[-0.05 - 0.28]	[-1.83 - 1.87]	[-1.74 - 1.94]	
$\beta_1 + \beta_2$	0.53	0.36	0.17	0.80
	[0.13 - 0.92]	[-0.86 - 1.57]	[-1.16 - 1.51]	
γ_1	0.26	0.20	0.06	0.89
	[0.17 - 0.35]	[-0.65 - 1.04]	[-0.78 - 0.91]	
$\gamma_1 + \gamma_2$	0.08	0.08	0.00	1
	[-0.01 - 0.17]	[-0.61 - 0.76]	[-0.66 - 0.66]	

NOTE: In column (1), we report the average predicted values according to the forecast model of Section 4.2, and in column (2) the average OLS estimates of regression (3): $F_{i,k} = \alpha_1 + \alpha_2 \text{Predict}_{i,k} + \beta_1 a_{t,k} + \beta_2 a_{t,k} \times \text{Predict}_{i,k} + \gamma_1 r_{t,k} + \gamma_2 r_{t,k} \times \text{Predict}_{i,k} + \epsilon_{i,k}$, estimated separately for each individual. 95% confidence intervals are in brackets. In column (4), we report the p-values of the t-tests that the difference in column (3) is equal to zero.

Table 4: Investment and Forecasts

Dep Variable	Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast	2.23***	2.19***	2.20***	1.72***	1.79***	1.80***
	(0.19)	(0.19)	(0.19)	(0.25)	(0.25)	(0.26)
Forecast*Predict				0.87***	0.68***	0.66**
				(0.27)	(0.26)	(0.27)
Predict				1.24	2.53	2.65*
				(2.20)	(1.61)	(1.53)
Individual FE	No	Yes	Yes	No	Yes	Yes
Round FE	No	No	Yes	No	No	Yes
Number of Obs	1,880	1,880	1,880	1,880	1,880	1,880
Number of Clusters	94		94/20	94		94/20
R-squared	0.19	0.57	0.58	0.20	0.58	0.60

NOTE: This table reports the results of OLS regressions. The dependent variable is the fraction of the endowment invested in the risky asset, in percentage points. "Forecast" is the forecast of next period returns in percentage points. "Predict" is a dummy equal to one if the subject declares that "Variable A" is useful to predict returns. Standard errors are in parenthesis. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Table 5: Investment and Confidence Intervals

Dep Variable	Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast	2.72***	2.55***	2.45***	2.24***	2.14***	2.07***
	(0.33)	(0.34)	(0.31)	(0.33)	(0.36)	(0.34)
High CI	-2.56	3.01	3.54**	1.19	2.54	2.06
	(2.99)	(2.08)	(1.74)	(2.93)	(2.30)	(1.41)
Forecasts*High CI	-0.17	-0.36	-0.31	-1.18*	-0.74*	-0.51
	(0.50)	(0.34)	(0.33)	(0.68)	(0.42)	(0.42)
Sample		Predict=1			Predict=0	
Individual FE	No	Yes	Yes	No	Yes	Yes
Round FE	No	No	Yes	No	No	Yes
Number of Obs	414	414	414	306	306	306
Number of Clusters	36	36	36/20	36	36	36/20
R-squared	0.25	0.62	0.67	0.17	0.58	0.61

NOTE: This table reports the results of OLS regressions. The dependent variable is the fraction of the endowment invested in the risky asset, in percentage points. "Forecast" is the forecast of next period returns in percentage points. "High CI " is a dummy equal to one in rounds where the reported confidence interval is above the subject's median value for the same round type – perceived as predictable or not by "Variable A". "Predict" is a dummy equal to one if the subject declares that "Variable A" is useful to predict returns. Standard errors are in parenthesis. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Table 6: Information and Investment – Outside Forecasts

Dep Variable	Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast	2.58***	2.45***	2.43***	1.70***	1.75***	1.76***
	(0.21)	(0.22)	(0.20)	(0.27)	(0.26)	(0.26)
a(t)	0.34	0.35	0.41*	0.35	0.44*	0.53**
	(0.24)	(0.24)	(0.24)	(0.28)	(0.25)	(0.25)
r(t)	-0.15	-0.14	-0.17	0.08	0.04	0.05
	(0.12)	(0.11)	(0.13)	(0.14)	(0.13)	(0.12)
Sample		Predict=1			Predict=0	
Individual FE	No	Yes	Yes	No	Yes	Yes
Round FE	No	No	Yes	No	No	Yes
Number of Obs	1,036	1,036	1,036	844	844	844
Number of Clusters	94	94	94/20	94	94	94/20
R-squared	0.25	0.62	0.65	0.12	0.58	0.60

NOTE: This table reports the results of OLS regressions. The dependent variable is the is the ECU next-period investment in the risky asset. "Forecast" is the forecast of next-period returns in percentage points. a_t is the last realization of "Variable A" and r_t the last realization of "Index return". Columns (1)-(3) are restricted to rounds perceived as predictable by "Variable A". Columns (4)-(6) are restricted to rounds perceived as unpredictable by "Variable A". Standard errors are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 7: Information and Investment – Inside Forecasts

Dep Variable	Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Forecast	2.20***	2.57***	2.46***	3.82***	1.77***	1.75***
	(0.20)	(0.41)	(0.21)	(0.71)	(0.26)	(0.47)
Instrument	a(t) and r(t)		a(t)		r(t)	
Sample	All		Predict=1		Predict=0	
Individual FE	Yes					
Round FE	Yes					
Number of Obs	1,880	1,880	1,036	1,036	844	844
Number of Clusters	94/20					
R-squared	0.56	0.27	0.64	0.24	0.60	0.21

NOTE: This table reports the results of OLS and 2SLS regressions. The dependent variable is the ECU next-period investment in the risky asset. "Forecast" is the forecast of next period returns in percentage points. "Predict" is a dummy equal to one if the subject declares that "Variable A" is useful to predict returns. In the IV columns, "Forecast" is instrumented by a_t, the last realization of "Variable A" and/or by r_t, the last realization of "Index Return". Standard errors are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 8: Forecast and Investment, Long Horizon

Dep Variable	Forecast(5)					Investment(5)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a(t)	-0.07	-0.07			-0.02		
	(0.07)	(0.08)			(0.07)		
a(t)*Predict	0.06	0.10			0.07		
	(0.08)	(0.08)			(0.08)		
r(t)			0.07**	0.08**	0.08**		
			(0.03)	(0.03)	(0.03)		
r(t)*Predict			-0.03	-0.05	-0.05		
			(0.06)	(0.05)	(0.06)		
Forecast(5)						0.75**	1.37***
						(0.31)	(0.49)
Forecast(5)*Predict							-0.86
							(0.59)
Predict	0.75	0.68	1.13**	1.34**	0.91		6.74
	(0.73)	(0.43)	(0.55)	(0.52)	(0.76)		(4.37)
Individual FE	No	Yes	No	Yes			
Round FE	No	Yes	No	Yes			
Number of Obs	1,160	1,160	1,160	1,160	1,160	1,160	1,160
Number of Clusters	58	58/20	58	58/20	58/20	58/20	58/20
R-squared	0.01	0.15	0.01	0.16	0.16	0.52	0.53

NOTE: This table reports the results of OLS regressions. In columns (1)-(5), the dependent variable is the forecast of the average returns over the next five periods, in percentage points. In columns (6)-(7), the dependent variable is the ECU investment in the risky asset for the next five periods. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. a(t) denotes the last realization of "Variable A". r(t) denotes the last realization of "Index Return". Standard errors are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 9: Forecast and Investment, Revealed Predictability

Dep Variable	Forecast					Investment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a(t)	0.18*	0.17**			0.25***		
	(0.09)	(0.08)			(0.10)		
a(t)*R.Predictive	0.21	0.22*			0.06		
	(0.13)	(0.13)			(0.12)		
r(t)			0.19***	0.18***	0.20***		
			(0.04)	(0.04)	(0.04)		
r(t)*R.Predictive			-0.31***	-0.31***	-0.26***		
			(0.05)	(0.05)	(0.05)		
Forecast						2.73***	2.43***
						(0.34)	(0.38)
Forecast*R.Predictive							0.63
							(0.40)
R.Predictive	-1.14	-1.19	0.99**	1.02*	0.37		-0.76
	(0.91)	(0.91)	(0.39)	(0.52)	(0.83)		(3.46)
Individual FE	No	Yes	No	Yes		Yes	
Round FE	No	Yes	No	Yes		Yes	
Number of Obs	720	720	720	720		720	
Number of Clusters	36	36/20	36	36/20		36/20	
R-squared	0.02	0.18	0.05	0.20	0.22	0.61	0.62

NOTE: This table reports the results of OLS regressions. In columns (1)-(5), the dependent variable is the next-period forecast of returns, in percentage points. In columns (6)-(7), the dependent variable is the ECU next-period investment in the risky asset. "R.Predictive", for "revealed predictive", is a dummy equal to one when subjects are told, before they form their forecasts and investments, that "Variable A" is useful to predict returns. a(t) denotes the last realization of "Variable A". r(t) denotes the last realization of "Index Return". Standard errors are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 10: Forecasts – Time Series Information other than $\{a_t, r_t\}$

Dep Variable	Forecast			
	(1)	(2)	(3)	(4)
$a(t)$	0.46***	0.48***		
	(0.10)	(0.07)		
$a(t-1)$	-0.40***	-0.40***		
	(0.07)	(0.06)		
$a(t-2)$	-0.15*	-0.14*		
	(0.08)	(0.08)		
$\overline{a}$	-0.15	-0.16		
	(0.28)	(0.25)		
$r(t)$			0.17***	0.19***
			(0.04)	(0.04)
$r(t-1)$			0.06	0.08*
			(0.04)	(0.05)
$r(t-2)$			0.04*	0.04*
			(0.02)	(0.02)
$\overline{r}$			0.47***	0.44***
			(0.14)	(0.10)
Sample	Predict=1		Predict=0	
Individual & Round FE	No	Yes	No	Yes
Number of Obs	1,036		844	
Number of Clusters	94	94/20	94	94/20
R-squared	0.11	0.24	0.07	0.23

Note: The dependent variable is the next-period forecast of returns, in percentage points. Columns (1)-(2) are restricted to rounds perceived as predictable by "Variable A". Columns (3)-(4) are restricted to rounds perceived as unpredictable by "Variable A". a_t, a_{t-1}, a_{t-2} and r_t, r_{t-1}, r_{t-2} are the last three realizations of "Variable A" and "Index Return" in the current round; $\overline{a}$ and $\overline{r}$ are their average values in the current round's full time series. "Predict" is a dummy equal to one if the subject declares that "Variable A" is useful to predict returns. Standard errors are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 11: Forecast and Investment, Learning

Dep Variable	Forecast			Investment	
	(1)	(2)	(3)	(4)	(5)
a(t)	-0.03		0.12		
	(0.09)		(0.08)		
a(t)*Late Rounds	-0.02		-0.07		
	(0.12)		(0.11)		
a(t)*Predict	0.30***		0.27***		
	(0.10)		(0.09)		
a(t)*Predict*Late Rounds	0.22**		0.19**		
	(0.09)		(0.09)		
r(t)		0.23***	0.23***		
		(0.05)	(0.05)		
r(t)*Late Rounds		-0.08	-0.07		
		(0.05)	(0.05)		
r(t)*Predict		-0.17***	-0.10		
		(0.06)	(0.07)		
r(t)*Predict*Late Rounds		0.02	-0.00		
		(0.07)	(0.07)		
Forecast				2.07***	1.74***
				(0.21)	(0.23)
Forecast*Late Rounds				0.26	0.13
				(0.28)	(0.41)
Forecast*Predict					0.54**
					(0.22)
Forecast*Predict*Late Rounds					0.24
					(0.39)
Predict	-1.35**	1.48***	-0.10		2.70*
	(0.64)	(0.38)	(0.66)		(1.58)
Late Rounds	-0.65	0.14	0.01	4.93***	4.81***
	(0.63)	(0.33)	(0.63)	(1.86)	(1.75)
Individual FE			Yes		
Number of Obs	1,880	1,880	1,880	1,880	1,880
Number of Clusters	94	94	94	94	94
R-squared	0.10	0.12	0.18	0.57	0.58

NOTE: This table reports the results of OLS regressions. In columns (1)-(3), the dependent variable is the next-period forecast of returns, in percentage points. In columns (4)-(5), the dependent variable is the ECU next-period investment in the risky asset. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. "Late Rounds" is a dummy equal to one for rounds 11-20, the second half of the baseline treatment. a(t) denotes the last realization of "Variable A". r(t) denotes the last realization of "Index Return". Standard errors are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 12: Forecast, Past Rounds Returns

