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A mia madre

E alla sua incorreggibile testardaggine nel credere in me.

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Chapter 1

General Introduction

"*In 2000 I thought that most people I met, from all walks of life, were puzzled over the apparently high levels of the stock market. It seemed very unsure whether the market levels made any sense, or whether they were indeed the result of some human tendency that might be called irrational exuberance. [...] Lacking answers from our wisest experts, many are inclined to turn to wisdom of the markets to answer our questions, to use the turns of the stock market as fortune tellers use tea leaves. But before we assume that the market is revealing some truth about this new era, it behooves us to reflect on the real determinants of market moves and how these market moves, in their effects, filter through the economy and our lives.*"

(Irrational Exuberance, Shiller, p. 9-10)

Macroeconomic theories have traditionally been tested using field data, while a recent and growing body of literature has resorted to experimental methods to address macroeconomic questions. On the one hand, changes in macroeconomic modelling towards more micro-founded models and the tendency to abandon the representative agent paradigm favoured the use of controlled laboratory experiments with paid human subjects. On the other hand, however, the recursive structure of equilibria arising in widely used dynamic stochastic general equilibrium models constituted a challenge for experimental testing. This complexity was overcome by experimental designs simplifying the macroeconomic environments to their essence. By doing so, experimental methods could shed light on important macroeconomic questions which otherwise would be difficult to be address with field data, ranging from the assessment of underlying microeconomic assumptions to validation of models predictions, from macro-coordination problems to equilibrium selections in models featuring multiple equilibria.

The potential of laboratory tests to study self-referential dynamics revealed to be particularly appealing in asset pricing theory, where expectations of future endogenous variables played a critical role in the determination of the current values of the same endogenous variables; in other words, beliefs affect prices which in turn, affect beliefs which affect prices, and so on and so forth. Since early contributions in asset pricing theory, a common assumption adopted to get around with the self-fulfilling feature was endowing agents with fully rational expectations. The controlled environment of the lab proved to be ideal since the experimenter could control the data generating process avoiding confounding effects present in field data, and could reproduce a framework where these feedback loops were at stake, while monitoring expectations dynamics.

This dissertation covers topics of research in the area of experimental macroeconomics, in particular in the field of experimental asset pricing. First, the literature related to consumption-based asset pricing à la Lucas (1978) is surveyed, with a focus on the literature that, by abandoning the full rationality assumption, can match empirical features of asset prices, such as asset returns predictability, equity premium and excessively volatile returns. From a methodological point of view, laboratory experiments emerge as a well suited tool to explore expectational feedback loops into prices. Using the latter as a starting point, the two consecutive chapters aim at providing a convincing explanation to two observed asset price patterns: the cyclicality of asset market booms and busts (chapter 3) and the sources of asset price volatility (chapter 4).

A survey of the consumption-based asset pricing literature constitutes the second chapter of this thesis. The Lucas (1978) model has been the fulcrum of modern asset pricing theory in the last forty years. By relating intertemporal investment and consumption decisions, equilibrium asset prices are determined as shadow prices in a no-trade equilibrium. Notwithstanding becoming a benchmark for the later literature, the Lucas (1978) model failed to predict the observed asset prices patterns. This review considers methodologically very different contributions that, by relaxing the model assumptions, can provide theoretical, empirical or experimental explanations to peculiar price behaviours, including cyclical deviations from fundamentals (so called *bubbles*) and asset price volatility patterns. Central to the analysis of the related literature is the abandon of the full rationality assumption. Relaxing this assumption appeared to be the most promising way to understand price patterns, especially when individual expectations emerged as a key driver of prices in a vast body of experimental and behavioural literature, starting from the pioneering work of Smith et al. (1988). These self-reinforcing price-beliefs dynamics have been incorporated in the adaptive learning literature that, on the one hand, relaxes the rational expectation assumption by introducing the concept of internal rationality and, on the other hand, borrows from the experimental and behavioural findings on adaptive expectations formation to shed light on observed price patterns.

The third chapter examines the cyclicality of asset market booms and busts in an experimental framework. A newly defined experimental set-up is designed to test an extended version of a consumption-based asset pricing model à la Lucas (1978) where expectational feedback loops are central for obtaining the cyclical pattern of asset prices, as in Adam et al. (2014). In line with recent experimental contributions by Crockett and Duffy (2013) and Asparouhova et al. (2016), I bring to the lab an infinite horizon stationary economy, that, given the practical limitations, is approximated by indefinite horizon with constant continuation probability. During the experiment, participants are asked to trade a storable asset on a competitive market and their expectations about future returns of the asset are elicited. On the one hand, the individual intertemporal asset allocation decisions affect prices as driven by a consumption-smoothing motive, and on the other hand self-reinforcing price-beliefs dynamics could drive market prices away from the fundamental value of the asset. I provide evidence that, despite the high degree of heterogeneity across experimental sessions, beliefs about the future profitability of the asset can contribute explaining these price deviations. Moreover, more optimistic subjects react to past price increases by demanding more of the asset, hence pushing the price even further away from fundamentals. Finally, a categorization of players according to the way their beliefs are revised hints at weakly cyclical prices in correspondence of a balanced mix of players revising their beliefs in an adaptive manner (*adaptive learners*) and players revising their beliefs in the opposite direction than the market (*contrarians*).

The fourth chapter presents a joint project with Timo Hoffmann aiming at assessing the sources of asset price volatility in a Lucas (1978) framework. By borrowing features of the experimental design specified in the second chapter, a two-treatment-design is defined to study the theoretical sources of asset price volatility. In one treatment, only a volatile stochastic discount factor is accountable for the asset price volatility, while in the other treatment the volatility of payoffs is the only driver of the volatility of asset prices. Aligned with previous implementation of the Lucas (1978) model in a lab, participants trade a perishable asset in a stationary economy for an *a priori* unspecified number of periods and are asked to provide their expectations about future asset profitability, so that expectational feedback is also controlled by the experimenters. We find that market clearing prices are substantially less volatile than the fundamental value of the asset, i.e. *negative excess volatility.* The latter is puzzling since, over a sufficiently long horizon, the price should reflect the fundamental value of the asset and its volatility. This is indeed not the case, as average market clearing prices are co-moving with the state of the world, but less than what the theory would have predicted. Moreover, price volatility in the two treatments does not statistically differ, even though it is slightly higher in the treatment where payoffs are the only source of volatility. The latter could be interpreted as the subjects' difficulty in understanding (or applying) optimal intertemporal trading decisions. Particularly, in the treatment where the stochastic discount factor is accountable for the asset price volatility, the price clears the market most of the times at a value in between the two state-dependent fundamental values and expectations dynamics are shown to display a weak link with individual asset allocation decisions.

Finally, a general remark for the reader of this Ph.D. thesis. All chapters are written as independent essays. Each of them contains its own introduction and appendices providing supplementary materials such as an English translation of the original instructions of the experiments, as well as additional graphs and tables. Hence, the essays can be read in any order of preference. References from all three chapters can be found in one bibliography at the end of this dissertation.

Chapter 2

Asset Price Volatility: A Survey

2.1 Introduction

The behaviour of asset prices has fascinated generations of investors, policy makers and economists, alike. Stock markets display common patterns, including high average returns, volatile and cyclical movements of prices that economists still struggle to understand completely. Moreover, if one considers consumption growth, this is much lower than dividend growth and the two are weakly correlated. These facts raise two important questions for macroeconomists: why are real stock returns so high compared to average short-term real interest rate? And why is the volatility of real stock returns so high compared to the volatility of short-term real interest rate?

The latter two perplexing behaviours are known respectively as the *equity premium puzzle* and the *equity volatility puzzle*. Trying to answer these questions has been at the core of the consumption-based asset pricing literature in the last thirty years. In this survey, I review the theoretical, empirical and experimental attempts to provide an answer to the second question, being aware that its response shed light on the first puzzle too.

In the late seventies, Lucas (1978) developed a consumption-based asset pricing model that became a workhorse for modern asset pricing theory. In a one-good pure exchange economy, a representative agent with standard time separable utility and rational expectations (RE) has to choose how to optimally allocate consumption intertemporally over an infinite horizon. In the model, the stock market risk is measured by the covariance of consumption growth with asset return in excess of the risk free rate, whilst the coefficient of relative risk aversion of the representative investor determines the price of risk. Mehra and Prescott (1985) studied the congruence of Lucas model with the historical US data and found that the average stock return is about seven percent per year, while the the average annual return of the Treasury bills is approximately one percent per year. They show that the difference in the covariances of these returns with consumption growth is not large enough to explain the differences in terms of returns, unless the representative agent is extremely risk averse. This fact is known as *equity premium puzzle,* i.e. quantitatively stocks are not sufficiently riskier than the risk free rate to explain the observed premium.