Dep Variable	Forecast						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$a_{-1}(t)$	-0.07		-0.07				-0.08
	(0.07)		(0.07)				(0.07)
$a_{-1}(t)$*Predict	-0.04		-0.05				-0.02
	(0.11)		(0.11)				(0.11)
$r_{-1}(t+1)$		0.04	0.04				0.01
		(0.03)	(0.03)				(0.04)
$r_{-1}(t+1)$*Predict		-0.06	-0.07				-0.04
		(0.05)	(0.05)				(0.05)
$\overline{a_{-}(t)}$				-0.03		-0.07	0.05
				(0.21)		(0.22)	(0.22)
$\overline{a_{-}(t)}$*Predict				-0.22		-0.18	-0.16
				(0.26)		(0.26)	(0.28)
$\overline{r_{-}(t+1)}$					0.22***	0.22***	0.22**
					(0.08)	(0.08)	(0.10)
$\overline{r_{-}(t+1)}$*Predict					-0.21**	-0.21**	-0.17*
					(0.10)	(0.10)	(0.10)
Predict	1.41*	1.54***	1.85**	2.47	2.48***	3.57**	3.58**
	(0.77)	(0.41)	(0.81)	(1.66)	(0.66)	(1.74)	(1.74)
Round number	0.02	0.03	0.03	0.03	0.02	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Individual FE	Yes						
Number of Obs	1,880	1,880	1,880	1,880	1,880	1,880	1,880
Number of Clusters	94	94	94	94	94	94	94
R-squared	0.09	0.09	0.09	0.09	0.09	0.09	0.10

NOTE: This table reports the results of OLS regressions. The dependent variable is the forecast of next period returns in percentage points in any given round $k > 1$. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns in round k. $a_{-1}(t)$ and $r_{-1}(t+1)$ denote the final realization of "Variable A" and of "Index Returns" in the previous round $k-1$. $\overline{a_{-}(t)}$ and $\overline{r_{-}(t+1)}$ denote the average of all final realizations of "Variable A" and of "Index Returns" in rounds 1 to $k-1$. The "Round number" variable is added to detect possible trends. Standard errors are in parenthesis. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Table 13: Forecast and Investment, Anchoring

Dep Variable	Forecast				Investment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past Forecast	-0.06*	-0.12***	0.05	-0.01			-1.08***	-0.11
	(0.03)	(0.03)	(0.07)	(0.07)			(0.26)	(0.24)
Past Forecast*Predict	0.09*	0.04	-0.06	-0.12			-0.02	-0.65*
	(0.05)	(0.05)	(0.10)	(0.09)			(0.37)	(0.33)
Past Error			0.10*	0.08*			0.21	0.17
			(0.05)	(0.05)			(0.21)	(0.20)
Past Error*Predict			-0.14**	-0.14**			-0.28	-0.45*
			(0.06)	(0.06)			(0.28)	(0.25)
Past Investment			0.01	-0.00	0.39***	-0.00	0.53***	0.06
			(0.01)	(0.01)	(0.06)	(0.05)	(0.07)	(0.06)
Past Investment*Predict			-0.01	-0.01	0.03	0.01	-0.03	-0.02
			(0.01)	(0.01)	(0.05)	(0.04)	(0.07)	(0.06)
Past Profit			-0.13	-0.11			-0.37	-0.33
			(0.09)	(0.09)			(0.47)	(0.40)
Past Profit*Predict			0.18	0.17			0.40	0.57
			(0.11)	(0.11)			(0.58)	(0.49)
Predict	0.54	0.95**	1.46**	1.67**	6.71***	8.19***	8.72***	11.80***
	(0.46)	(0.45)	(0.65)	(0.65)	(2.82)	(2.41)	(3.09)	(3.23)
Round Number	0.03	0.03	0.03	0.03	0.34**	0.65***	0.28*	0.62***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.11)	(0.16)	(0.14)	(0.15)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of Obs	1,880	1,880	1,880	1,880	1,880	1,880	1,880	1,880
Number of Clusters	94	94	94	94	94	94	94	94
R-squared	0.01	0.10	0.01	0.10	0.18	0.43	0.22	0.43

NOTE: This table reports the results of OLS regressions. In columns (1)-(4), the dependent variable is the next-period forecast of returns, in percentage points. In columns (5)-(8), the dependent variable is the ECU next-period investment in the risky asset. “Predict” is a dummy equal to one if the subject declares “Variable A” is useful to predict returns. “Past Forecast”, “Past Error”, “Past Investment” and “Past Profit” are, respectively, the next-period forecast of returns, the error between the realized next-period return and the forecast, the ECU next-period investment in the risky asset, and the ECU profit made on the risk investment in the preceding round. The “Round number” variable is added to detect possible trends. Standard errors are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 14: Forecast and Investment, High versus Low Risk Investment

Dep Variable	Forecast				Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
a(t)	0.18**	0.04				
	(0.09)	(0.10)				
a(t)*High θ	0.26**	-0.09				
	(0.12)	(0.15)				
r(t)			0.05	0.15***		
			(0.05)	(0.05)		
r(t)*High θ			-0.01	0.04		
			(0.07)	(0.08)		
Forecast					1.90***	1.66***
					(0.21)	(0.20)
Forecast*High θ					0.41	0.03
					(0.36)	(0.43)
Predict						1.23
						(1.52)
Predict*High θ						-0.09
						(3.36)
Forecast*Predict						0.40
						(0.29)
Forecast*Predict*High θ						0.73
						(0.47)
High θ	-1.23	0.80	0.49	0.10	34.24***	33.93***
	(0.97)	(1.00)	(0.55)	(0.60)	(3.26)	(4.09)
Sample	Predict = 1	Predict = 0	Predict = 1	Predict = 0	All	All
Number of Obs	1,036	844	1,036	844	1,880	1,880
Number of Clusters	94	94	94	94	94	94
R-squared	0.03	0.00	0.00	0.05	0.44	0.45

NOTE: This table reports the results of OLS regressions. In columns (1)-(4), the dependent variable is the next-period forecast of returns, in percentage points. In columns (5)-(6), the dependent variable is the ECU next-period investment in the risky asset. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. "High θ" is a dummy equal to one if the subject takes larger risk investments, on average, than the median. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 15: Forecast and Investment, Fast versus Slow

Dep Variable	Forecast				Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
a(t)	0.20**	-0.00				
	(0.08)	(0.10)				
a(t)*Fast	0.22**	-0.02				
	(0.12)	(0.18)				
r(t)			0.08	0.14***		
			(0.05)	(0.05)		
r(t)*Fast			-0.08	0.09		
			(0.06)	(0.06)		
Forecast					2.00***	1.88***
					(0.19)	(0.23)
Forecast*Fast					0.40	-0.31
					(0.30)	(0.44)
Predict						0.74
						(3.02)
Predict*Fast						0.85
						(4.42)
Forecast*Predict						0.22
						(0.29)
Forecast*Predict*Fast						1.20**
						(0.52)
Fast	0.03	-0.57	1.76***	-0.70	1.82	0.60
	(0.89)	(1.18)	(0.48)	(0.54)	(3.18)	(4.30)
Sample	Predict = 1	Predict = 0	Predict = 1	Predict = 0	All	All
Number of Obs	1,036	844	1,036	844	1,880	1,880
Number of Clusters	94	94	94	94	94	94
R-squared	0.03	0.00	0.03	0.06	0.19	0.21

NOTE: This table reports the results of OLS regressions. In columns (1)-(4), the dependent variable is the next-period forecast of returns, in percentage points. In columns (5)-(6), the dependent variable is the ECU next-period investment in the risky asset. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. "Fast" is a dummy equal to one if the subject is faster, on average, than the median of 61 seconds in answering each round's questions. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 16: Forecast and Investment, High versus Low Ability

Dep Variable	Forecast				Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
a(t)	0.30***	-0.06				
	(0.08)	(0.10)				
a(t)*High Ability	0.08	0.10				
	(0.13)	(0.15)				
r(t)			0.10**	0.18***		
			(0.04)	(0.05)		
r(t)*High Ability			-0.15**	0.01		
			(0.07)	(0.08)		
Forecast					2.28***	1.66***
					(0.27)	(0.37)
Forecast*High Ability					-0.14	0.13
					(0.37)	(0.46)
Predict						0.33
						(3.13)
Predict*High Ability						2.87
						(4.07)
Forecast*Predict						1.03***
						(0.39)
Forecast*Predict*High Ability						-0.45
						(0.49)
High Ability	0.22	0.59	1.24**	1.23	1.26	-0.01
	(0.97)	(0.97)	(0.61)	(0.62)	(5.16)	(5.75)
Sample	Predict = 1	Predict = 0	Predict = 1	Predict = 0	All	All
Number of Obs	1,036	844	1,036	844	1,880	1,880
Number of Clusters	94	94	94	94	94	94
R-squared	0.03	0.01	0.01	0.06	0.19	0.20

NOTE: This table reports the results of OLS regressions. In columns (1)-(4), the dependent variable is the next-period forecast of returns, in percentage points. In columns (5)-(6), the dependent variable is the ECU next-period investment in the risky asset. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. "High Ability" is a dummy equal to one if the subject is better than the median in identifying when "Variable A" is useful or not. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 17: Forecast and Investment, Grades

Dep Variable	Forecast				Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
a(t)	0.36***	0.06				
	(0.10)	(0.12)				
a(t)*High Grades	-0.06	-0.15				
	(0.13)	(0.15)				
r(t)			0.05	0.15***		
			(0.05)	(0.05)		
r(t)*High Grades			-0.01	0.06		
			(0.07)	(0.08)		
Forecast					1.80***	1.33***
					(0.27)	(0.36)
Forecast*High Grades					0.94**	0.96**
					(0.37)	(0.48)
Predict						0.98
						(3.41)
Predict*High Grades						0.92
						(4.27)
Forecast*Predict						0.88**
						(0.43)
Forecast*Predict*High Grades						-0.17
						(0.49)
High Grades	-0.57	0.10	-0.88	-0.93	2.34	3.98
	(0.98)	(1.02)	(0.56)	(0.60)	(5.04)	(5.71)
Sample	Predict = 1	Predict = 0	Predict = 1	Predict = 0	All	All
Number of Obs	1,036	844	1,036	844	1,880	1,880
Number of Clusters	94	94	94	94	94	94
R-squared	0.03	0.00	0.01	0.06	0.21	0.22

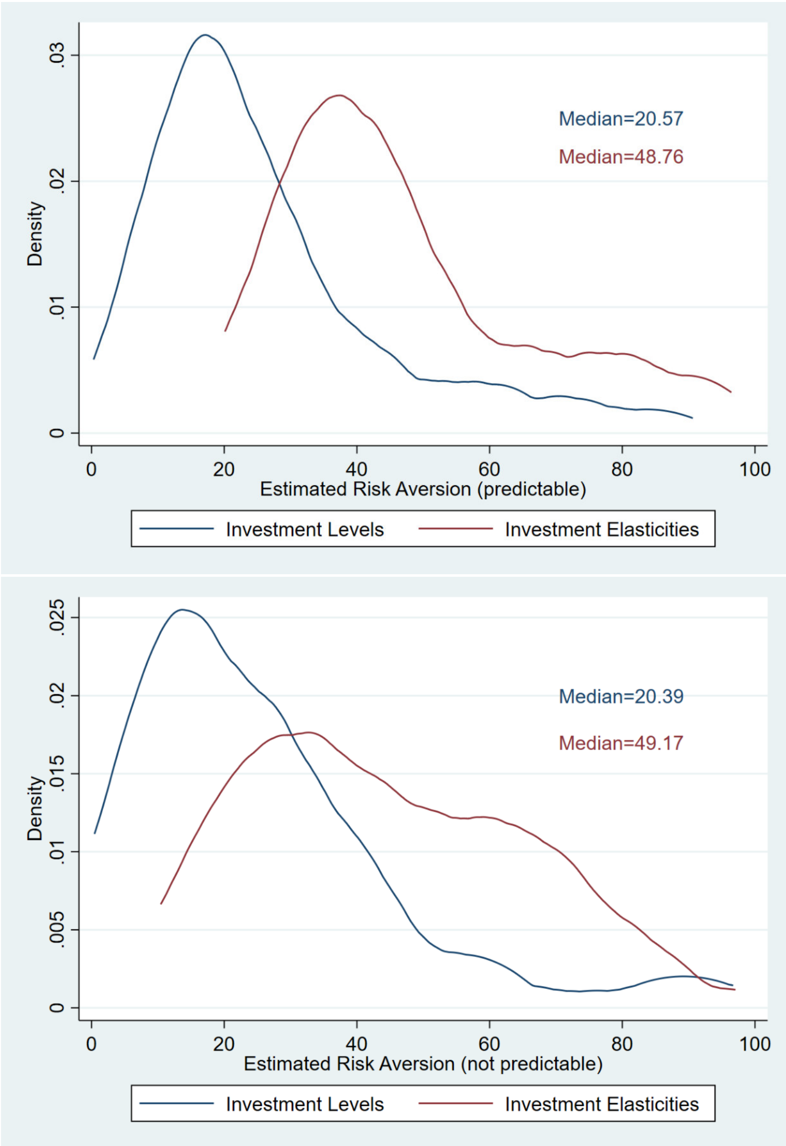
NOTE: This table reports the results of OLS regressions. In columns (1)-(4), the dependent variable is the next-period forecast of returns, in percentage points. In columns (5)-(6), the dependent variable is the ECU next-period investment in the risky asset. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. "High Grades" is a dummy equal to one if the subject has average grades above her/his cohort's median in TSE Masters' program. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 18: Forecast and Investment, Gender