To understand the second puzzle, instead, possible sources of stock market volatility should be considered. Since prices, dividends and returns are linked via an accounting identity, then if the price of a stock is high today, it has to be the case that either its dividend is expected to be higher tomorrow, or its return to be low between today and tomorrow, or its price is expected to be even higher tomorrow. If one excludes the possibility that asset prices grow *ad infinitum*, then a high stock price today can only be explained by some combination of changing expectations about future dividends and future returns over the infinite horizon. Hence, future expectations are the key for explaining the *equity volatility puzzle.*

Explaining the *equity premium puzzle* in a general equilibrium framework is thus linked to solving also the *equity volatility puzzle.* LeRoy and Porter (1981) and Shiller (1981a) have shown that measures of expected dividends are far less volatile than real stock prices, setting the path for future research on expectations about future returns being pivotal for understanding asset price volatility. Namely, the observed stock prices tended to be often higher than the discounted sum of dividends, the so called fundamentals. For such episodes, Allen et al. (1993) coined the term *"bubble"*. They define a bubble as "*the situation in which the price of an asset is higher than it would be warranted given the fundamentals of the asset*".[1] Although the economic literature is not unanimous on a definition, for the purpose of this review, this is the definition of bubbles adopted hereafter.

The goal of this survey is to study those anomalous price behaviours by having as a reference point the consumption-based asset pricing model à la Lucas (1978). Since the model fails to explain both price deviations from fundamentals and observed asset price volatility patterns, I review the literature that by relaxing its key assumptions, can account for both price and volatility dynamics. I start my analysis by introducing frictions that can help explaining the puzzles: I consider a change of the preference specification (Epstein-Zin preferences and consumption habits), then move to frictions related to the asset markets, by first looking at market incompleteness and then to the presence of trading costs. Nevertheless, the core of the review relates to relaxing the assumption of rational expectations in the light of recent empirical and experimental contributions.

The abandon of the efficient market hypothesis, as originally developed by Fama (1965), gave birth to the behavioural finance literature. The latter explains excessively volatile prices as resulting from non-fully rational behaviours, being those disagreement among agents concerning the fundamental value of the stock, momentum trading or overconfidence. Those models abandon the representative agent paradigm, introduce the behavioural heterogeneity of agents as key element of the modelling framework and stress the central role played by the expectation formation side. Future expectations about market outcomes have been investigated in different streams of literature: the empirical one by means of survey data,

[1] Allen et al. (1993) p. 208.

the experimental one in the field of macroeconomic experiments and in both theoretical and applied adaptive learning approach. The picture emerging from these methodologically different contributions is that investigating future expectations and their feedback into prices is essential for understanding bubble phenomena and asset price volatility. The adaptive learning literature explores further those self-reinforcing price-beliefs mechanisms, by borrowing from the behavioural, experimental and survey data the individual expectation formation dynamics.

The rest of the paper is structured as follows. Section 2 describes a baseline consumption asset pricing model and its fundamental modelling assumptions. Section 3 explores the potential for explaining the two puzzles by relaxing each key assumption, with a particular focus on relaxing full rationality. Section 4 concludes.

2.2 Consumption-based asset pricing: baseline model

Due to its centrality in asset pricing literature, Lucas (1978) asset pricing model is the reference point of the latter analysis. The section describes its main features, focusing in particular on its key assumptions, as relaxing them lead to interesting explanations for the observed *equity premium* and *equity volatility puzzle*.

The original version of Lucas (1978) model is a one-good pure exchange economy with a single agent, interpreted as a representative for a large number of identical consumers, facing an intertemporal investment decision. The agent wishes to maximize a discounted infinite sum of *strictly concave utility functions* (constant relative risk aversion utility functions) by choosing at each point in time the quantities of a consumption good and the asset holdings to be held in the consecutive period. Output is produced via an exogenous production function following a stochastic Markov process and its units are perishable every period. They are perfectly divisible and their ownership is determined every period on a competitive stock market. *Frictionless trading* of the shares ("*trees*") is possible in each period (*complete markets*) and holding the asset entitles the unit mass agent to all output ("*fruits*") produced. Every period the market clears, i.e. all the output is consumed and all shares are held.

Since all individuals have identical constant relative risk aversion utility function (CRRA) over future consumption streams, they want consumption in different states of the world to be similar, as they dislike risk, but they also want consumption at different point in times to be similar, as they dislike consumption growth. In such an environment, the equilibrium price supported is a *no-trade general equilibrium price.* Moreover, if the representative agent's expectations over future consumption streams are assumed to be *rational expectations,* then the market clearing price function implied by the consumer's optimal behaviour will be the same as the price function on which his optimal consumption and portfolio decisions are based. Hence, the price of the asset can be determined by solving recursively the agent stochastic Euler equation.[2] In this stationary framework, aggregate risk is measured by aggregate consumption and the price of an asset reflects essentially both the intertemporal marginal rate of substitution of consumption and risk aversion, i.e. the more desirable is an asset, the higher is its ability to smooth consumption over time and across different states of the world.

To quantitatively evaluate the consumption-based asset pricing model, Mehra and Prescott (1985) compute the risk premium implied by the model pricing equation. They construct an economy replicating the main features of Lucas (1978) model and by looking at US data, they provide empirical evidence of a large differential in the average real yield of the S&P500 and the average yield on short-term debt.[3] The striking finding, afterwards called *equity premium puzzle*, is that the model predicted average yield on equity is, in the largest case, 0.35 percent, in sharp contrast to the 6 percent premium observed in the data. In order to get the latter value, an intertemporal elasticity of substitution of around 10 needed to be chosen, i.e. agents would need to be extremely risk averse for the real equity premium to be observed. This is at odds with previous findings regarding the willingness of agents to substitute consumption between successive years that instead consider the coefficient of risk aversion to range between 0 and 2.

The authors point at some possible ways of solving this puzzle such as introducing heterogeneous agents, non-time-additive separable preferences or introducing features making intertemporal trades infeasible (e.g. contracts with unborns in an OLG framework).[4] These lines of reasoning were indeed pursued in a later asset pricing literature and revealed themselves to be successful in explaining the patterns observed in the data.

In the following, along the line of Kocherlakota (1996), I discuss the literature relaxing the key assumptions of the Lucas (1978) model in the attempt to solving asset pricing puzzles.

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[2] A transversality condition is defined to avoid explosive price paths and market clearing conditions ensuring that all output is consumed and all shares are held are also imposed.

[3] Consumption growth rates are targeted to the mean, variance and serial correlation observed for the US economy in 1889-1978 period, whilst intertemporal elasticity of substitution of consumption is consistent with micro and macro data.

[4] Mehra and Prescott (1985) explicitly state that matching price volatility is out of the scope of the paper.

2.3 Relaxing assumptions

2.3.1 Preferences

In the original version of the Lucas (1978) model, all individuals have CRRA preferences over future consumption streams. From a modelling perspective, these preferences have attractive features as they allow for aggregation, time-consistent planning and they are scale invariant. However, in the specific context of asset pricing they have the drawback to directly link the intertemporal elasticity of substitution with the degree of risk aversion, i.e. the coefficient of relative risk aversion is constrained to be equal to the reciprocal of the elasticity of intertemporal substitution. This implies that, in order to match the *equity premium*, a high coefficient of risk aversion forces the intertemporal elasticity of substitution to be low, that is highly risk averse agents must view consumption in different time periods as being highly complementary.

An alternative utility specification that bypasses this problem and still nests the CRRA preferences is the Epstein-Zin specification. In the generalized expected utility specification, utility today is a constant elasticity function of current consumption and future utility, with intertemporal rate of substitution being separated from the degree of risk aversion. Alternatively said, those preferences can explain the puzzle by allowing intertemporal substitution and risk aversion to be high simultaneously. Bansal and Yaron (2004) resorted to Epstein-Zin time non-separable preferences to solve the *equity premium puzzle*. The change in the specification of the preferences goes hand-in-hand with other peculiar features of the model that are essential to arrive at the magnitude of the premium, i.e. consumption and dividend growth rates processes. Based on empirical evidence, both consumption and dividends have a small persistent expected growth rate component and a fluctuating volatility term which captures time-varying economic uncertainty, i.e. time-varying conditional volatility of consumption. Essentially, news regarding future expected growth rates transmits into persistent large reactions of the price-dividend ratio and determines the risk premium on the asset. Since those reactions positively co-vary with the marginal rate of substitution of the representative agent, large equity premia can be observed. Furthermore, price-dividend ratios are also affected directly by the fluctuations of conditional volatility of consumption (economic uncertainty), as a rise in economic uncertainty leads to a fall in asset prices. This channel is therefore important for capturing the volatility feedback effect; that is news about the returns and news about return volatility are negatively correlated. For parameter values that are in line with Mehra and Prescott (1985) they show that more than the half of the volatility of price dividend ratio is due to the variation in expected growth rates and the other half can be attributed to variation in economic uncertainty.

In contrast to Bansal and Yaron (2004), Abel (1990), Gali (1994) and Campbell and Cochrane (1999) introduce a consumption habit component affecting the curvature of the utility function, hence risk aversion, by modifying the standard CRRA preferences but retaining time-separability. The habit component takes either the form of an individual consumption habit or it depends on the aggregate consumption which is unaffected by any individual's decisions. The latter is known as *catching up with the Joneses* pattern. Abel (1990) specifies the agent utility as a power function of the consumption-habit ratio, where the habit is meant as the aggregate past consumption, i.e. in a representative agent world, the agent's own past consumption level. Holding consumption today and expected consumption tomorrow constant, an increase in yesterday's consumption increases the marginal utility of today's consumption. This makes the representative agent willing to borrow from the future, driving up the interest rate, hence affecting the risk premium. However, these preferences make marginal utility volatile even when consumption is smooth, because agents derive utility also from their recent past consumption levels. By affecting also the expected marginal utility of consumption, the real interest rate is also highly volatile.