Dep Variable	Forecast				Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
a(t)	0.36***	0.07				
	(0.10)	(0.11)				
a(t)*Female	-0.03	-0.17				
	(0.13)	(0.15)				
r(t)			0.03	0.11*		
			(0.04)	(0.06)		
r(t)*Female			0.02	0.13*		
			(0.07)	(0.08)		
Forecast					2.54***	1.84***
					(0.28)	(0.41)
Forecast*Female					-0.61*	-0.22
					(0.37)	(0.50)
Predict						-1.73
						(3.24)
Predict*Female						6.23
						(4.44)
Forecast*Predict						1.13***
						(0.40)
Forecast*Predict*Female						-0.56
						(0.54)
Female	0.58	2.73***	0.27	1.44**	2.47	-0.86
	(0.98)	(1.00)	(0.56)	(0.61)	(5.06)	(5.81)
Sample	Predict = 1	Predict = 0	Predict = 1	Predict = 0	All	All
Number of Obs	1,036	844	1,036	844	1,880	1,880
Number of Clusters	94	94	94	94	94	94
R-squared	0.03	0.02	0.00	0.07	0.19	0.20

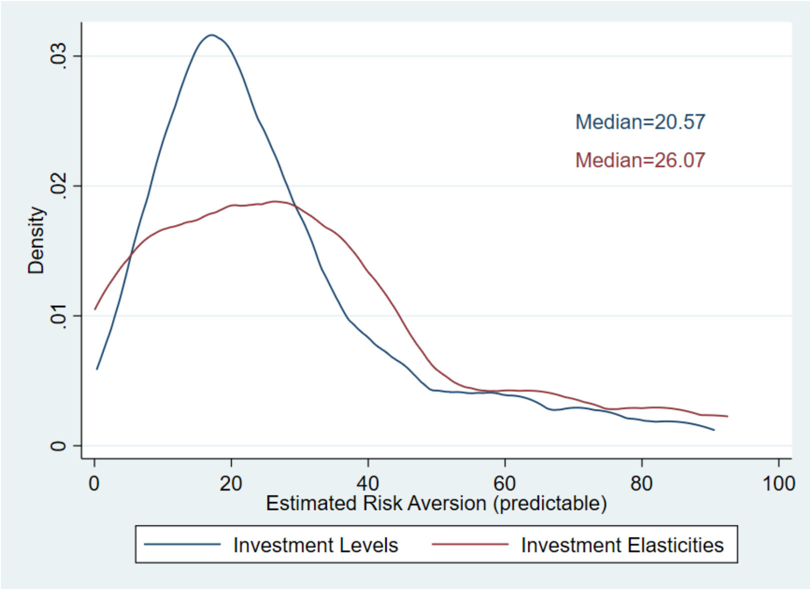
NOTE: This table reports the results of OLS regressions. In columns (1)-(4), the dependent variable is the next-period forecast of returns, in percentage points. In columns (5)-(6), the dependent variable is the ECU next-period investment in the risky asset. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. "Female" is a dummy equal to one if the subject is a woman. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Figure 1: Implicit Risk Aversion



NOTE: This figure plots the kernel density of estimated relative risk aversion coefficient γ across individuals. In the top panel, estimates are from rounds perceived as predictable; in the bottom panel, estimates are from rounds perceived as not predictable. In both panels, the kernel density obtained from the average investment to forecast ratio in Equation (13) is in blue; the kernel density obtained from the elasticity of investments to forecasts in Equation (13) is in red. We use the true variances of processes (1) and (2), weighted by the probabilities of mistakes, as in footonote 19. The density is estimated by the Epanechnikov kernel function with Stata's default bandwidth.

Figure 2: Implicit Risk Aversion – IV elasticities



NOTE: This figure plots the kernel density of estimated relative risk aversion coefficient γ across individuals from rounds perceived as predictable. The kernel density obtained from the average investment to forecast ratio in Equation (13) is in blue; the kernel density obtained from the elasticity of investments to "informed" forecasts, corresponding to the analysis of Equation (12), in Equation (13) is in red. We use the true variances of processes (1) and (2), weighted by the probabilities of mistakes, as in footonote 19. The density is estimated by the Epanechnikov kernel function with Stata's default bandwidth.

Appendix

A Return Process

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

$$r^p_{1,t+1} = \alpha x_{1,t} + \varepsilon_{1,t+1}, \qquad (15)$$
$$x_{1,t+1} = \beta x_{1,t} + \delta_{1,t+1},$$

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 $\rho_{\varepsilon,\delta}$. We use the estimated parameters from Cochrane (2009) on US equity (CRSP, 1927-1998): $\alpha = 0.16$, $\beta = 0.92$, $\sigma(\delta_1) = 15.2\%$, $\sigma(\varepsilon_1) = 19.2\%$, $\rho_{\varepsilon,\delta} = -0.72$.

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 (15) above. For any simulated series from process (15) 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

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

corresponding to the predictable returns process (2).

From a simulated series from process (15): $\{r_{1,2}, r_{1,3}...r_{1,5\times T+1}\}$ 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:

$$r_{1,t+1} = \mu + e_{1,t+1}, \tag{16}$$

where $\mu = 6.07\%$ as in (15) 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 (15). 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 (16).

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

$$Var_t(Nr_{N,t+1}) = N\sigma^2(e_1). \tag{17}$$

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 $Var_t(r^p_{5,t+1}) = 0.67Var_t(r_{5,t+1})$; $Var_t(r^p_{25,t+1}) = 0.61Var_t(r_{25,t+1})$.

B Experimental Protocol

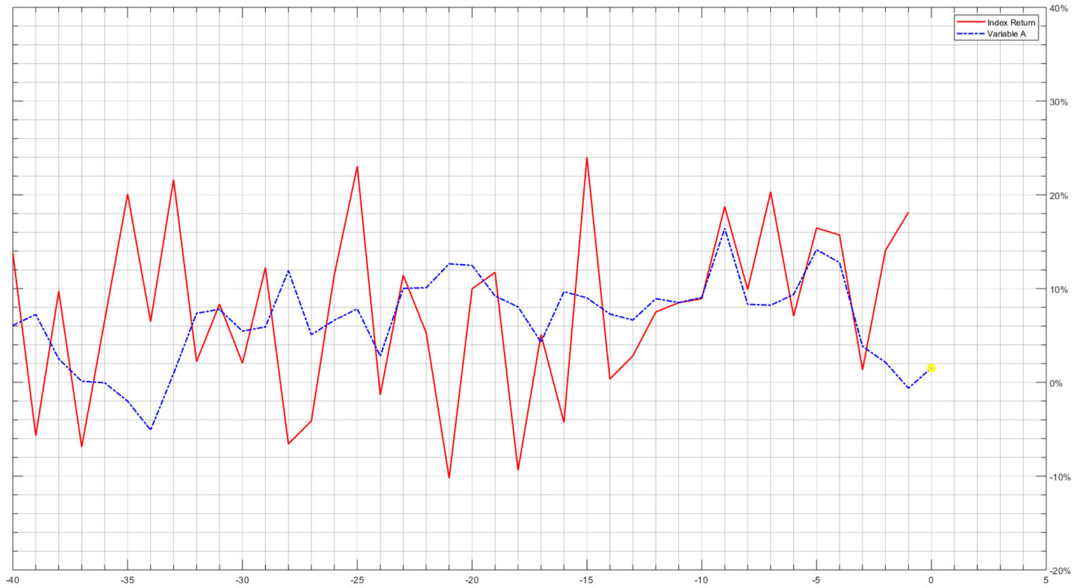
The experiment starts with the instruction page (as in Figure 4), followed by 20 rounds of Question Page / Result Page (as in Figures 5 and 6). Each round corresponds to a new simulation of returns, 10 rounds for the i.i.d. process (1) and 10 rounds for the predictable process (2).

For the predictable rounds, we obtain the simulated returns of process (2) via a simulation of length 225 of the VAR process (15), 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 0.57, 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 (16), 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 (15) 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 19 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 3: Simulations: i.i.d. case (top panel) and predictable case (bottom panel)



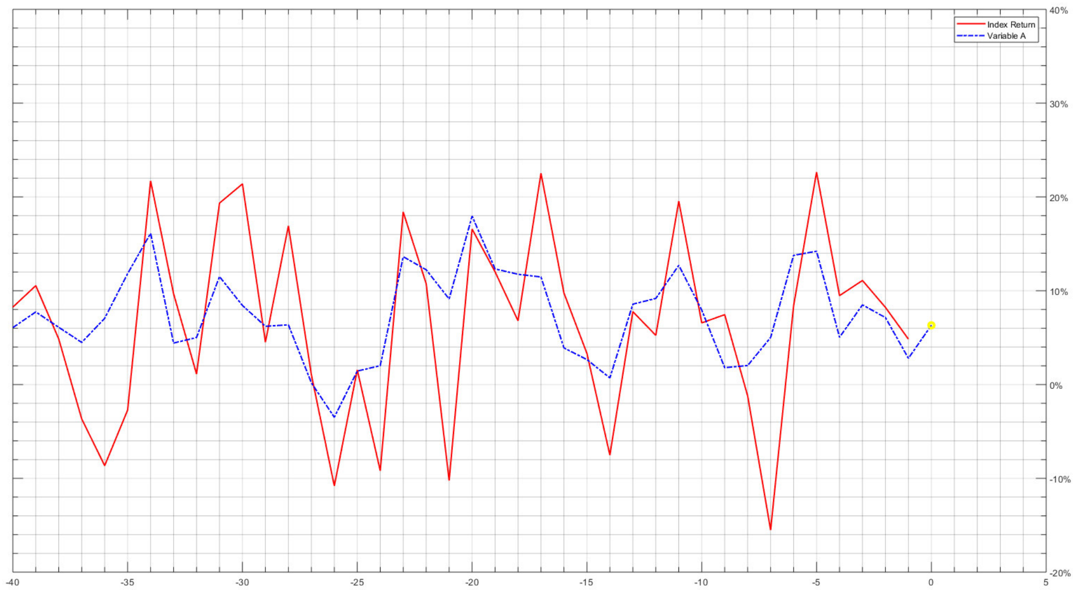


Figure 4: Instruction page

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

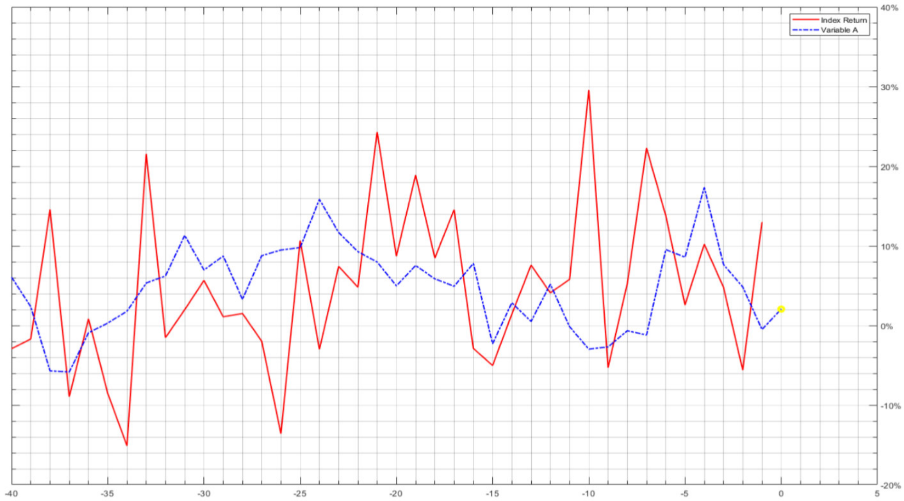
Figure 5: Question page

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

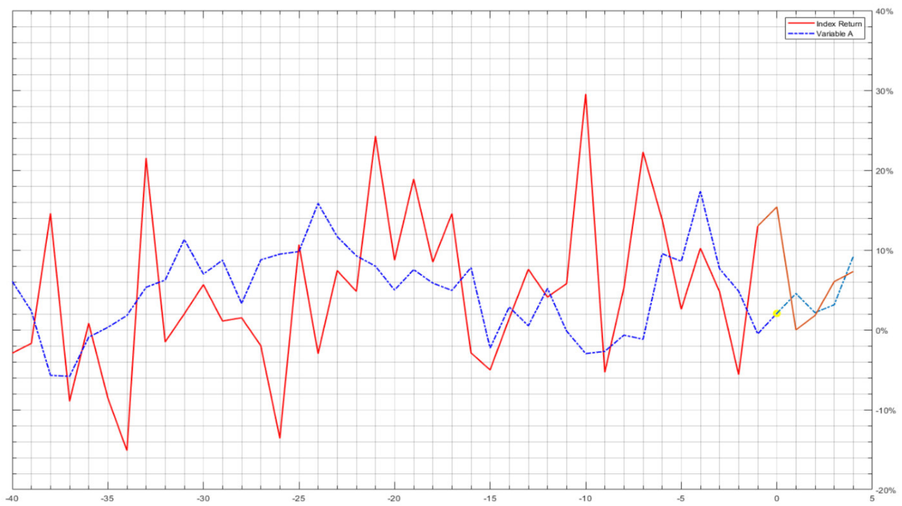
Figure 6: Answer page

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

Graph no.	Predictable	a(t-1)	p-value	R-squared	r(t-1)	p-value	R-squared
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	No	0.07	0.79	0	-0.13	0.45	0.02
2	No	-0.05	0.88	0	-0.01	0.96	0.00
3	No	0.09	0.78	0	0.16	0.34	0.02
4	No	-0.02	0.95	0	0.02	0.89	0.00
5	No	-0.27	0.4	0.02	0.13	0.44	0.02
6	No	-0.12	0.58	0.01	0.58	0.6	0.01
7	No	-0.02	0.94	0	-0.1	0.52	0.01
8	No	-0.05	0.91	0	-0.3	0.06	0.09
9	No	0.01	0.96	0	-0.34	0.04	0.11
10	No	-0.01	0.98	0	-0.04	0.81	0.00
11	Yes	1.17	0	0.34	0.21	0.21	0.04
12	Yes	1.53	0	0.38	-0.07	0.67	0.01
13	Yes	1.19	0	0.38	0	0.99	0.00
14	Yes	1	0	0.36	0.03	0.87	0.00
15	Yes	0.96	0	0.33	0.07	0.64	0.01
16	Yes	0.99	0	0.32	0.04	0.79	0.00
17	Yes	1.11	0	0.4	0	0.99	0.00
18	Yes	1.09	0	0.35	0.14	0.4	0.02
19	Yes	1.06	0	0.35	-0.11	0.5	0.01
20	Yes	0.85	0	0.32	-0.14	0.39	0.02

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), (7) and (8) report the coefficient, p-value and R^2 of the regression on r_{t-1}.