Differently from Abel (1990) and Gali (1994), Campbell and Cochrane (1999) solved the equity premium puzzle by producing time-varying risk aversion. In their framework, the representative agent derives utility from the difference between consumption and a time-varying subsistence level (habit level) that evolves over time in response to aggregate consumption following an autoregressive process. The mechanism proposed is aligned with Abel (1990), with the main difference being the presence of an autoregressive component of the habit that forces the agent to smooth gradually to the new level of consumption, creating mean reversion in marginal utility. Moreover, their habit specification allows for precautionary saving motives that make the consumer more willing to save, driving the interest rate up, as uncertainty about the marginal utility increases. If consumption is low relative to the habit component (in a recession), then prices are low relative to dividends. The time variation of risk aversion generates predictable movements in the expected stock returns with respect to the risk free rate that are aligned with Shiller (1981a) findings.

2.3.2 Incomplete markets

In Mehra and Prescott (1985) individuals diversify away any idiosyncratic differences in consumption streams thanks to market completeness. This results into consumption streams that look similar to each other and so does the per capita consumption. Significant examples of the Lucas framework in presence of market incompleteness are Heaton and Lucas (1995) and Constantinides and Duffie (1996). Constantinides and Duffie (1996) find that an equity premium can be observed even with low risk aversion, if heterogeneous agents face different labour income shock realizations. Since labour income shocks are permanent, uncorrelated with market returns and more volatile than market returns, agents cannot smooth consumption by trading with each other. Hence, the equity premium results from the fact that agents are facing a higher risk of low consumption due to low labour income realization when market returns are low.

2.3.3 Frictionless markets

In Lucas (1978) trading happens at zero cost for any amount of available securities. If we introduce borrowing constraints, only few investors could afford trading, i.e. those that are not borrowing constrained. Therefore, when solving the first order condition, one should consider that only per capita consumption of those actively trading should be considered and not the overall per capita consumption growth as in Mehra and Prescott (1985). Borrowing constraints lower the risk free rate by reducing the borrowing side of the market, hence affecting the equilibrium interest rate via market clearing. However, for this effect to be present, a sizeable fraction of agents need to face borrowing constraints both on equity and bond market. If agents are simultaneously borrowing constrained on both markets, then no shift of resources from the bond to the equity market (or vice versa) takes place and such constraint would imply that both the risk free rate would fall in order to clear the bond market in the present of fewer agents trading, with the average stock return also falling as result of the stock market clears. Moreover, for the equity premium to be affected, trading on the stock market would have to be substantially more expensive than on the bond market. In this context, the premium on stock would be a compensation for bearing additional costs, rather than a compensation for risk.

However, using households panel data, Campbell (1993) and Mankiw and Zeldes (1991) show that market segmentation alone cannot explain the equity premium as consumption growth of stockholders co-varies substantially more with stock returns than with consumption growth of non-stockholders. Hence only if stockholders are highly risk averse, they would be marginally indifferent between stocks and bonds, i.e. an equity premium would be observed if consumption only of those involved in trading would be considered.

2.3.4 Rationality

Another key assumption of the traditional Lucas (1978) framework is that agents are rational. The following section reviews the literature that relaxes the rationality assumption focusing first on an early behavioural finance approach.[5] Subsequently, the section analyses the surveys and experimental evidence, finally the adaptive learning literature and the recent development of the internal rationality concept.

2.3.4.1 Behavioural finance

In a rational frictionless economy à la Lucas (1978) the Efficient Market Hypothesis (EMH) by Fama (1965) holds, hence the price of an asset equals its fundamental value. Behavioural finance argues that some features of asset prices could be interpreted as resulting from deviations from rationality and that those deviations are brought about by some forms of non rationality. The EMH lost part of its charm following the publication in early eighties by Shiller (1981b) and LeRoy and Porter (1981) papers on volatility tests. Both of them found that stock market volatility, measured as price variance, is too high to be justified *"in terms of random arrival of new information about the fundamental determinants of price"* suggesting that *"markets are irrational and subjects to fads"*.[6]

An early objection to rational agents due to Friedman (1953) and further developed in De Long et al. (1990) relates to the concept of the of so called *noise traders*. Those agents are irrational investors buying the asset when its price is high and selling it when the price is low. In doing so, they destabilize the market by pushing the price away from its fundamental value. These irrational traders are taking more risk than rational agents (*arbitrageurs*) as they are consistently overly optimistic (or pessimistic). If noise traders are pessimistic about the future prices, they drive the price down and a rational agent buying the asset should

[5] A good compendium of early behavioural finance literature is provided by Barberis and Thaler (2003) in the Handbook of the Economics of Finance.

[6] Shiller (1981b), p.291 and 304.

recognize that in the future noise traders might become even more pessimistic and drive the price further down with the rational agent potentially incurring a loss. Conversely, in the case of bullish noise traders the rational agents need to consider that if they want to buy back the asset, the price at which they will execute the trade might have been pushed by the optimistic beliefs of the noise traders. Because of the unpredictability of noise traders' future opinions, the arbitrage opportunities for rational agents are limited, prices are diverging significantly from fundamental values even when there is no fundamental risk and be excessively volatile.

Shiller (2003) reviews excess volatility in recent behavioural finance works. From a modelling perspective, three are the dominant approaches: *difference-of-opinion*, *feedback trading* and *biased self-attribution*.

The most representative contribution of in the *difference-of-opinion* stream of literature is Scheinkman and Xiong (2003). In their continuous time framework, agents' overconfidence generate disagreement about the fundamental value of the asset, as in Miller (1977). Heterogeneous agents are facing short-sale constraints. When an agent buys an asset, the agent acquires the option to re-sell the asset to other overoptimistic agents. This re-sale option (*"bubble"*) has a recursive structure that causes in each period a significant deviation of the price from fundamentals that is higher, the greater is the divergence of opinion about the return from the security. Similarly to Harrison and Kreps (1978), even small differences in beliefs are sufficient to generate trade, since agents are willing to pay a price exceeding the value of future dividend streams, believing that they will be able to find a future buyer willing an even higher price. In equilibrium, the model generates market prices that are above fundamentals, accompanied by large trading volumes and excess volatility.

On the contrary, DeLong et al. (1990) and Hong and Stein (1999) present *feedback trading* as a key feature to explain asset prices bubbles and excess volatility. Both frameworks are characterized by the presence of a group of irrational traders that pushes the price above fundamentals, reacting excessively to a price increase due to the arrival of positive news. DeLong et al. (1990) model contains three group of traders: passive investors, feedback traders and informed rational speculators. When the rational speculators receive good news and subsequently trade on this news, they speculate that the initial price increase is stimulating asset demand by feedback traders in the consecutive trading period. In anticipation of these additional purchases, informed traders buy even more, driving the price even further away from fundamentals. At the point when feedback traders are willing to buy the asset, the price is already inflated and, foreseeing returns opportunities, rational traders are then selling the asset, stabilizing the asset price. Even if part of the price increase is rational, trading by rational investors destabilizes the market triggering *momentum*. Hong and Stein (1999) instead consider two types of agents: news watchers and momentum traders, i.e. feedback traders. Both types are boundedly rational, i.e. agents are able to process only a subset of the available public information. News watchers forecast prices based on observed private signals of asset fundamentals, but without conditioning their trades on past price changes. In contrast, momentum traders do not observe any signals about fundamentals, but condition their expectations on past price changes basing their forecast on simple functions of past price movements. In particular, their trading strategy is profitable early in the momentum cycle, i.e. shortly after substantial news has arrived to news watchers, whilst when prices overshoot the long run equilibrium price they incur a loss. Information spread among the news watcher is slow and the price reacts slowly to news. For this reason, ideally momentum strategy should be applied whenever a price increase is observed, as this signals the arrival of good news on fundamentals that is not yet fully incorporated into the price. However, a price increase can also be the result of previous rounds of momentum trading. Because momentum traders cannot detect whether or not the news has arrived, they do not know if they are in an early stage of the momentum cycle, hence tend to overreact pushing the price to overshoot fundamentals in the long run. The resulting asset returns are therefore highly autocorrelated and predictable.

Finally, the *biased self-attribution* literature identifies a cognitive bias extensively studied in psychology, i.e. people tend to take into account signals that confirm their beliefs and dismiss contradictory signals as noise. Daniel et al. (1998) introduce a model in which biased self-attribution generates a bubble. If an investor overestimates his ability to identify the significance of existing data that others neglect, then the investor will tend to underestimate forecast errors. If on the other hand the investor is overconfident, in the sense that she overestimates the precision of her private signal, then she would tend to give more weight to her signal relative to publicly available signals. This behaviour causes price overreaction, while the arrival of public signal determines price underreaction. The overreaction correction pattern due to *overconfidence* is consistent with long run negative autocorrelation of stock returns and unconditional volatility exceeding the one corresponding to fully rational agents. Overconfidence is also identified by Odean (1999) as the source of excessive trading, since overconfident agents might trade even when their expected trading gains are not enough to offset the trading costs incurred.

2.3.4.2 Survey data

Early behavioural finance contributions raised quite some scepticism among economists as the resulting behavioural picture seemed rather at odds with the fully rationality assumption. However, the availability of survey data on individual expectations supported the behavioural models and assumptions.

A prominent example of this stream of literature is a seminal paper by Vissing-Jorgensen (2004). Her research provided direct evidence that investor beliefs and actions are important for assessing whether the assumptions made in the behavioural asset pricing models are valid and convincing. Her innovative approach is based on the analysis of individual survey data - the UBS Gallup for US investors - on wealthy investor beliefs from 1998 and 2002, mainly focusing on aggregate stock market expectations. She provides evidence that individual expected returns were at the peak of the market during the dot-com bubble, pointing at the most optimistic agent driving up the demand for the asset, hence its price. The higher the expectations about future returns of the asset, the more the investor is willing to buy it, even though the market was thought to be overvalued. Moreover, investors beliefs on own past performance are consistent with a biased self-attribution and affect their stock holdings. Finally, at odds with the rational expectations models, the data shows a stunning degree of belief heterogeneity that varies across age groups and experience.

Experience emerged as an important dimension affecting investors' expectations and asset allocations as seen in Malmendier and Nagel (2011) and Amromin and Sharpe (2014). The latter, using the Michigan Survey of Consumer Attitudes, shows that investors expectations about future returns are formed extrapolating from recent years realized returns. However, differently from Vissing-Jorgensen (2004), they find that there is no substantial difference between wealthy and less wealthy investors. Moreover, they provide evidence about the procyclicality of expected returns, i.e. when expectations about the macroeconomic conditions are positive, then expectations about future asset returns are also optimistic and perceived economic uncertainty is lower. Together these results imply that a forward-looking Sharpe ratio is also procyclical, and is at odds with the predictions of rational asset pricing models that would imply a countercyclical ratio.

Pattern of expectations that are inconsistent with the fully rational ones are also emerging from the empirical analysis in Bacchetta et al. (2009) and Greenwood and Shleifer (2014). Bacchetta et al. (2009) provide empirical evidence based on a broad set of surveys that the predictability of excess returns goes hand-in-hand with the predictability of forecast errors, suggesting that understanding expectations is crucial for explaining excess returns. Their findings are also supported by Greenwood and Shleifer (2014) that show that future market beliefs tend to be extrapolative and are negatively correlated with expected returns as implied by the asset pricing model. This pattern could be interpreted as rejection of the rational expectation hypothesis *"with considerable confidence"*.[7] By exploiting the time series dimension of survey data about future stock market expectations, regardless of how expected returns are measured, expectations are persistent and positively correlated with the price-dividend ratio. At odds with previous literature, consumption and its growth rate do not seem to have explanatory power for investor expectations.

2.3.4.3 Experimental evidence

An alternative innovative approach that is achieving resounding success is the use of experiments in macroeconomics.[8] For the purpose of this review, this paper will concentrate on experiments studying asset price anomalies and focusing more on those experiments where beliefs are key for the understanding such peculiarities.

While experimental economics had been around since the forties, addressing questions such as the competitiveness of different markets, only in the late eighties, experiments begin to appeal also for studying asset market dynamics. A laboratory seemed to be a perfectly neutral environment where the experimenter had full control of the fundamental value of the asset and could measure the key parameters of theoretical models, like risk aversion, discount factor and beliefs and isolate their contribution to the variability of prices.

For these reasons, it is possible to identify the presence of a *bubble* as a situation in which the price of an asset exceeds the fundamental value of that asset because its current owner believes that he can earn a capital gain by reselling it at an even higher price in the future. The extent of these deviations are measured in experiments via several metrics, including the average bias (difference between the actual price and the fundamental price), total dispersion

[7] Greenwood and Shleifer (2014), p. 2.

[8] For a survey of the laboratory experiments addressing a broad spectrum of macroeconomic phenomena see Duffy (2008).

(sum of absolute value of all differences between actual price and fundamentals), turnover (trading volumes), amplitude (magnitude of all price changes relative to fundamentals) and normalized deviations weighted by the corresponding trading volumes.[9]

The great advantage of resorting to the lab to test asset markets efficiency and the price formation mechanism became widely accepted after the publication of the seminal paper by Smith et al. (1988) (SSW).

SSW's experimental design to study asset market price dynamics remained for a long time the benchmark for a vast literature of experiments trying to provide an explanation for price deviations. The experiment studied the patterns of bubbles and crashes in asset prices in a double auction market where 9 or 12 subjects had to trade an asset for a finite number of periods, either 15 or 30. The number of periods subjects could trade the asset was known ex-ante, as well as the dividend process common to all subjects within one session. Every period the asset paid a random dividend extracted from a uniform distribution with positive expected value. Hence, the fundamental value of the asset for a risk-neutral participant was declining over time. By design, subjects differ only because of their initial cash and asset endowments: some are endowed with relatively more cash and fewer stocks, i.e. in the first period the buyers, while others are endowed with relatively less cash and more stocks, i.e. in the first trading period the sellers.

Even though there is no asymmetric information and the probability distribution of the dividend process is known, substantial trades were observed and the price of the asset initially raised despite a declining fundamental value. The market clearing price pattern displayed three distinct phases: it initially started out below the fundamental value of the asset, then overshooting it around the second to fourth period and crashed reaching fundamentals in the last periods played. This evidence of bubble-crash in the asset market was robust to different time horizons (it is common to 15 and 30 periods living asset) and to both sizes of the markets (it is common to both 9 and 12 participants markets) and it was at odds with rational expectation theoretical predictions that would imply a price tracking fundamentals.

Smith et al. (1988) experimental results appeared to be puzzling and several modifications of their design were performed in an attempt to find an explanation for the price patterns displayed, varying the fundamental value structure (Smith et al. (2000), Noussair et al. (2001) and Kirchler et al. (2012)), the level of experience of participants (Dufwenberg et al. (2005) and Lahav (2011)), introducing forms of irrationality (Lei et al. (2001) and Oechssler et al.

[9]See Stöckl et al. (2010) for a review of bubble measures in experimental asset markets.

(2011)) and long run expectations (Haruvy et al. (2007)).

Smith et al. (2000), Noussair et al. (2001) and Kirchler et al. (2012) try to assess whether high prices compared to fundamentals are related to a particular structure of declining fundamentals, by considering either an asset not paying dividends, i.e. an asset with constant fundamentals or different structure of fundamentals (increasing, constant or decreasing) combined with different structure of the cash-to-asset (C/A) value ratio. Mispricing of the asset appears as a robust finding that Kirchler et al. (2012) associated in the case of declining fundamentals with confusion in the case of declining fundamental value coupled with increasing C/A ratio, as in the SSW framework. Overvaluation of the asset significantly reduces when confusion reduces, i.e. when the stock is defined as *"stock of depletable gold mine"* instead of *"stock"* it is clear to subjects that the fundamentals are decreasing over time, hence prices are tracking fundamentals closer and the typical SSW price pattern is not observed any longer.

In line with the previously highlighted survey evidence, Dufwenberg et al. (2005) find that experience matters for the systematic deviation of price from fundamental pricing of the asset.[10] In fact, even the presence of a small fraction (one third) of experienced players is sufficient to eliminate or substantially reduce asset mispricing, i.e. the more experienced traders are, the more prices tend to closely track fundamental values. However, if the cause of bubbles and crashes is the lack of experience, then it would remain unexplained why in field asset markets multiple bubbles and crashes are typically observed. Lahav (2011) attempts to provide experimental evidence of this fact by designing a long horizon experimental asset market where subjects are asked to trade the asset for 200 periods.[11] If experience mattered for bubbles to disappear, then one would expect that independently of the number of periods played, after few rounds prices should converge to the fundamentals and should not move further away after few consecutive rounds of trade. Instead, Lahav (2011) observed multiple bubbles and crashes which cast some doubts on the external validity of experience as a convergence device to fundamentals. However, those cyclical patterns would be consistent with individual expectations following adaptive dynamics.

An alternative explanation to the price patterns observed is related to some form of irrationality. Oechssler et al. (2011) focus on irrationality à la Shiller (2016), i.e. the spreading of

[10] In this context experience is defined as subjects having previously participated in an experimental market of the same design.

[11] In Lahav (2011) experiment subjects trade the asset on a call market rather than on a double auction as in the SSW design. Despite the different trading institution, Van Boening et al. (1993) show that the market microstructure does not matter for the presence of bubbles, as similar price patterns are observed in both double auction and call markets.

news of a price change spurs traders' enthusiasm and is contagious via person-to-person communication. Essentially, insider's information and communications are potential ingredients for bubble formation. All participants in their framework are experienced of asset markets and they understand the fundamental value of the asset, so both sources of bubble formation analysed before are excluded as possible drivers of price deviation from fundamentals. Rather than communication among players, the presence of informed traders is a key ingredient for the bubble formation, with overconfidence being a driver for a bubble to appear. Overconfident traders are aware of mispricing when it occurs, but speculate on being able to resell the asset at an even higher price. When at least one trader considers the asset to be overvalued, then it is more likely that the bubble is pricked.