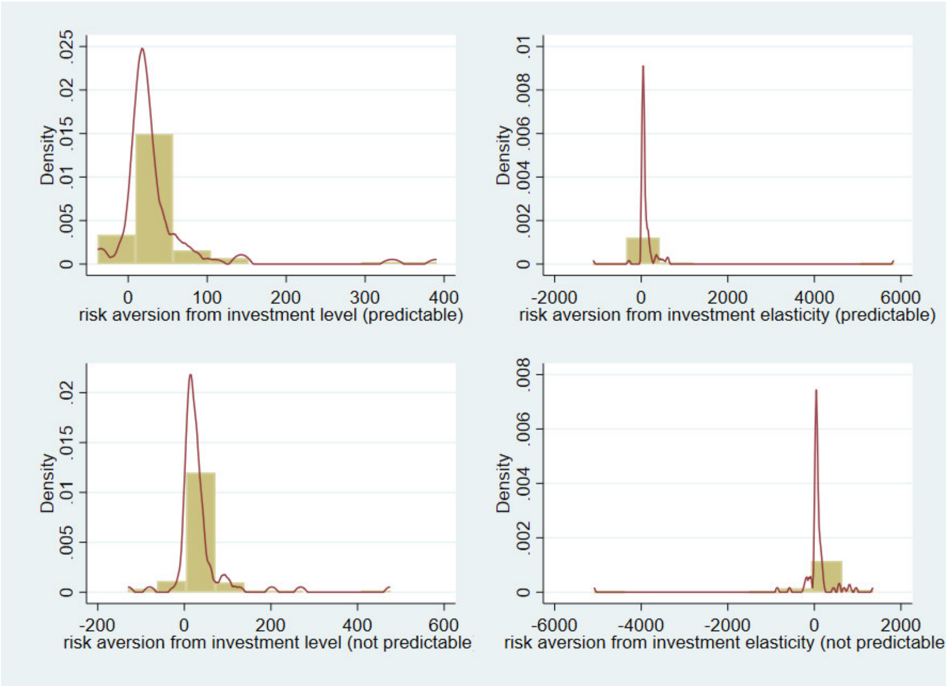
Table 20: Descriptive Statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
a(t)	20	6.04	5.48	3.24	2.06	12.17
r(t)	20	3.19	2.95	8.60	-11.79	19.25
			Predict=1			
a(t)	20	6.22	6.22	3.27	2.06	12.17
r(t)	20	3.78	3.37	8.15	-11.79	19.25
			Predict=0			
a(t)	20	5.81	4.75	3.18	2.06	12.17
r(t)	20	2.47	-1.12	9.08	-11.79	19.25

NOTE: This table reports the statistics for the last realizations of "Variable A" and of "Index Return", $a(t)$ and $r(t)$, that subjects observe, each round, in the "Question page".

C Additional Results

Figure 7: Implicit Risk Aversion



NOTE: This figure plots the kernel density of estimated relative risk aversion coefficient γ across individuals. In the top panels, estimates are from rounds perceived as predictable; in the bottom panels, estimates are from rounds perceived as not predictable. In the right panels, we report estimates from investment levels in Equation (13); in the left panels, we report estimates from investment elasticities in Equation (13). We use the true variances of processes (1) and (2), weighted by the probabilities of mistakes, as in footonote 19. Each graph plots the density as histogram and as estimated by the Epanechnikov kernel function with Stata's default bandwidth.

Table 21: Subjects Characteristics — Correlation Matrix

	High θ	Fast	High Ability	High Grades	Female
High θ	1.00	0.07	-0.01	0.14	0.10
Fast	0.07	1.00	-0.06	0.01	0.04
High Ability	-0.01	-0.06	1.00	0.10	0.19
High Grades	0.14	0.01	0.10	1.00	0.14
Female	0.10	0.04	0.19	0.14	1.00

NOTE: This table reports the correlations between the characteristics dummies: "High θ" is a dummy equal to one if the subject takes larger risk investments, on average, than the median; "Fast" is a dummy equal to one if the subject is faster, on average, than the median of 61 seconds in answering each round's questions; "High Ability" is a dummy equal to one if the subject is better than the median in identifying when "Variable A" is useful or not; "High Grades" is a dummy equal to one if the subject has average grades above her/his cohort's median in TSE Masters' program; "Female" is a dummy equal to one if the subject is a woman.

Table 22: Forecast and Investment, Fast versus Slow

Dep Variable	Forecast				Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
a(t)	0.19**	0.02				
	(0.09)	(0.10)				
a(t)*Fast	0.34**	-0.11				
	(0.13)	(0.19)				
r(t)			0.08	0.20***		
			(0.05)	(0.04)		
r(t)*Fast			-0.10	-0.01		
			(0.07)	(0.06)		
Forecast					1.95***	1.54***
					(0.23)	(0.34)
Forecast*Fast					0.51*	0.51
					(0.26)	(0.42)
Predict						0.67
						(2.25)
Predict*Fast						3.57
						(3.03)
Forecast*Predict						0.71*
						(0.36)
Forecast*Predict*Fast						-0.06
						(0.49)
Fast	-1.35	-0.00	1.20**	-0.33	-0.17	-2.27
	(1.01)	(1.27)	(0.51)	(0.37)	(1.54)	(2.21)
Individual FE	Yes					
Sample	Predict = 1	Predict = 0	Predict = 1	Predict = 0	All	All
Number of Obs	1,036	844	1,036	844	1,880	1,880
Number of Clusters	94	94	94	94	94	94
R-squared	0.15	0.14	0.12	0.20	0.57	0.58

NOTE: This table reports the results of OLS regressions. In columns (1)-(4), the dependent variable is the next-period forecast of returns, in percentage points. In columns (5)-(6), the dependent variable is the ECU next-period investment in the risky asset. "Predict" is a dummy equal to one if the subject declares "Variable A" is useful to predict returns. "Fast" is a dummy equal to one if the subject is faster than her usual median time, for rounds of same type (per = 1 or per = 0), in answering the round's questions. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Chapter 3: Managers' Expected Returns and Project Valuation*

September 30, 2021

Abstract

While expected returns are time-varying and predictable by the predictive variables, managers seem to hold expectations of returns different from the market. This difference in expectations may lead to mis-valuation of projects. For instance, when managers hold expectations of excess returns that are higher than the market, they may undervalue their own projects under the market's view. I use managers' expected returns and market reactions to the bidders' stocks around the announcements of $M\&A$ deals to show that the difference in expectations between managers and the market may cause over-valuation/under-valuation of the targets, which entails lower/higher cumulative abnormal returns.

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1 Introduction

The Capital Asset Pricing Model (CAPM) (Sharpe (1964), Lintner (1975)) has been widely used by practitioners to estimate the cost of capital of their firms or projects[1]. The expected returns of the market portfolio above the risk-free rate (the market risk premium) play an important role in the CAPM formula and subsequently affect firms' valuation of projects.

This market risk premium component is known to vary a lot over time as it captures the fluctuations in investors' required returns, which is possibly driven by the variation in their risk aversion (Campbell and Cochrane (1999), Barberis, Huang, and Santos (2001)) or in the risk itself (Bansal and Yaron (2004), Gabaix (2012)). Such fluctuation can be partly reflected in today's movement of valuation ratios such as the aggregate dividend-price ratio, the earning-price ratio or the book-to-market ratio[2]. The market risk premium is also known to be a function of cyclical macro variables such as the consumption wealth ratio cay (Lettau and Ludvigson (2001)).

Surveys on managers' expected returns suggest that managers may hold expected excess returns on the market portfolio that are different from the market, including extrapolation on past returns and on price level (Greenwood and Shleifer (2014), Graham and Harvey (2018)). Greenwood and Shleifer (2014) also show that survey forecasts of the $S\&P$ 500 excess returns (including those of managers) are negatively correlated with the dividend-price ratio. This suggests these forecasts may also be negatively correlated with expected returns computed using economic predictors (referred in Greenwood and Shleifer (2014) as the model expected returns.). Additionally, they find that subsequent realized returns are likely to be low when forecasts are high and vice versa. At the same time, the model expected returns consistently predict subsequent returns in the same direction. Since managers' expected returns enter the valuation formula through the cost of capital that is used to discount the future cash-flows, the difference in expected

[1]In Graham and Harvey (2001), seventy-four percent of the CFOs (of US public firms) surveyed reported that they always or almost always use CAPM to estimate the cost of equity capital. Ninety percent of the respondents of the Association for Financial Professionals survey also said that they use CAPM in estimating the cost of equity (Jacobs and Shivdasani (2012)).

[2]Fama and French (2021) and Campbell and Shiller (1988) show that the dividend-price ratio can predict subsequent returns in the same direction. Campbell and Shiller (2001) uses international data to show that the earning-price ratio and smoothed earning-price ratio are helpful to predict future index returns. Kothari and Shanken (1997) presents evidence that the book-to-market ratio and dividend yield track the variation in expected returns.

returns between managers and the market may lead to mis-valuation of their projects and inefficient investment decisions.

I show that managers having expectations of returns that are different from the market has important implications on firms' capital budgeting decisions. During the period of time when managers are pessimistic relative to the market, i.e., managers' expected excess returns (on the market portfolio) are low relative to the level perceived by the market, they may end up using a discount rate that is higher than the market. The consequence is that the valuation of projects by managers during these times tends to exceed their market valuation. Therefore, managers may want to undertake these projects at a cost that is too high in the view of the market. The news of acquiring these projects is less favorable, and therefore one should expect a lower market reaction. The reverse also holds for periods when managers are optimistic relative to the market, i.e., managers' expected excess returns are high relative to the level perceived by the market. In this case, one should expect more favorable market reactions to news of such projects.

To test this prediction, I use forecasts of average returns for the next ten years (period 2000Q2 to 2019Q4) from Graham, and Harvey CFO survey as managers' expectations and data on M&A deals with U.S. public bidders and U.S. private targets. I focus on merger and acquisition deals as these are large-scale investments that firms can make and the deal details are publicly available. Additionally, the market reaction around the announcement of such deals can be observed and measured using event study methodology. I show that the market reaction to the bidders' stock around the announcement of the M&A deals is higher when managers' expected excess returns are high relative to the market. Specifically, a one percentage point difference between the managers' expected excess returns and the ones of the market is associated with around 0.2 to 1.1 percentage point increase in the market reaction to the bidder's stock around the announcement date, depending on the measures of the market's expected returns.

My paper contribution is to show that the bias in managers' expected excess returns relative to the market and their reliance on the CAPM has a real consequence in their capital budgeting decisions. Specifically, if managers hold expected returns that are high relative to the market when discounting projects' future cash-flows, they tend to use a cost of capital that is too high in the market's point of view. Firms are therefore prone to underpay for projects or only take on very profitable projects in the view of the market.

As a result, the announcements of such investments are considered favorable news to their investors. The opposite also holds when managers' expected returns are lower than the market's expected returns.

The current paper is related to the literature on the real effect of the use of CAPM in corporate finance. Most related to my work is Dessaint, Olivier, Otto, and Thesmar (2021). Their paper starts from the observation that the empirical security market line is less steep compared to the CAPM-implied security market line. Firms' reliance on the CAPM model to estimate their cost of capital may cause them to use a higher cost of capital than the market for high-beta projects and a lower cost of capital than the market for low-beta projects. The consequence is that firms tend to undervalue high-beta projects while overvaluing low-beta projects. My paper is also related to Krüger, Landier, and Thesmar (2015). Their paper is based on the observation that diversified firms rely on CAPM to estimate their cost of capital but tend to apply the beta of their core divisions to projects of different risks. This consequently causes over-valuation for high-beta projects and under-valuation for low-beta projects. My paper shares the common interest with the above literature in that I also focus on the potential inefficiency due to the use of a wrong discount rate relative to the market. However, I assume the component of CAPM that is perceived differently by managers compared to the market is the market risk premium. Specifically, I ask the question of what is the real impact on firms' valuation of projects and their capital budgeting decisions if they hold an expectation of excess returns that is different from the market's point of view.

2 Prediction

To provide a framework for my prediction, I introduce a simple model that captures the main arguments. Consider a bidder who is a public firm that offers a bid B to acquire a private target. The offer is accepted at a given probability p. Suppose the target is entirely financed by equity. The bidder's valuation of the target is:

$$V_t^b = \sum_{\tau=t+1}^{\infty} \frac{FCF_\tau + s_\tau}{(1 + r_{t,N}^b)^{\tau-t}} \tag{1}$$

The value of the target is the sum of discounted free cash-flows (FCF_τ) created by the target's assets plus the sum of discounted synergy (s_τ) conditional on the fact that the acquisition is successful. $r^b_{t,N}$ is the cost of capital estimated at time t over an N-year horizon, for a large N. The bidder uses this cost of capital to discount the target's free cash-flows and the potential synergy. He is assumed to use CAPM to estimate the cost of capital:

$$r^b_{t,N} = r^f_{t,N} + \beta E^b_t[r^e_{t,N}] \tag{2}$$

where $E^b_t[r^e_{t,N}]$ denote the bidder's expectation on the annualized excess returns of the market portfolio for an N-year horizon. $r^f_{t,N}$ is the risk-free rate for the same horizon. Since the target is un-levered, β used in the CAPM formula is the asset beta, which is associated with the risk in the target industry.
Similarly, the market's valuation of the target is:

$$V^m_t = \sum_{\tau=t+1}^{\infty} \frac{FCF_\tau + s_\tau}{(1 + r^m_{t,N})^{\tau-t}} \tag{3}$$

where the cost of capital $r^m_{t,N}$ is estimated using the market risk premium from the market's point of view:

$$r^m_{t,N} = r^f_{t,N} + \beta E^m_t[r^e_{t,N}]$$

where $E^m_t[r^e_{t,N}]$ denote the market's expectation on the annualized excess returns of the market portfolio for an N-year horizon. Similar to the assessment of the bidder, the market uses the same discount rate $r^m_{t,N}$ to discount the free cash-flows and the synergy.

For simplicity, I assume that the bidder holds the same expectation as the market on the cash-flows and on the synergy created when the acquisition is successful. He also uses the same asset beta as the market. Therefore, the only difference in the assessment of the target between the bidder and the market is the cost of capital used to discount the cash-flows and synergy, or more precisely, the market risk premium that is used to compute this cost of capital. Next, assume that the bidder offers a bid:

$$B^b \equiv \sum_{\tau=t+1}^{\infty} \frac{FCF_\tau}{(1 + r^b_{t,N})^{\tau-t}} + \lambda \sum_{\tau=t+1}^{\infty} \frac{s_\tau}{(1 + r^b_{t,N})^{\tau-t}} \tag{4}$$

where $\lambda \in [0, 1]$ is the target shareholders' share of the synergy determined through bilateral Nash bargaining and is perceived in the same way by the bidder and the market.

The cumulative abnormal returns to the bidder's stock upon the announcement of the bid is given by the difference between the bid value B^m that would have been proposed by the bidder's investors and the bid B^b actually proposed by the bidder himself, scaled by the bidder's market capitalization at the beginning of the event window $V_{t-\delta}^{Bidder}$:

$$
\begin{aligned}
CAR_t &= p\frac{B^m - B^b}{V_{t-\delta}^{Bidder}} \\
&= \frac{p}{V_{t-\delta}^{Bidder}} \sum_{\tau=t+1}^{\infty} (FCF_\tau + \lambda s_\tau)(\frac{1}{(1+r_{t,N}^m)^{\tau-t}} - \frac{1}{(1+r_{t,N}^b)^{\tau-t}})\Bigg]
\end{aligned}
$$

where:

$$r_{t,N}^m = r_{t,N}^f + \beta E_t^m[r_{t,N}^e] \tag{5}$$

$$r_{t,N}^b = r_{t,N}^f + \beta E_t^b[r_{t,N}^e] = r_{t,N}^f + \beta(E_t^m[r_{t,N}^e] + BIAS_t) \tag{6}$$

where BIAS is the difference between the bidder's and the market's expectation of returns $BIAS_t \equiv E_t^b[r_{t,N}^e] - E_t^m[r_{t,N}^e]$.

Taking the first derivative of the cumulative abnormal returns with respect to $BIAS_t$:

$$\frac{\partial CAR_t}{\partial BIAS_t} = \frac{p}{V_{t-\delta}^{Bidder}} \left[\sum_{\tau=t+1}^{\infty} (FCF_\tau + \lambda s_\tau) \frac{\beta(\tau - t)(1 + r_{t,N}^b)^{\tau-t-1}}{(1 + r_{t,N}^b)^{2(\tau-t)}} \right] > 0 \tag{7}$$

Prediction *The cumulative abnormal return around the announcement increases in the difference of the expected excess return on the market portfolio between the bidder and the market ($BIAS_t$).*

The intuition is as follows. When the bidder is pessimistic relative to the market in the sense that his expected excess return is below the one held by the market, he discounts the target's cash-flows and the synergy at a discount rate that is lower than the one by the market. Consequently, he tends to overvalue the target and offers a bid that is too high in the market's view. Conversely, when the bidder is optimistic relative to the market, he tends to undervalue the target and offers a bid that is viewed as being too low by the market. Therefore, we should expect a less favorable market reaction to the announcement in the former case compared to the latter one.

3 Data

Data on bid announcements are from Thomson Financial's SDC Platinum M&A database. I focus on private targets because the tasks of valuing these targets are considered more complicated than the ones for public targets. One main reason is that there is no available market value that can be used by managers as a counter-weight for their own assessment. Additionally, for public targets, even when managers undervalue their targets, it is unlikely that they can get the targets' shareholders to accept a bid that is lower than the market price (Dessaint et al. (2021)). On the contrary, such low bids can be accepted in the case of private targets when there is undervaluation from both sides. I also require deals to have all information about the bidder's name and industry, the target industry, the deal size, and the payment method. The sample includes deals from June 2000 to December 2019 [3], with public bidders and private targets and with a deal value greater than USD 10 million (inflation-adjusted to December 2019).

Daily valued weighted market returns scaled by the equity beta of the bidders[4] are subtracted to obtain the daily abnormal returns for the bidder's stock. The bidder's daily abnormal returns are accumulated through eleven days around the bid announcements ($[-5, +5]$ days for a bid announcement on date 0). Panel A of table 1 presents the descriptive statistics for the variables related to the M&A deals. The average cumulative abnormal returns (for an event window of [-5, +5] days around the announcement) is 1.57%. This is consistent with the evidence in the past literature (e.g., Betton, Eckbo, and Thorburn (2008); Schneider and Spalt (2017). The average deal value in my sample is USD 122.78 million, and the average deal size relative to the bidder's market capitalization is 0.15.

Panel B of table 1 presents the descriptive statistic for variables related to the expected returns either held by CFOs or by the market. As a proxy for managers' expectations, I use the average CFO forecasts from 2000Q2 to 2019Q4 on the annualized returns of $S\&P500$ in the next ten years. The data is from the CFO survey of Graham, Harvey, and Duke University. Every quarter since June 2000, their research team sent out a questionnaire to CFOs of public firms in the US to survey their prospects on different topical issues, including the long-term expectation on the $S\&P500$ returns. The average number

[3] To match with the CFO forecast data.

[4] Equity betas are from CRSP, estimated using monthly data in a three-year window.

of respondents for each survey wave is 395 CFOs. The average forecasts were reported in Graham and Harvey (2018) for the period 2000-2018 and in their quarterly reports available on the survey website[5]. Other information such as the disagreement between CFOs of each survey wave (measured by the standard deviations of their forecasts) and the median forecasts are also provided by Graham and Harvey in these reports. The first row of table 1, panel B suggests that the mean of CFO forecasts does not vary much through time. The standard deviation of the aggregate CFO forecasts of the excess returns on $S\&P500$ for the next ten years is around 0.6% while the mean is 3.7%. Despite the low variation across time, the disagreements between CFOs are pretty large relative to the average forecasts.

The next three rows of panel B, table 1 presents the descriptive statistic for different measures of market expected returns (session 4 gives a more detailed description of these measures). To compute the historical average excess returns, I compound the monthly S&P 500 returns from January 1871 into annual returns and subtract the ten-year US government bond rate. Next, I compute the moving ten-year annualized excess returns by taking the arithmetic average of annual excess returns for every ten-year period. Finally, for every quarter from 2000Q2 to 2019Q4, the historical returns are computed by taking the average of all ten-year annualized excess returns data from 1871. Data on S&P 500, dividends, and ten-year US government bond rate are from Robert Shiller's website. Panel B suggests that CFO forecasts of ten-year annualized excess returns on average are about 2.51 percentage points lower compared to the historical mean. The next row of Panel B presents the descriptive statistics of expected returns computed using the kitchen sink regression (a predictive regression in which all of the predictors are included as in Welch and Goyal (2008)). The predictors used in this regression include aggregate book-to-market ratio (BM_t), default spread (DS_t), short-term US treasury notes and certificates ($STRfree_t$), net equity expansion ($ntis_t$), inflation ($infl_t$), long-term US government bond yield ($Rfree_t$), long-term corporate bond returns (ltr_t), S&P 500 stock return variance (var_t), aggregate earning-price ratio (EP_t), moving average cyclically adjusted price-earnings ratio ($CAPE10_t$), and dividend-price ratio (DP_t). Table 7 provides the description of these variables. All data except for the last three variables are from Amit Goyal's website. The price ratios are obtained from Robert Shiller's website. All these

[5]https://cfosurvey.fuqua.duke.edu/release/

variables are at monthly frequency [6]. The expected returns are the in-sample fitted value of the regression of the ten-year annualized excess returns from month $t+1$ to month $t+120$ on the predictors at the month t. The fourth row of Panel B, table 1 shows the descriptive statistic for the quarterly expected returns computed using the kitchen sink regression corresponding to the period 2000Q2 to 2011Q2[7]. The next row corresponds to the realization of the ten-year annualized returns from 2010Q2 to 2021Q2. These returns, as later explained, are used as a proxy for expected returns in the period from 2000Q2 to 2011Q2. The fourth and fifth rows of Panel B suggest that CFO forecasts are quite low compared to the model-based expected returns and the realization of returns. The average ten-year treasury bond rate from the second quarter of 2000 to the fourth quarter of 2019 is 3.36%, which is a bit lower than the average of 4.45% computed using treasury bond rate back from 1871.

4 Cumulative Abnormal Returns around M&A announcements and manager's bias

To test the prediction, I estimate the following model:

$$\begin{aligned} CAR =& \beta BIAS + \gamma' \times Deal\ Controls + \delta' \times Target\ Controls + \kappa' \times Bidder\ Controls \\ &+ \zeta' Other\ Controls + Bidder\ industry\ FE + Target\ industry\ FE + \epsilon \end{aligned}$$

CAR is the cumulative abnormal return of the bidder's stock eleven days ([-5, +5] days) around the announcement. $BIAS$ is my variable of interest that is measured by the difference between the average forecasts of the next ten-year returns on $S\&P500$ from the CFO survey and the market expected returns. *Deal controls* includes the deal value (in logs), bidder's market capitalization (in logs), bidder's relative size (deal size in dollar divided by the bidder's market capitalization), same industry (dummy), multiple bidders (dummy) and payment method (dummy). The *bidder's controls* include the book-to-market ratio, returns on total asset, cash-flows on total asset, long-term debt on total asset, and depreciation on total asset of the bidder. *Target's controls* include the same

[6] The reason that monthly data is used instead of quarterly data is to have more observations.

[7] At the moment of this analysis, the realized returns are available up to July 2021, therefore only the expected returns up to the second quarter of 2011 are computed.

variables as in *bidder's controls* except these variables are at the target's industry level[8]. I also include in *other controls* the ten-year treasury bond yield and CFOs' disagreements measured as the standard deviation of CFO forecast. Table 7 shows the definitions of variables. There might also be waves of M&A in some certain industries and the market may react differently to the announcements of deals depending on the industries of the bidder and the target. To take this into account, I include the bidder's and the target's industry fixed effect. Finally, since both CAR and $BIAS$ may be correlated with the economic cycle, I also include in *macro controls* an NBER recession indicator, consumption growth (including durable consumption, non-durable consumption and service consumption), employment growth and industrial production index (in log). The standard errors are clustered by the target industry.

To construct the variable BIAS, the difference in expected excess returns between managers and the market, I need further assumptions on how the market forms its expectations.

First, I assume that the market expected excess return is constant. For example, the market can hold an expected return of 1%, the normative level calibrated by Weil (1989) given a constant relative risk aversion of 10 and an intertemporal elasticity of substitution of 1. If the market has constant expected returns, all the variation in BIAS should come from managers' expectations. Then it would be enough to consider the effect of managers' expectations on the cumulative abnormal returns of the bidder around the announcement date. Table 2 presents the regression results. There is no control variable in the first column except for the bidder's and target's fixed effect. In the second column, I include managers' disagreement and the risk-free rate at the end of the quarter in which the forecasts were made. I include the deal controls in the third column and the bidder's and target's controls in the fourth column. Finally, in the fifth column, macro controls are added. In all column, the coefficients on $BIAS$ is positive and significant. One percentage point higher in the bidder's expectation of returns is associated with an increase of 0.77 to 1.03 percentage point in the cumulative abnormal returns of the bidder's stock around the announcement. The magnitudes of the coefficients decrease when the bidder's controls, target's controls, and macro controls are included. This suggests that the cyclical variables are likely to correlate positively with both the

[8] Industry is defined as the groups of firms that share the same three first digit of the SIC codes.

bidders' expectation of returns and the market reaction to the bidder's stock around the announcement date.