Lei et al. (2001) form of irrationality, instead, is related to speculation arising from lack of common knowledge of rationality. If traders are uncertain about future prices tracking the fundamental value because they doubt of the rationality of other traders, then they might expect to earn capital gains whenever they think that there might be irrational traders on the market. A rational trader would then buy the asset even if its price exceeds its fundamental value in anticipation of a gain from reselling it to an irrational trader. The authors do not find convincing evidence that bubble phenomena arise necessarily from speculation. In the beginning of the experiment, participants might be confused about the asset market functioning and their trading decision might *per se* be irrational and this might explain why prices initially overshoot fundamental values. Later on in the experiment, some traders might realize that others might act irrationally and speculation might arise. Through practice, confusion reduces and irrationality may vanish and the information of the change in the environment transmits into the price, i.e. a market crash would make the rationality of participants common knowledge. However, rather than a lack of common knowledge of rationality, rational traders might simply believe that others make small mistakes (instead of being irrational), such as purchasing at prices above the maximum possible dividend stream and selling below the minimum dividend stream and base their trading decisions accordingly.

Hence, a promising way to understand price dynamics relates to exploring the link between future expectations and prices.

In the SSW framework the feedback mechanism of expectations into prices was analysed for the first time by Haruvy et al. (2007). Prior to trading on a call market, subjects were asked to predict market prices in every future period over the periods remaining for trading on that market. Prediction accuracy was rewarded according to a linear rule along with payoffs for the transactions. Despite a clear hedging problem in the sense of Blanco et al. (2010), beliefs elicitation did not affect the qualitative price patterns, i.e. observed prices were aligned with the SSW ones. Interestingly, as the price tracked closer the fundamental value, individual long term price expectations were getting more and more precise and the degree of belief heterogeneity was reducing. However, along this convergence process, individual predictions of market peaks tended to be inaccurate and on average price peaks occurred earlier than predicted. Hence, individuals' price expectations were not unbiased predictors of future price movements, but were useful in predicting future short-term market price movements, despite knowing the entire history of past prices and the true fundamental value of the asset. If traders were to form their expectations in an adaptive manner, past prices would affect their current trading strategy which in turn would affect the trajectory of future prices via a beliefs-price feedback mechanism.

The centrality of beliefs in asset market experiments was the focus of a separate stream of the experimental literature aiming at understanding expectation formation *per se*. Differently from the SSW design, those experiments elicit beliefs about future variables of interest for the purpose of assessing whether the considered theoretical model is robust to expectation dynamics, mostly providing supportive evidence of adaptive learning behaviours. The stream of literature originated from a paper by Marimon and Sunder (1994) highlighting that in designing experiments one has *"to be able to study individual learning rules and to distinguish between learning to forecast and learning to solve intertemporal optimization problem"*.[12] In a rational expectations model, on one side, agents are asked to forecast of a future economic variable (*learning to forecast - LtF*), on the other hand they are asked to take economic decisions (*learning to optimize - LtO*). To reduce the dimensionality of the problem that subjects faced in the lab, those two dimensions have often been kept separate, i.e. participants were asked to either forecast or to take an optimal decision.

Most of the market experiments investigating expectations formation in an asset pricing perspective followed the *LtF* approach: participants were only asked to provide their expectations about the following period price of an unspecified risky asset.[13] Subjects did not know the underlying market equations, they only knew the history of past prices and their own

[12] Marimon and Sunder (1994), p. 134.

[13] The *learning-to-forecast* approach has been widely used also in other macro experiments eliciting expectations, see for example Adam (2007) for inflation expectations and Bernasconi et al. (2009) for expectations about fiscal variables.

past predictions, while a computer program computed the associated aggregate demand for the asset and consequently the market equilibrium price. The simplicity of this experimental design is at the core of a series of experiments conducted by Hommes focusing on expectations dynamics in Lucas asset pricing framework (Hommes et al. (2005), Hommes et al. (2008), Heemeijer et al. (2009) and Hommes (2011)). His experiments explore heterogeneity of beliefs, coordination of expectations and adaptive learning dynamics as source of price deviations from fundamental value and excess volatility. If one considers the market as an expectations feedback system, expectations about past market behaviour influence individual expectations which, in turn, determine current market behaviour. Depending on the type of price expectation feedback mechanism, two types of markets can be distinguished: those characterized by positive feedback and those by negative feedback. In the first case, if many agents were to expect a price increase, then they would buy the asset and this would transmit positively into prices. If subjects were to form their expectations extrapolating from past prices, then the expected price increase would be self-fulfilling and purely-expectations-driven price bubbles could emerge. This is the case for most speculative markets that are demand-driven, like the stock markets. The opposite is true for supply-driven markets, e.g. commodity markets, where the expectational feedback is negative, i.e. an increase in expected price leads to an increase in production, hence a lower realized asset price.

For the scope of this review, this paper will focus only on the positive feedback mechanisms as these are the ones characterizing asset markets. In positive feedback markets, individuals mostly form expectations in an adaptive manner, i.e. when forecasting future prices, they take into account the information provided by past price movements. Trend following behaviours can trigger price bubbles if once observed a small price increase, the future price is predicted to increase even further. This self-reinforcing mechanism drives the price even away from fundamentals, up to a point where the revision of expectations forces participants to realize that the price exceeds the true value of the asset, hence they revise their beliefs along a path of convergence to the fundamental value of the asset. Those price patterns correspond to heterogeneous individual expectations that are on average overly-optimistic at the peak of the market, whilst they tend to converge to a common prediction strategy, i.e. belief heterogeneity shrinks, along the convergence path to reach the fundamental value. Convergence takes place thanks to a learning process that guides an equilibrium outcome that is sustained by the expectation dynamics, as in Marimon et al. (1993).

However, a big methodological caveat of these experiments is that since participants in the experiment are not asked to actively trade, the feedback mechanism that the adaptive learning literature identifies as source of price deviation from fundamentals could not be assessed entirely and it is questionable whether subjects could understand the underlying price process related to rational expectations pricing. On the other hand, Bao et al. (2013) show that when performing both a forecasting and an optimizing task concurrently, subjects tend to forecast without conditioning on their optimal decisions and convergence to the rational expectations equilibrium happens at a slower rate than when participants had to solve only one of the two tasks.

All these experiments, although providing highly influential results, depart in significant ways from the original general equilibrium consumption based asset pricing models à la Lucas mainly because the asset traded was living for a finite number of periods and the economy was not stationary. Those two important peculiarities of the asset market experimental design are abandoned in Crockett and Duffy (2013), Asparouhova et al. (2016), Donini (2016) and Donini and Hoffmann (2016) in favour of a greater proximity to the original theoretical framework. The latter experiments implement a simple version of an infinite horizon general equilibrium consumption-based asset pricing model where income and dividend processes are chosen in line with the SSW design. Differently from the SSW framework, the stationarity associated with an infinite horizon model is induced and time discounting is introduced by proxing it with an indefinite horizon with constant continuation probability. All those features allow to consider the consumption smoothing motive driving asset prices in the model.

With exception of Donini (2016), the asset is traded on a double auction for an *a priori* unknown number of periods. Following Camerer and Weigelt (1993), the infinite horizon economy is converted into one with a stochastic number of periods. Subjects participate in a number of sequences with each sequence being composed of a number of trading periods. Each trading period has a pre-specified length during which subjects can trade the asset on the market. At the end of each period, a random draw determines if there is another period with a constant continuation probability. By choosing this continuation probability, the experimenter defines the average length of a sequence, hence determines the discount factor common to all subjects. In the original Lucas' spirit, asset holdings are carried over from one period to the next, while the dividend is perishable in the sense that it goes out of the economy at the end of each trading period. The fact that the asset becomes worthless at the end of a period (a sort of bankruptcy risk) is a novelty with respect to the SSW design, where the only risk faced by participants is the price risk and the experiment abstracts completely from consumption smoothing rationale for the trading of the asset. Additionally, to ensure the stationarity of the economy, a termination protocol is defined and followed as not to alter the equilibrium price in the last periods played as participants could foresee that the asset could become worthless soon.

The potentiality of these new experimental designs lies in the fact that the core of the mechanism driving asset pricing can be fully explored by monitoring individual consumption, asset holdings and beliefs. Asparouhova et al. (2016) bring to the lab a version of Lucas' model with heterogeneous agents and time-varying private income streams. The longed-lived asset is then a vehicle for smoothing intertemporally consumption, given the exploiting of the price differential between stocks and bonds in the different states. Aligned with the model predictions, agents are able to offset income differences across periods and trade so to have high consumption in high states (when the asset pays high dividends) of the world and vice-versa in low states. The resulting market clearing prices from these individual behaviours co-move with fundamentals, but appear to be excessively volatile in the meaning of Shiller (1981a) and LeRoy and Porter (1981). The authors relate that to a failure of one of the key assumptions of the model, i.e. agents have perfect foresight and their beliefs about dividend and prices are *exactly* correct. In the experiment, participants are told the dividend process, but they would still need to learn about the price process. In a way, beliefs about the price process can be *approximately* correct and still be far from the price process predicted by the Lucas model in line with Adam et al. (2016). This would explain why subjects are able to solve optimally the investment problem and smooth their consumption accordingly, but still make small mistake in beliefs about the price process. Since the price process is endogenous, those little mistakes are then creating a positive feedback.