In the following analysis, I assume that the market has access to the historical returns and all predictors. Accordingly, I treat the historical average of the ten-year annualized excess returns of the S&P 500 as the market expected returns[9]. I then define the variable of interest $BIAS$ as the difference between managers' forecasts and the historical mean of the ten-year annualized excess returns computed using returns up to the quarter that the forecasts were made. Hence, a high $BIAS$ at time t would mean that managers are on average optimistic relative to the market and vice versa. The difference in expectation between the managers and the market should lead to a market reaction to the announcement of the bid that is considered misvalued by the market. Table 3 presents the results of the regression of the cumulative abnormal returns around the announcement date of the bid on the managers' bias. The format is similar to table 2. One percentage point increase in the difference between managers' expected returns and the market's expected returns is associated with a 0.61 to 1.09 percentage points increase in the market reaction to the bidder's stock around the announcement date. For an average bidder in the sample, this is translated to an increase of \$ 50.76 million to \$ 90.70 million in the bidder's market capitalization.

In the next analysis, I assume that the market can get access to information beyond the past realization of returns and of the predictors, which is a stronger assumption on the information that the market uses. Dahlquist and Ibert (2021) show that expected returns from some of the largest asset managers in the world are consistent with model expected returns computed using predictors. Given the increase of equity ownership by professional asset managers over the past few decades (Ben-David, Franzoni, Moussawi, and Sedunov (2021)), it is plausible that the market can get access to quite sophisticated information when forming expectations. Specifically, the market can rely on the predictors available in quarter t to make a forecast of return for the next 40 quarters ($r_{t+1\to t+40}$), using the in-sample coefficients. As described in section 3, the ten-year average annualized returns

[9] In a separated (unreported) analysis, it can be shown that none of the regression including individual economic predictors, kitchen sink regression, regression with the sentiment index as a predictor (Baker and Wurgler (2006)) and regression with the projection of the economic predictors on their first principle component can produce a positive out-of-sample R-squared. The computation uses the average historical returns from 1871 as a benchmark (as in Campbell and Thompson (2008)). This suggests that no long-horizon predictive regressions can beat the historical mean.

from 2010Q2 to 2021Q2 are regressed on eleven predictors from 2000Q2 to 2011Q2. The fitted value of this regression is then used as the market expected returns for the period 2000Q2 to 2011Q2. I then define the variable of interest *BIAS* as the difference between managers' forecasts and the market expected returns. Table 4 shows the results of the regression of the cumulative abnormal returns on *BIAS*. The data used in this analysis is the 2000Q2 to 2011Q2 sub-sample of the one used in table 2 and 3. The results are consistent with my prediction: an increase of 1 percentage point in the difference between managers and the market's expected returns is associated with a 0.17 to 0.26 percentage points increase in the market reaction to the bidder's stock. For an average bidder in the sample, this is equivalent to an increase of \$ 14.15 million to \$ 21.64 million of the bidder's market capitalization.

Next, I assume the market holds perfect expectations of future returns. That is to say, the market's expected excess return is entirely in line with the realization of returns. Under this assumption, I use subsequent ten-year annualized realized return as a proxy for market expected returns. Specifically, annualized excess returns from quarter $t+1$ to $t+40$ correspond to the ten-year annualized expected excess returns at time t. BIAS is defined as the difference between managers' forecasts of ten-year excess returns, and the corresponding subsequent ten-year realized returns. Therefore, BIAS is equal to minus the forecast errors made by managers. Higher BIAS means that managers' forecasts are more optimistic relative to the market expected returns (and the subsequent realized returns) and vice versa. Table 5 presents the result when the variable BIAS is defined as above. The latest ten-year annualized return in my data is for the second quarter of 2021 which corresponds to managers' ten-year annualized forecast at the end of the second quarter of 2011. Therefore, merging these two series leads to a reduction in the number of observations of nearly one-half. The table format is similar to the previous tables. After taking into account the risk-free rate, CFO's disagreement, deal controls, bidder and target controls, one percentage point bias in managers' forecasts are associated with a 0.12 percentage point increase in the market reaction to the bidder's stock around the announcement of the bid, which is translated into an increase of \$ 9.99 million in the market capitalization of an average bidder in the sample. Even if the market has access to all private information, its private information is unlikely to be perfect, therefore realized returns still equal expected returns held by the market plus some i.i.d. shocks containing some unexpected news. Hence, the results in table 5 may be noisy as it is driven by not only the bias from managers' expectations but also by the part of realized returns from the unexpected shocks. Consequently, the coefficients of interest become insignificant, although their sides are still consistent with my prediction.

5 How do managers form their expectations?

Some studies have shown that the short-term forecasts (for the next year's returns) are extrapolative in the sense that they tend to respond positively to current returns or price level (Greenwood and Shleifer (2014), Amromin and Sharpe (2014)). Additionally, these forecasts are negatively correlated with the model expected returns (expected returns computing using predictors such as the dividend-price, earning-price, etc.) and negatively correlated with subsequent realized returns. Since the data on CFO forecasts that I use in the above analysis are CFOs' ten-year average return forecasts on the S&P 500 instead of the next year expected returns as in other studies, it is interesting to see whether these long-term expectations of returns would follow the same patterns as short-term expected returns. This session aims to give some preliminary ideas on how CFOs form such long-term forecasts compared to how the market forms the expected returns.

First, I check whether managers make their ten-year forecasts that depend on past returns. Table 6 shows the regression of managers' forecasts on the past twelve-month excess returns and the average past ten-year annualized excess returns. The results suggest that, unlike shorter-term forecasts, long-term forecasts do not depend or only slightly depend on the past twelve-month realized returns. The corresponding coefficients have negative sides and are of minimal magnitude. However, the loading on past ten-year annualized returns is positive and significant but also small in magnitude after controlling for the risk-free rate, unemployment rate, and aggregate earning growth. Overall, managers' forecasts for long-term returns do not seem to have a (strong) extrapolative tendency as observed in shorter-term forecasts.

Figure 1 plots the subsequent ten-year annualized realized returns on the corresponding managers' forecasts. The negative correlation between managers' forecasts and realized returns are in line with what has been observed with short-term return forecast data in Greenwood and Shleifer (2014). Specifically, when managers forecast the next ten-year excess returns that are high, the realized excess returns are likely to be low and vice versa. A simple regression line suggests a coefficient of -1.49, which is negative and also large in magnitude.

Figure 2 through 5 contrast how managers' forecasts of the next ten-year average excess returns and the subsequent ten-year annualized excess returns depend on different variables. Figure 2 suggests that the subsequent ten-year excess returns are negatively correlated with the past ten-year excess returns. Conversely, managers' forecasts seem to be slightly positively correlated with the past ten-year excess returns. Figure 4 contrasts how managers' forecasts and the subsequent returns load on the current dividend-price ratio. Consistent with the empirical evidence on return predictability, the dividend-price ratio in the sample predicts subsequent (long-term) returns in the same direction, i.e., higher dividend-price ratios today are likely to be followed by higher realized returns. Conversely, managers' forecasts do not seem to depend (or depend very little) on the current dividend-price ratio. Similarly, figure 4 shows the loading on the (smoothed) cyclically adjusted price-earning ratio (CAPE10). The ratio, based on the cyclically adjusted price-earning ratio (CAPE), has the numerator smoothed out by using the ten-year moving average earnings. This is to eliminate the yearly fluctuation in earnings which are less related to expected returns. As expected, this CAPE10 ratio is negatively correlated with subsequent returns. Managers' forecasts, on the other hand, seem to respond positively to the ratio.

Finally, figure 5 plots managers' forecasts and subsequent returns on the current value of *cay*, the deviation from common consumption trend (Lettau and Ludvigson (2001)). Interestingly, contrary to the empirical evidence on the predictability of *cay* where this variable positively predicts short to medium-term future returns, the regression line of the ten-year annualized excess returns on the current value of cay suggest a negative correlation[10] (and also of high magnitude). This is possibly because a much shorter and more recent period (2000Q2 to 2020Q1) has been used to estimate the coefficient. Conversely, managers' forecasts are slightly positively correlated with *cay*, which is consistent with the evidence on the predictability of *cay*.

Overall, managers' expectations of long-term returns do not seem to be (strongly) extrapolative on either the past twelve-month returns or the past ten-year returns. This

[10]The same regression is run while expanding the estimation window to use data from 1963 when the first value of *cay* is available gives a positive coefficient as observed in other studies.

observation is in contrast with asset managers' long-term expectation of returns, which is shown to be countercyclycal and consistent with the model expected returns (Dahlquist and Ibert (2021)). Additionally, managers' expectations are unlikely to depend on the current state variables. As mentioned earlier, the findings in this chapter are instead to give a preliminary idea on the discrepancy between managers' forecasts and expected return held by the market. To further conclude how managers/firms form their expectations over such a long horizon, one may need a larger data set that spans over a longer period.

6 Discussion and Conclusion

In this paper, I use managers' expected returns on S&P 500 (Graham and Harvey CFO survey) and M&A deal announcements (SDC Platinum) to show that the difference in expectation between managers and the market can lead to mis-valuation of their own projects that can be observed through the market reaction to the bidders' stock around the announcements of the deal. One percentage point increase in the difference in expected returns between the manager and the market is associated with a 0.2 to 1.1 percentage point increase in the market reaction, depending on the measures of the market's expected returns. Additionally, I show how managers' long-horizon expected returns are different from the market. Overall, managers' expected returns are strongly negatively correlated with subsequent realized returns. The loading of managers' forecasts on past returns, dividend-price ratio, price-earning ratio, and cay are either of relatively small magnitude or of the wrong direction compared to the market.

Throughout the analysis, I assume that managers are less rational compared to the market. As Dessaint, Olivier, Otto, and Thesmar (2021) has pointed out, managers' or financial advisors' expertise are often not lying in spotting underlying assets comparing to traders. They, therefore, may not have as much information and are more prone to bias relative to the market. Another reason is that they may believe that deal negotiation is more important than valuing the target more accurately. Therefore, they may spend fewer resources on estimating a more accurate cost of capital.

It is also common for bidders to retain and M&A advisors, especially for large deals with complex payment methods where financial advisors play an important role in securing a more significant share of the synergy for the bidders. Although having a good advisor can help the bidder with larger synergy gain (Golubov, Petmezas, and Travlos (2012)), their potential targets may also retain a tier-one advisor themselves. In such a case, the initial valuation of the targets can significantly affect the outcome of the deal and mis-valuation of the targets can still cause market reaction around the announcement date.

As managers usually have less access to market information compared to traders, it is not surprising that they may hold biased expectations on the market excess returns. One implication from the finding is that managers can simply use the all-time historical average returns as their expected returns rather than just using certain rules of thumb.

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Tables and Figures

Table 1: Descriptive statistics

Panel A: SDC Platinum Private US target (2000-2019, deal value ≥ \$M10)						
	Obs	Mean	SD	25%	50%	75%
Bidder CAR (in percentage point)	3,007	1.57	9.00	-3.10	0.97	5.69
Deal Value (in M)	3,007	122.78	164.24	23.50	51.50	150
Bidder Market Cap (in M)	3,007	8,321.39	32,284.97	362.59	996.69	3,201.59
Deal Value/Bidder Size	3,007	0.15	0.50	0.02	0.06	0.14
100% Stock	3,007	0.09	0.28	0	0	0
100% Cash	3,007	0.50	0.50	0	0	1
Same industry	3,007	0.07	0.25	0	0	0
Panel B: Expected excess returns						
Graham-Harvey CFO forecast	78	3.68	0.59	3.16	3.75	4.09
CFO disagreement	78	2.86	0.46	2.55	2.81	3.05
Historical average of excess return	78	6.19	0.14	6.20	6.32	6.51
Expected returns (kitchen sink regression)	45	6.37	4.22	4.96	6.22	9.78
Realization of excess returns	45	6.16	4.26	4.52	5.97	8.79
10-year Treasury Bond	78	3.36	1.18	2.33	3.29	4.27

This table presents the descriptive statistics for private US target from 2000Q2 to 2019Q4 (Panel A) and the expected excess return and related variables from 2000Q2 to 2019Q4 (row 1, 2, 3 and 6 of Panel B) and from 2000Q2 to 2011Q2. Bidder CAR is the cumulative abnormal returns around the announcement date of the deal ([-5, +5] days). *Deal value* is the value of the bid (in \$M). 100% *Stock* and 100% *Cash* are two indicators that take a value of 1 if the deal is made 100% in cash and 100% in equity, respectively. *Same industry* takes a value of 1 if the bidder and the target perform in the same industry (share the first three digits of SIC codes) *Graham-Harvey CFO forecast* is the average forecasts made at the end of each quarter by American CFOs. *CFO disagreement* is the cross-sectional standard deviation of the quarterly CFO forecasts.