A similar picture is provided in Donini (2016), bringing to the lab a version of the Lucas model in line with Crockett and Duffy (2013), that mainly differs in the degree of heterogeneity, the market microstructure and eliciting subjects' beliefs about future returns of the asset. In the experiment, subjects are homogeneous with respect to their initial endowments, partly in stocks and partly in cash, whilst being heterogeneous with respect to their homeground beliefs. Risk aversion is induced, similarly to Crockett and Duffy (2013), via a concave payment function for consumption that translates consumption levels into consumption points, hence into monetary payoffs. The participants are asked to solve two tasks, first to forecast the expected return of the asset, then to trade the asset on a call market. Differently from previous implementations of a call market, participants have to indicate price thresholds corresponding to their willingness to buy, to hold and to sell the asset. Demand and supply functions will then be determined accordingly by aggregating the specified individual demand and supply schedules. The novelty of this approach lies in the fact that the self-reinforcing price-beliefs dynamics can be studied, as both future expectations about the asset profitability and trading decisions are observable. The observed trading prices tend to often be above fundamentals and display excessive volatility that can be linked to adaptive beliefs dynamics, as in Asparouhova et al. (2016). Aligned with Crockett and Duffy (2013), the paper finds that individuals are willing to smooth their consumption across states of the world, with more participants with more optimistic future return expectations more willing to buy the asset. However, in both experiments the asset is traded in few occasions at a price below fundamentals, displaying an underpricing that is at odds with asset pricing experiments following the SSW design.

Excess volatility and its sources are studied in more detail in a related paper by Donini and Hoffmann (2016). This experiment is designed to assess whether asset price volatility is driven by a volatile stochastic discount factor or volatile future payoffs. The authors define two treatments where in each of them one of the two sources of price volatility under rational expectations is at place. Similarly to previous lab experiments on the Lucas model, participants are asked to forecast the return of the asset and trade it on a double auction market. The observed market clearing prices are substantially less volatile than the fundamental value of the assets, i.e. negative excess volatility is observed and a between treatment comparison reveals that the realized price volatility arising from volatile payoffs is higher than in the one of a volatile stochastic discount factor. This seems to be related to that fact that it is difficult for subjects to apply a trading strategy which would lead to optimal intertemporal consumption smoothing. The latter difficulty translates into prices co-moving with the state of the world, as in Crockett and Duffy (2013) and in Asparouhova et al. (2016), but way less than the theory would predict.

2.3.4.4 Adaptive learning

Behavioural finance and experimental economics provided a clear evidence that asset price dynamics and excess volatility in a consumption-based asset pricing model are related to the abandoning of full rationality. The rational expectation approach underlying asset pricing model à la Lucas presupposes that agents know the structure of the model and the values of the parameters. This appears to be unrealistic, whilst it seems more natural to assume that agents have only a limited knowledge of the economy (i.e. bounded rationality) and act as econometricians when forecasting the future state of the relevant variables, adjusting their forecasts as new data becomes available over time. Adaptive learning introduces dynamics that are not present in the rational expectations model and provides an asymptotic justification of the rational expectation hypothesis.[14]

In the case of asset pricing, adaptive learning has been shown to be a powerful tool in explaining features of asset prices. Agents in those models are learning about the dividend process (Timmermann (1993) and Timmermann (1996)) or about mean and variance of the stock returns (Branch and Evans (2011)) or are internally rational and learn about price growth rates (Adam and Marcet (2011), Adam et al. (2016) and Adam, Marcet and Beutel (2014)) .

Timmermann (Timmermann (1993) and Timmermann (1996)) argues that adaptive learning can explain predictability of stock market returns and the excess volatility displayed in the data by amplifying the effect of dividend shock to prices. In his framework, agents know the form of the dividend process, but not the true parameter values of the dividend process and they use dividends to predict future prices. If there is positive shock to the dividend and agents estimate the growth rate of the dividend to be above the true value, then the shock to the stock price with learning is unambiguously higher than the rational expectation shock to the stock price. In substance, learning about the fundamentals amplifies the magnitude of the shocks and affects prices volatility and excess returns predictability.

The observed volatility of asset prices is also matched in Branch and Evans (2011). The authors develop a theoretical framework in which the recursive updating of expected returns and conditional variance impact stock prices. Bubbles and crashes emerge as endogenous responses of shocks to fundamentals to which agents adjust their estimate of risk and expected returns. In a period of small shocks to the prices, assets are considered relatively non risky,

[14]See Evans and Honkapohja (2001) for an exhaustive review of adaptive learning models in macroeconomics.

hence their demand increases and this pushes the price well above the fundamental value of the asset, while on the bubble path, the estimate of the risk increases over time. This countervailing effect might contract the demand of the asset until price collapses well below fundamentals and a market crash materializes.

A recent stream of adaptive learning literature spearheaded by Adam and Marcet (2011) that has significant potential in explaining the observed patterns of asset prices has been developed around the concept of *internal rationality.* Essentially the authors decompose the standard rationality requirements into two components: the *internal* and the *external* component. Internally rational agents maximize their discounted expected utility given a dynamically consistent system of subjective probability beliefs about the future variables beyond their control, including prices. External rationality, instead, assumes that agents' subjective probability beliefs equals the objective ones of the external variables (including future market outcomes and fundamentals) in equilibrium. By applying this approach to a simple asset pricing model, they show that the equilibrium asset price is determined by investors' price and dividend expectations next period, rather than by the discounted sum of dividends. In contrast with Timmermann's approach, but in line with Shiller's interpretation, they show that learning about price behaviour affects equilibrium prices, while learning about the discounted sum of dividends does not have any impact on the equilibrium outcome. In this framework, expectations about future outcomes become essential determinants of the current market price (independently of expectations about fundamentals) and this lack of complete market knowledge of the agents is essential for the propagation of beliefs-price feedback.

This new modelling approach of learning is particularly appealing because it is fully consistent with the optimizing agent behaviour, but it gives rise to equilibrium outcomes that differ from the ones under the rational expectations hypothesis and are more aligned with the ones in Lansing (2010). Adam et al. (2014) and Adam et al. (2016) develop models that can explain asset pricing behaviours with agents being internally rational. The first provides an explanation for the cyclicality of asset market booms and busts, while in the second one the model is able to replicate volatility and persistence of the price-dividend ratio and the predictability of long horizon excess returns.

In Adam et al. (2014), asset prices deviate substantially and cyclically from the fundamental value of the asset due to beliefs dynamics in a simple asset pricing model à la Lucas (1978). Imperfect knowledge about the price behaviour has strong implications for equilibrium asset prices as it can temporarily push asset prices away from the fundamental values of the asset and give rise to booms and bust cycles in stock prices that are driven by beliefs dynamics. In an attempt to learn about the process governing the behaviour of capital gains, agents make use of past observed capital gains. This learning process is accountable for feedback between expectations about future capital gains and realized gains and gives rise to momentum in asset prices, i.e. when beliefs about future capital gains are optimistic, prices tend to increase pushed by substitution effects dominating the wealth effect. On the contrary, the price increase comes to a halt when the wealth effect dominates, as too optimistic expectations do not lead to further price increases and investors realize that their expectations are too far from the realized outcomes and revise downwards their expectations, leading to a reversal of the asset price.

Differently from the latter contribution, Adam et al. (2016) develop a simple asset pricing model à la Lucas with time-separable preferences that is able to replicate the observed asset price volatility by allowing for small deviations of future price expectations from the rational expectation ones. In their framework, agents learn about the average growth rate of stock market prices and revise their expectations using a constant gain learning. Asset prices volatility emerges over time from the belief updating process of one-step-ahead expectations, since subjective price expectations contribute to fluctuations in actual prices. Asset prices departure from fundamentals, momentum and mean reversion are sustained from the feedback mechanism generated by the learning dynamics.

2.4 Conclusion

This paper reviews the academic literature on asset price puzzles that developed having Lucas (1978) asset pricing model as the baseline model. By relaxing each key assumption of the model, this paper studies the mechanism driving asset prices away from the fundamental value of the asset and the sources of excessive volatility, focusing in particular on the abandon of the rationality assumption.

In an attempt to solve the puzzles arising in a consumption-based asset pricing model, the earlier literature proposed changes in preferences, incomplete markets and the introduction of transaction costs, whilst more recent streams of literature abandoned the assumption of full rationality. Relaxing the rationality assumption appeared to be the most promising way to explore for understanding price patterns, as soon as individual expectations emerged as a key driver of prices in behavioural finance and in the experimental literature. The latter dynamics have been incorporated in the most recent contributions in the adaptive learning literature that, on one side relaxes the rational expectation assumption by introducing the concept of internal rationality, on the other, borrows from the experimental and behavioural findings on expectations formation mechanism to shed light on observed price patterns.