Table 2: CAR and CFOs' forecasts

Dependent Variable:	Bidder CAR [-5 +5], in percentage point				
$CFOforecast$	0.77**	1.03***	0.91**	0.85**	0.80**
	(2.07)	(3.28)	(2.47)	(2.19)	(1.97)
$Rfree$		0.44**	0.45**	0.45*	0.42
		(2.25)	(2.27)	(1.91)	(1.42)
$CFOdisagree$		0.12	0.04	-0.08	0.16
		(0.23)	(0.08)	(-0.15)	(0.26)
$dealval$			0.84***	0.85***	0.85***
			(3.09)	(2.74)	(2.82)
$Biddersize$			-0.74***	-0.85***	-0.84***
			(-4.08)	(-4.61)	(-4.75)
$dealRsize$			1.12	1.17*	1.13
			(1.57)	(1.66)	(1.64)
$sameSIC3$			0.90	0.93	1.02
			(1.39)	(1.45)	(1.46)
$equity$			0.68	0.70	0.27
			(0.54)	(0.53)	(0.21)
$cash$			0.12	0.24	-0.20
			(0.12)	(0.20)	(-0.18)
$m.Bidder$			5.58***	6.47***	6.38***
			(4.75)	(3.76)	(3.49)
Bidder SIC3 FE	Y	Y	Y	Y	Y
Target SIC3 FE	Y	Y	Y	Y	Y
Bidder Controls	N	N	Y	Y	Y
Target Controls	N	N	N	Y	Y
Macro controls	N	N	N	N	Y
No.obs	3,007	3,007	3,007	2,788	2,731

This table shows the OLS estimates of the impact of managers' forecasts on the market reaction to the announcement of the deals. The dependent variable is the cumulative abnormal returns within [-5, +5] days around the event date. Bidder's controls include the book-to-market ratio, returns on total asset, cash-flows on total asset, long-term debt on total asset and depreciation on total asset. Target's controls are defined analogously but at the industry level. Macro controls include the NBER recession dummy, consumption growth (durable, non-durable and service consumption), employment growth and the industrial production index (in log). Definition of all variables are provided in table 7. t-statistics, based on standard errors clustered by the target's industry, are reported in parentheses. *p <.1; **p <.05;***p <.01.

Table 3: CAR and CFOs' BIAS (based on the historical returns)

Dependent Variable:	Bidder CAR [-5 +5], in percentage point				
$BIAS$	0.61*	1.09***	0.96**	0.88**	0.77*
	(1.67)	(3.25)	(2.39)	(2.04)	(1.74)
$Rfree$		0.55***	0.55***	0.54**	0.45
		(2.75)	(2.63)	(2.11)	(1.57)
$CFOdisagree$		0.02	-0.05	-0.14	0.14
		(0.04)	(-0.10)	(-0.28)	(0.59)
$dealval$			0.84***	0.84***	0.84***
			(3.06)	(2.73)	(2.81)
$Biddersize$			-0.74***	-0.85***	-0.84***
			(-4.09)	(-4.60)	(-4.75)
$dealRsize$			1.12	1.17*	1.13*
			(1.57)	(1.66)	(1.64)
$sameSIC3$			0.90	0.93	1.02
			(1.38)	(1.45)	(1.47)
$equity$			0.65	0.69	0.26
			(0.52)	(0.52)	(0.20)
$cash$			0.13	0.25	-0.19
			(0.13)	(0.21)	(-0.17)
$m.Bidder$			5.47***	6.41***	6.37***
			(4.74)	(3.75)	(3.37)
Bidder SIC3 FE	Y	Y	Y	Y	Y
Target SIC3 FE	Y	Y	Y	Y	Y
Bidder Controls	N	N	Y	Y	Y
Target Controls	N	N	N	Y	Y
Macro controls	N	N	N	N	Y
No.obs	3,007	3,007	3,007	2,788	2,731

This table shows the OLS estimates of the impact of managers' bias in expected returns on the market reaction to the announcement of the deals. The dependent variable is the cumulative abnormal returns within [-5, +5] days around the event date. BIAS is the difference between CFO forecasts and the historical returns computed each quarter, using return data from 1871. Bidder's controls include the book-to-market ratio, returns on total asset, cash-flows on total asset, long-term debt on total asset and depreciation on total asset. Target's controls are defined analogously but at the industry level. Macro controls include the NBER recession dummy, consumption growth (durable, non-durable and service consumption), employment growth and the industrial production index (in log). Definition of all variables are provided in table 7. t-statistics, based on standard errors clustered by the target's industry, are reported in parentheses. *p <.1; **p <.05;***p <.01.

Table 4: CAR and managers' BIAS (based on the fitted value of the kitchen sink regression)

Dependent Variable:	Bidder CAR [-5 +5], in percentage point				
BIAS	0.23***	0.26***	0.19*	0.17	0.26*
	(4.59)	(2.61)	(1.70)	(1.34)	(1.84)
Rfree		-0.16	-0.04	-0.10	-0.63
		(-0.33)	(-0.07)	(-0.20)	(-1.01)
CFOdisagree		0.34	0.26	0.08	0.39
		(0.48)	(0.39)	(0.11)	(0.54)
dealval			0.44	0.40	0.40
			(1.13)	(0.98)	(0.95)
Biddersize			-0.55**	-0.70***	-0.71***
			(-2.28)	(-3.04)	(-3.09)
dealRsize			1.04	1.06	1.01
			(0.79)	(0.82)	(0.79)
sameSIC3			0.51	0.32	0.30
			(0.61)	(0.40)	(0.38)
equity			1.84	1.91	1.96
			(1.56)	(1.59)	(1.64)
cash			1.06	1.28	1.26
			(0.96)	(1.09)	(1.08)
m.Bidder			4.99***	5.47***	5.35***
			(3.71)	(2.69)	(2.57)
Bidder SIC3 FE	Y	Y	Y	Y	Y
Target SIC3 FE	Y	Y	Y	Y	Y
Bidder Controls	N	N	Y	Y	Y
Target Controls	N	N	N	Y	Y
Macro controls	N	N	N	N	Y
No.obs	1,919	1,919	1,919	1,822	1,822

This table shows the OLS estimates of the impact of managers' bias in expected returns on the market reaction to the announcement of the deals. The dependent variable is the cumulative abnormal returns within [-5, +5] days around the event date. BIAS is the difference between CFO forecasts and the fitted value of the kitchen sink regression. Bidder's controls include the book-to-market ratio, returns on total asset, cash-flows on total asset, long-term debt on total asset and depreciation on total asset. Target's controls are defined analogously but at the industry level. Macro controls include the NBER recession dummy, consumption growth (durable, non-durable and service consumption), employment growth and the industrial production index (in log). Definition of all variables are provided in table 7. t-statistics, based on standard errors clustered by the target's industry, are reported in parentheses. *p <.1; **p <.05;***p <.01.

Table 5: CAR and managers' BIAS (based on realization of returns)

Dependent Variable:	Bidder CAR [-5 +5], in percentage point				
$BIAS$	0.23***	0.19	0.17***	0.12*	0.12
	(5.04)	(3.81)	(2.83)	(1.68)	(1.42)
$Rfree$		0.56*	0.54*	0.70**	0.91**
		(1.78)	(1.72)	(2.17)	(1.96)
$CFOdisagree$		0.25	0.16	-0.02	0.05
		(0.35)	(0.24)	(-0.03)	(0.07)
$dealval$			0.46	0.43	0.43
			(1.18)	(1.03)	(1.02)
$Biddersize$			-0.57**	-0.74***	-0.74***
			(-2.34)	(-3.17)	(-3.12)
$dealRsize$			1.12	1.13	1.09
			(0.82)	(0.86)	(0.83)
$sameSIC3$			0.62	0.47	0.48
			(0.72)	(0.57)	(0.59)
$equity$			1.89	2.02*	2.00*
			(1.61)	(1.66)	(1.67)
$cash$			1.22	1.43	1.37
			(1.12)	(1.23)	(1.18)
$m.Bidder$			4.78***	5.62***	5.28**
			(3.39)	(2.71)	(2.44)
Bidder SIC3 FE	Y	Y	Y	Y	Y
Target SIC3 FE	Y	Y	Y	Y	Y
Bidder Controls	N	N	Y	Y	Y
Target Controls	N	N	N	Y	Y
Macro controls	N	N	N	N	Y
No.obs	1,887	1,887	1,887	1,791	1,791

This table shows the OLS estimates of the impact of managers' bias in expected returns on the market reaction to the announcement of the deals. The dependent variable is the cumulative abnormal returns within [-5, +5] days around the event date. BIAS is the difference between CFO forecasts and the realization of returns. Bidder's controls include the book-to-market ratio, returns on total asset, cash-flows on total asset, long-term debt on total asset and depreciation on total asset. Target's controls are defined analogously but at the industry level. Macro controls include the NBER recession dummy, consumption growth (durable, non-durable and service consumption), employment growth and the industrial production index (in log). Definition of all variables are provided in table 7. t-statistics, based on standard errors clustered by the target's industry, are reported in parentheses. *p <.1; **p <.05;***p <.01.

Table 6: Determinants of managers forecasts

Dependent Variable:	CFO forecasts				
lastret	-0.00		-0.01	-0.01**	-0.01
	(-0.96)		(-1.30)	(-2.23)	(-1.19)
last10ret		0.04	0.04*	0.02	0.06**
		(1.09)	(1.93)	(0.96)	(2.01)
$log(SP500)$				0.57*	-0.56*
				(1.71)	(-1.69)
Rfree					-0.37***
					(-3.89)
Unemploy					-0.07
					(-0.99)
Eg					0.01
					(0.19)
Constant	3.70***	3.49***	3.40***	-0.57	9.18***
	(27.28)	(15.04)	(22.11)	(-0.23)	(13.20)
No.obs	78	78	78	78	78
R^2	0.02	0.07	0.11	0.17	0.39

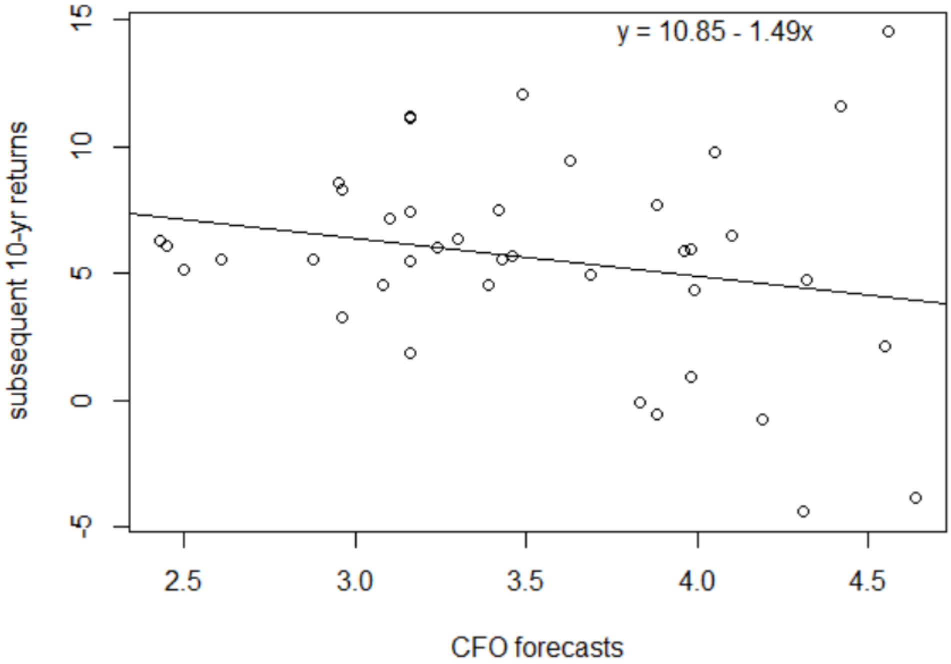
The table shows the determinants of managers' forecasts. *lastret* is the last 12-month return. *last10ret* is the last ten-year annualized returns. $log(SP500)$ is the log of the $S\&P500$ level at the end of the quarter that the forecasts were made. *Rfree*, *unemploy* and *Eg* are the ten-year treasury bond rate, the unemployment rate and the aggregate earning growth, respectively. t-statistics, based on Newey-West standard errors, are reported in parentheses. *p <.1; **p <.05;***p <.01.

Table 7: Variable Definitions

Variable	Definition
$B.BM$	Bidder's book-to-market ratio
$B.RA$	Bidder's return on total asset
$B.CA$	Bidder's free cash-flow on total asset
$B.DA$	Bidder's long-term debt on total asset
$B.DEA$	Bidder's depreciation on total asset
$bidderSalegr$	Last-year sale growth of the bidder's industry
$biddersize$	Natural logarithm of the bidder's market capitalization in USD million 6 days before the announcement.
BM	The aggregate book-to-market ratio, computed by taking the average of the book-to-market ratio of all firms whose accounting book value is available on both Compustat and CRSP.
$CAPE10_t$	moving average cyclically adjusted price-earnings ratio
CAR	Cumulative abnormal return of the bidder's stock over the eleven-day window around the bid announcement (i.e., from $t = -5$ to $t = +5$ for a bid announced on date t = 0). Abnormal returns are the realized returns deducting the CRSP value-weighted returns multiplied by the firms equity beta. Outliers are dropped by trimming the final distribution of CARs at the 0.5% level in each tail.
$cash$	A binary variable taking value of 1 if the main payment (more than 50%) is in cash.
cay	log consumption - wealth - income ratio constructed by Lettau and Ludvigson using the aggregate consumption, aggregate wealth and aggregate income. Data is available on Lettau's website.
$CFOdisagree$	Standard deviation of CFO forecasts each quarter
$CFOforecast$	The average forecasts of CFO for the next ten-year returns on the $S\&P500$.
$consgrowth$	Individual consumption (durable, non-durable and service) growth, data is from BEA National Income Accounts
$dealRsize$	Value of the deal in USD million divided by the bidder's market capitalization in USD million.
$dealval$	Natural logarithm of the bid value in USD million

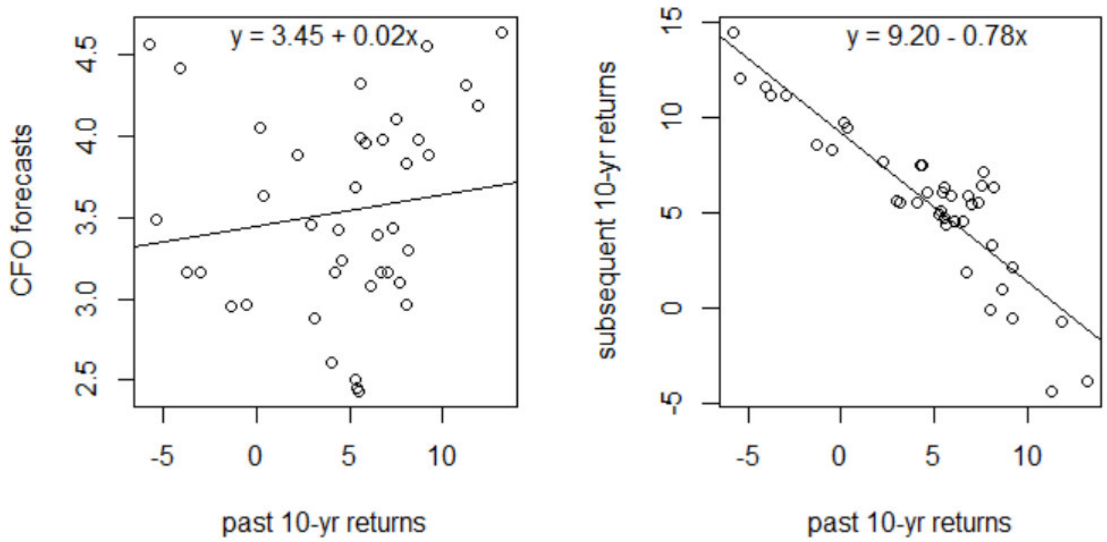
DP	The aggregate dividend-price ratio on $S\&P500$. Dividends are twelve-month moving sums of dividends paid on the S&P 500 index. Data for the construction is from Shiller's website.
DS	Default spread, defined by the difference between the BAA and the AAA corporate bond rate
Eg	Aggregate earning growth computed using data on earnings from Robert Shiller's website.
EP	The earning-price ratio on the $S\&P500$. This ratio is computed by Campbell and Shiller and available on Shiller's website.
$equity$	A binary variable taking value of 1 if the main payment (more than 50%) is in stock.
$infl$	CPI index
$Inpro$	The industrial production index (in log).
$last10ret$	The average excess returns on the S&P 500 in the last ten years
$lastret$	The excess returns on the S&P 500 in the last twelve months
ltr	long-term corporate bond returns
$multibidder$	A binary variable taking value of 1 if there are more than one bidders.
$ntis$	The ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks
$sameSIC3$	A binary variable taking value of 1 if the bidder and the target share the same last three digits of the SIC code.
$TargetSalegr$	last-year sale growth of the target's industry
$STRfree$	Short-term US treasury notes and certificates
$recess$	an NBER indicator of recession.
$Rfree$	10-year Treasury bond yield.
$T.BM$	Average Book-to-market ratio of the industry that the target operates in.
$T.RA$	Average return on total asset of the industry that the target operates in.
$T.CA$	Average free cash-flow on total asset of the industry that the target operates in.
$T.DA$	Average long-term debt on total asset of the industry that the target operates in.
$T.DEA$	Average depreciation on total asset of the industry that the target operates in.
$Unemploy$	US unemployment rate, data is from St Louis Fed website.
var	S&P 500 stock return variance

Figure 1: Managers' forecasts and subsequent realized returns



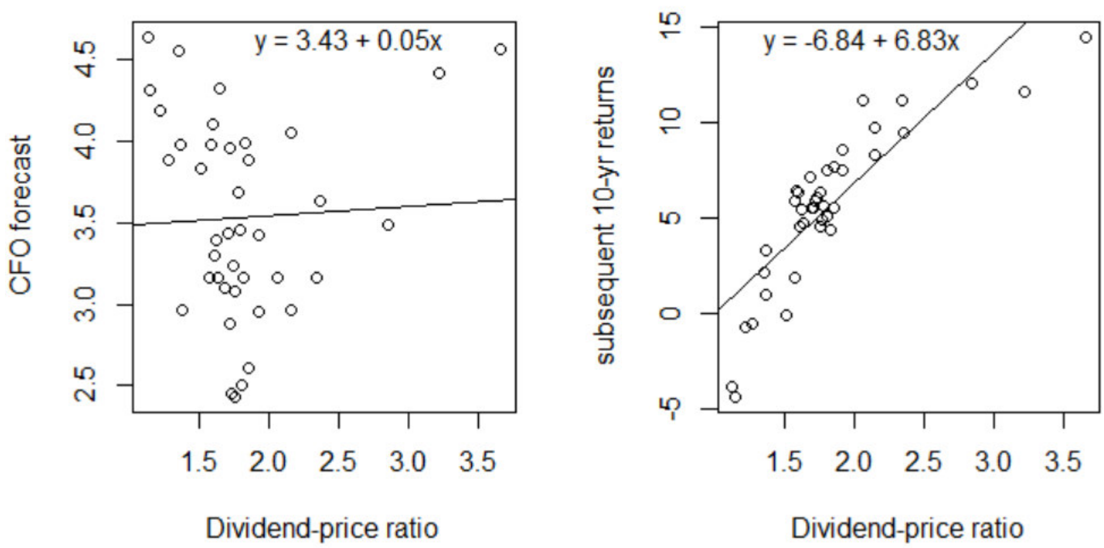
Subsequent ten-year annualized realized returns (2010Q2 - 2021Q2) are plotted against the corresponding managers' forecasts (2000Q2 - 2011Q2).

Figure 2: Past 10-year returns, managers' forecasts and subsequent realized returns



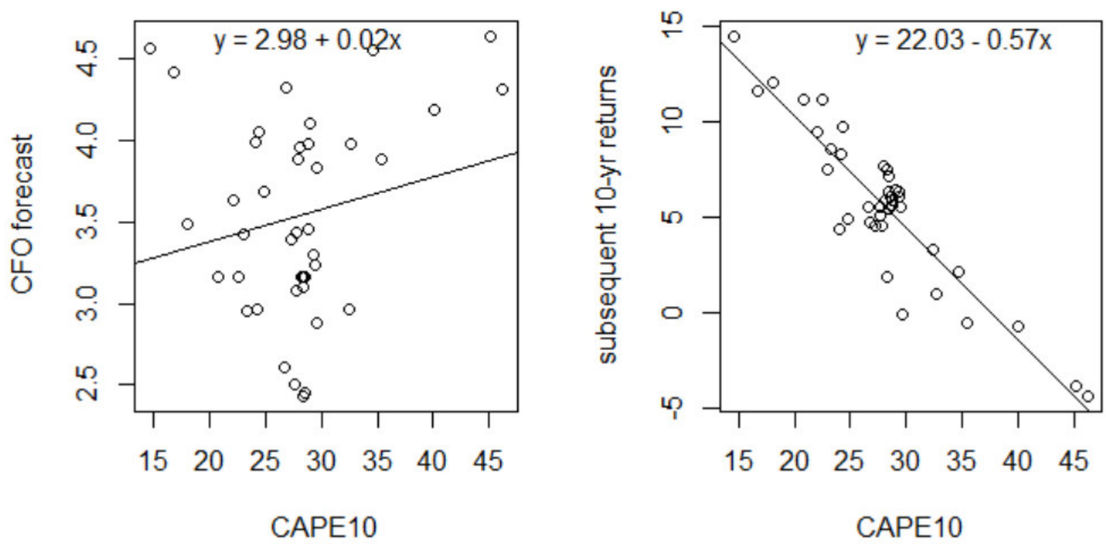
This figure contrasts how managers' forecasts (2000Q2 - 2011Q2) and subsequent realized returns (2010Q2 - 2021Q2) depends on the last ten-year returns.

Figure 3: Dividend-price ratio, managers' forecasts and subsequent realized returns



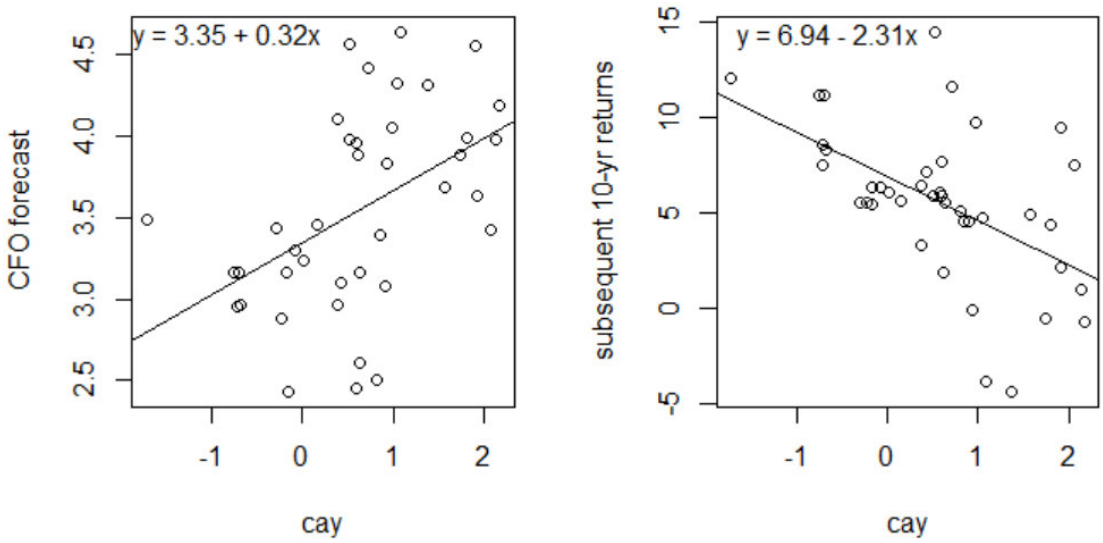
This figure contrasts how managers' forecasts (2000Q2 - 2011Q2) and subsequent realized returns (2010Q2 - 2021Q2) depends on the current dividend-price ratio.

Figure 4: CAPE10 ratio (Campbell and Shiller (2001)), managers' forecasts and subsequent realized returns



This figure contrasts how managers' forecasts (2000Q2 - 2011Q2) and subsequent realized returns (2010Q2 - 2021Q2) depends on the current CAPE10 ratio (Campbell and Shiller (2001)).

Figure 5: cay (Lettau and Ludvigson (2001)), managers' forecasts and subsequent realized returns



This figure contrasts how managers' forecasts (2000Q2 - 2011Q2) and subsequent realized returns (2010Q2 - 2021Q2) depends on the current value of cay (Lettau and Ludvigson (2001)).

Abstract

This thesis contains three chapters that study different aspects of the implications of return predictability for portfolio allocation and corporate decisions. The first chapter provides a review of the literature on the topic of return predictability. The second chapter uses the experimental method to study how investors form expected returns when they have access to useful information besides the history of returns. This chapter also aims to relate ones' expectations of returns to their investment decisions. The third chapter shows that managers' biased expectations of returns and their reliance on the CAPM model may lead to inefficient investment decisions.

Keywords: Return Predictability, Expectations Formation, Long-Term Investment, Extrapolation, Model Uncertainty, CAPM, Capital Budgeting, Inefficiency, Stock Market Expectation.

Résume

Cette thèse contient trois chapitres qui étudient différents aspects des implications de la prévisibilité des rendements pour l'allocation de portefeuille et les décisions d'entreprise. Le premier chapitre présente une revue de la littérature sur le thème de la prévisibilité des rendements. Le deuxième chapitre utilise la méthode expérimentale pour étudier comment les investisseurs forment les rendements attendus lorsqu'ils ont accès à des informations utiles en plus de l'historique des rendements. Ce chapitre vise également à établir un lien entre les attentes de rendement des individus et leurs décisions d'investissement. Le troisième chapitre montre que les attentes de rendement biaisées des gestionnaires et leur recours au modèle CAPM peuvent conduire à des décisions d'investissement inefficaces.

Mots clés: Prévisibilité des rendements, Formation des attentes, Investissement à long terme, Extrapolation, Incertitude du modèle, CAPM, Budgétisation du capital, Inefficacité, Anticipation du marché boursier.