However, much still remains to be learned also on the instance of recurrent bubbles in different markets and their relationship with individual asset demand and investment decision in a framework with heterogeneous agents. Abandoning the paradigm of a representative agent constitutes, in my view, the next necessary step to bridge the gap between theoretical, empirical and experimental literature. Gaining a deeper understanding on the interaction of individual decision making process and expectations formation can be beneficial for assessing the impact of policy measures affecting the feedback price-beliefs, e.g. the Tobin Tax.

Chapter 3

Can Price Expectations Feedback Generate Persistent Asset Market Booms and Busts? A Laboratory Test

I am particularly indebted to Klaus Adam, Dirk Engelmann, Timo Hoffmann and Stefan Penczynski for fruitful discussions and suggestions. Thanks go also to participants at Macro Brown Bag Lunch Seminar in Mannheim, ESA World Meeting in Zurich and Barcelona GSE Summer Forum.

3.1 Introduction

Asset markets display persistent price movements, where booms are cyclically followed by busts. Both theoretical and experimental literature have been studying bubbles and their causes extensively, though rather little attention has been given to understanding what drives this cyclical behaviour of asset market prices.[1] The workhorse model used in the macro-finance literature to address such issues is the consumption-based asset pricing model introduced by Lucas (1978). In Lucas (1978) framework asset prices are determined as a no trade equilibrium where all agents have rational expectations, correctly forecast future prices and optimally decide their asset holdings so to intertemporally smooth their consumption plans.

Recently the adaptive learning literature has relaxed these requirements by introducing the possibility that agents have imperfect knowledge of the price process, see Branch and Evans (2011), LeBaron (2012) or Adam et al. (2014). The latter presents a simple consumption-based asset price model with heterogeneous agents who hold priors infinitesimally different from the rational expectations priors. Bayesian updates of agents' beliefs about future returns of the asset causes low frequency booms and busts. While investors are improving their knowledge about the behaviour of asset returns, self-reinforcing dynamics might appear as a consequence to expectation feedback into price.

This price-beliefs dynamic is particularly difficult to test by means of field data as it requires assessing how investors' return expectations influence on the one hand the asset demand and on the other hand how expectations are updated in the light of new information embedded in the price. Expectations about the future profitability of an asset (market) have been traditionally proxied by means of survey data, see Bacchetta et al. (2009), Hurd et al. (2011) or Greenwood and Shleifer (2014). Though return expectations can be measured with errors, no causal link between investors' beliefs, individual trading decisions and market outcomes can be assessed via surveys, owing to the lack of control of the information available to each market participant and how information is processed.

To avoid these two critical dimensions, I follow a different path and design a lab experiment. On the one hand, in a lab I have the full control of the information disclosed, on the other hand I can measure individual beliefs. Those two elements are key for studying the theoretical

[1] Hereafter, the term bubble refers to *"the situation in which the price of an asset is higher than it would be warranted given the fundamentals of the asset"* as in Allen et al. (1993).

beliefs-price feedback mechanism that generates asset market booms and busts. I implement a simple version of an infinite horizon consumption-based asset pricing model in line with other recent experimental contributions, additionally eliciting individual beliefs about future returns of the asset. Moreover, in the lab the experimenter can determine the intrinsic value of the asset by choosing the income and dividend process that are faced by the participants in the experiment. A clear definition of the fundamental value of the asset facilitates the study of bubbles (busts) as defined by excessively optimistic (pessimistic) stock valuations reflected by the market clearing price. Furthermore, the lab allows me to draw near to Lucas (1978) model by re-creating a stationary environment where infinite horizon feature is approximated by an indefinite horizon with constant continuation probability.

Experimental economics has studied extensively asset market bubbles, both in finite and infinite horizon model, starting from the early nineties paper by Smith et al. (1988). Their experimental design became the benchmark for several other finite horizon bubble experiments, such as the one by Haruvy et al. (2007) where beliefs about future prices are seen, for the first time, as drivers for bubbles. Infinite horizon asset pricing models, though very popular in theoretical literature, have not been the focal point of interest for experimentalist, if not in recent times. Crockett and Duffy (2013) and Asparouhova et al. (2016) brought the workhorse model of the macro-finance literature, the Lucas (1978) asset pricing model, to the lab to study both intertemporal (e.g. consumption smoothing) and cross-sectional predictions (e.g. equity premium puzzle). Differently from the Smith et al. (1988) design, in the latter studies the original infinite horizon feature of the model is preserved. In their framework, the asset traded lives for an a priori unknown number of periods and its trade affects the individual period-by-period budget constraint. At the end of each trading period, each subject carries over the next (if any) the asset holdings, while the subject's cash balance denominated in experimental currency (Taler) leaks out of the economy, i.e. it is consumed. In Lucas (1978) terminology, the asset represents the *"tree"*, while the Taler are the *"fruits"*.

According to the adaptive learning literature, studying expectations dynamics is crucial for understanding asset pricing persistence, as price expectations feedback are responsible for the cyclicality of asset market booms and busts. Adam et al. (2014) have shown that a simple consumption-based asset pricing model with agents learning about future asset returns can generate bubbles and crashes as endogenous response to waves of optimism and pessimism à la Shiller (2016). In a pure exchange economy where agents have imperfect knowledge of the returns process and interpret differently the information embedded in the price, adaptive learning can induce momentum. Namely, in a boom, agents become optimistic about future asset returns, hence demand more of the asset and have even more optimistic consumption plans. At the peak of a boom phase, return expectations are too optimistic when compared to the realized outcomes, but as soon as the agents notice this misalignment, they start revising their expectations downwards. Consequently the asset boom can come to an end, due to negative price momentum.[2] In this context, a bubble is forming as beliefs are driving the market price far away from its fundamental value, as defined by a Rational Expectation Equilibrium (REE) price.

The aim of this paper is to test experimentally the cyclicality of the asset market booms and busts resulting from these learning behaviours. I propose a new experimental design, where the mechanism highlighted by Adam et al. (2014) can be verified in the lab. I bring to the lab a consumption-based asset pricing model where the expected length of the life of the asset is long enough for participants to experience a boom and a bust phase. Before each trading decision is taken, I elicit participants' beliefs about future returns of the asset so as to observe how agents process the information conveyed by the prices and assess whether learning is taking place.[3] Furthermore, having the full control of the beliefs structure permits, on the one hand, to study the beliefs-price link by relating beliefs to the individual demand and trading decisions, and on the other hand, to focus on the revision of beliefs as a reaction to market price changes. The novelty of this paper is therefore studying the self-reinforcing mechanism from both sides.

In the experiment I find that the market price exceeds the fundamental value of the asset in a substantial number of periods. These deviations can be attributed to beliefs and to a great extent to cross-sectional heterogeneity of expectations that do not vanish over time. The latter comes from a twofold source of heterogeneity: subjects react heterogeneously to observed price changes and adjust their asset demand accordingly (more optimistic subjects demanding more of the asset), but also update heterogeneously their beliefs as a reaction to price realizations. Moreover, it is the case that returns display weak form of momentum whenever adaptive behaviours are balanced with contrarians behaviours. On the contrary,

[2]Similar mechanisms have been proposed in the adaptive learning literature also by Branch and Evans (2011)and LeBaron (2012).

[3]Other experiments in the so called *learning-to-forecast* literature have studied expectation formation, see Hommes et al. (2008). In this experiment, participants were not actively trading, therefore changes in the demand of the assets were not tracked.

mean reversion in returns appears as a limiting case in the session where adaptive learning is not taking place.

In terms of price dynamics, the results are in line with previous experiments that implemented the Lucas model, while the contribution that beliefs gives in explaining asset markets bubbles seems milder in my framework than in Haruvy et al. (2007). The latter might be related to the fact that it is hard for participants to provide return expectations first and think in terms of prices once they have to trade. This issue has been recently pointed out by Bao et al. (2013), where the fact that participants have to perform both a forecasting and a trading task seem to lead to more unstable price dynamics.

The next section describes the key features of the theoretical model relevant for the experimental design. Section 3 presents in detail the experimental set-up, while section 4 discusses the experimental results. Section 5 concludes.

3.2 Theoretical model

In the following, I present a simplified version of Adam et al. (2014), focusing on the features relevant for the design of the experiment.[4]

The core of their model is a consumption-based asset pricing à la Lucas (1978) with heterogeneous agents having time-separable consumption preferences and imperfect information about the asset return process. This endowment economy is populated by I infinitely living agents ($i = 1, 2, 3, 4...I$) trading one unit of a risky asset S_t (stock) on a competitive market. The stock is exchanged at an ex-dividend price P_t and pays a dividend D_t at the beginning of each period.[5] Dividends follow a simple persistent Markov process of the following type:

$$D_t = \begin{cases} D^H \\ D^L \end{cases} \quad with\ M = \begin{bmatrix} p & 1-p \\ 1-p & p \end{bmatrix} \tag{3.1}$$

with $D^H,\ D^L > 0$ being respectively the dividend in the high state (D^H) and in the low state (D^L) and M being the transition matrix where p indicates the probability that in the consecutive period, the state of the world will remain unchanged.

Each agent i is a risk averse utility maximizer who has to choose period-by-period how much to consume (C_t^i) and invest (S_t^i) given her period-by-period budget constraint and

[4] The main simplification consists in having discrete persistent dividends, while in the original version of the model dividends are following an AR(1) process.

[5] Time sub-index always indicates beginning-of-period variables.

her subjective set of beliefs about the asset returns. Therefore, the individual investment problem can be stated as follows:

$$\max_{C_t^i>0,\, S_t^i\in[0,\overline{S}]} E_t^{\mathcal{P}^i}\sum_{t=0}^{\infty}\delta^t\cdot\frac{(C_t^i)^{1-\gamma}}{1-\gamma} \tag{3.2}$$

subject to

$$C_t^i + P_t S_t^i = (P_t + D_t)S_{t-1}^i + Y_t \tag{3.3}$$

$$S_t^i \geq 0\ \forall t \tag{3.4}$$

$$S_t^i \leq \bar{S}\ \forall t \tag{3.5}$$

$$C_t^i \geq \underline{C}\ with\ \underline{C} > 0\ \forall t \tag{3.6}$$

$$S_{-1}^i\ \ given \tag{3.7}$$

where δ denotes a common discount factor, C_t^i individual consumption at time t, S_t^i the individual stock holdings at time t while S_{-1}^i indicates the individual initial endowment, $Y_t = \alpha D_t$, $\alpha > 0$ an exogenous income proportional to the dividends, $\bar{S}$ the number of outstanding shares, and $\mathcal{P}^i$ indicates the subjective probability measure of each agent i, as in Adam et al. (2016).

Concerning the expectations formation ($\mathcal{P}^i$), each agent is *internally rational* in Adam and Marcet (2011) sense, i.e. taking fully optimal decisions, given her system of beliefs. An internally rational agent forms beliefs about both price realizations and future dividends, i.e. about $\omega = \{P_t,\, D_t\}_{t=0}^{\infty}$, where $\omega \in \Omega$, element of the space of all possible realizations.

Hence, an agent makes contingent consumption plans subject to a resource constraint of the usual type, a no-short selling constraint, an upper bound on asset holding $\bar{S}$ and cannot consume less than a minimum positive level of consumption $\underline{C}$.

Under the assumption that beliefs are not overly optimistic and intertemporal elasticity of substitution is smaller than one ($\gamma^{-1} > 1$), the optimal consumption plan is uniquely defined.[6] Hence, the individual implicit asset demand function resulting from the optimization problem described is

[6]See assumption 1 in Adam et al. (2014).

$$\left[(S_{t-1}^i - S_t^i) \cdot \frac{P_t}{D_t} + (S_{t+1}^i + \alpha)\right]^{-\gamma} = \delta E_t^{\mathcal{P}^i}\left[\left((S_t^i - S_{t+1}^i) \cdot R_{t+1} \cdot \frac{P_t}{D_t} + (S_{t+1}^i + \alpha) \cdot \frac{D_{t+1}}{D_t}\right)^{-\gamma} R_{t+1}\right] \quad (3.8)$$

where $R_{t+1} = \frac{P_{t+1}+D_{t+1}}{P_t}$ indicates the gross expected return that an agent has at the beginning of time t for the end of period $t+1$. The demand for the asset is a function of the individual stock holdings, the price-dividend ratio and the agent's subjective beliefs about the future profitability of the asset.

Clearly the demand function does not have a close form solution, hence three price thresholds are defined to approximate it: the *sell-all* price P_t^{SA}, the indifference price P_t^{IND} and the *buy-all* price P_t^{BA}. The first price threshold $\left(P_t^{SA}\right)$ represents the lowest price at which an agent is willing to sell all her assets, the middle price $\left(P_t^{IND}\right)$ the inaction point at which she wants to hold her stock endowments, while $\left(P_t^{BA}\right)$ the highest one at which the agent is willing to buy as many assets so as to exhaust her budget. For the derivations of these price thresholds, see Appendix 3.6. Interestingly, these thresholds can be interpreted as proxy for the degree of optimism (pessimism) of an agent at time t about the return of the asset in period $t+1$.

If all the agents entertain the same set of rational beliefs $\mathcal{P}^i$ about the return of the asset, know the beliefs of all other traders, and have full knowledge of the two sources of risks, i.e. the continuation probability δ and the dividend process, then the market clearing price corresponds to the Rational Expectation Equilibrium (REE). Therefore, the above-mentioned infinite horizon investment problem would have the following solution:

$$P_t^{REE} = E_t\left[\sum_{j=1}^{\infty} \delta^j \left(\frac{D_{t+j}}{D_t}\right)^{-\gamma}\right] \quad (3.9)$$

$$= \frac{\delta}{1-\delta} D_t^{\gamma} \cdot E_t\left[\sum_{j=1}^{\infty} (D_{t+j})^{1-\gamma}\right] \quad (3.10)$$

$$= \frac{\delta}{1-\delta} D_t^{\gamma} B \quad (3.11)$$

where B is a constant defined as $B \equiv p \cdot (D^H)^{1-\gamma} + (1-p) \cdot (D^L)^{1-\gamma}$.[7]

In the specific case, the REE price depends on the discount factor, on a constant defined by

[7] See Adam and Marcet (2011) for further discussion on the underlying probability space.

the transition probability of the dividend realizations corrected for the risk aversion parameter and on the same period dividend D_t. Given the dividend structure specified above, two prices are possible in rational expectations depending on the state of the world: one in correspondence of D^L and one of D^H. Similarly, the REE stock return will also be dependent on state of the world.

In the REE, the price of the asset is equal to its fundamental value, so no bubble is taking place. However, if one considers agents doubting that the asset return is constant over time, beliefs dynamics might cause deviation from an REE, hence asset price booms or busts might appear. If agents entertain beliefs about the future returns of the asset deviating from the fully rational outcome, then the market clearing price can deviate from the intrinsic value of the stock. These deviations are shown in Adam et al. (2014) to be dependent on agents' adaptive beliefs, i.e. more optimistic (pessimistic) beliefs might drive the price above (below) the fundamentals. Moreover, if beliefs revision is taking place according to an adaptive rule, then price displays a cyclical behaviour. Unlike rational expectations models, learning can generate endogenously asset market price swings, by associating high values of price-dividend ratio to optimistic return expectations.

The following section describes the experimental set-up designed to test the proposed mechanism in a lab.

3.3 Experimental design

3.3.1 General set-up

The experiment constitutes of one unique treatment composed of rounds and sequences. A sequence is defined by a random number of rounds and it has a stochastic end, whilst each round consists of a forecasting and a trading task. In a round, each participant first forecasts the return of the asset, then decides at which price will buy/ hold/ sell the asset on a computerized market.

At the start of a sequence (at time $t = 0$), twelve participants are endowed with equal initial endowments, made up of 50 units of stock and ($S_t^i = 50 \, \forall i = 1, 2...12$, so $\bar{S} = 600$) and a positive balance of tradable income denominated in the experimental currency, the Taler. Before forecasting the return of the asset, the subjects know the first dividend drawn and the additional income, their initial endowments and the number of stock outstanding, $\bar{S}$. $\bar{S}$

remains constant throughout the experiment.

Dividends follow a simple persistent Markov process, as specified in Section 3.2, where $D^H = 5$ and $D^L = 1$, with probability $p = 0.7$ to be in the same state in the consecutive period and $1 - p = 0.3$ to move to the other state. The income process is proportional to the dividend draw, $Y_t = \alpha D_t$, where $\alpha = 100$. Similarly to Asparouhova et al. (2016), the additional income co-moved with the dividend draw, i.e. income is high-dividend state and *vice versa* for in the low-dividend state.[8]

Below is a description of the structure of one round starting at time t. See figure 3.1.

1. A random draw from a known distribution determines the state of the world, hence the dividend D_t and the correspondent tradable income Y_t for the period starting.
2. Each participant is asked to forecast the expected return of the asset at the end of the consecutive period conditional on an information set ω^t , $E_t^{\mathcal{P}^i}(R_{t+1} \mid \omega^t)$, knowing P_{t-1}, D_t, R_{t-1}, S^i_{t-1} and S^i_t .
3. Participants submit individual demand/supply schedules by specifying three price thresholds: the price at which they are willing to sell all assets they own (P_t^{SA}), the one at which they neither want to buy nor to sell (P_t^{IND}) and the one at which they would like to buy as many assets as they can (P_t^{BA}).
4. After the trading phase ends, aggregate supply and demand schedule are determined via piecewise linear interpolation between the price thresholds. Hence, a market clearing price (P_t) is defined. Given the asset price, the individual stock (S^i_t) and cash holdings can be updated.
5. Consumption points (CP) and forecasting points (FP) can be assigned to each participant. CP are assigned via induced utility method and forecasting points (FP) by means of a scoring rule assigning more points to more precise forecasts. Participants were only informed about their individual CP and FP on a feedback screen, though they were not aware of CP and FP of other subjects taking part in the experiment.
6. The computer determines via a random number if another round in the same sequence takes place. If there is another round, then the there is another round with the same structure for all subjects within a session. If the sequence continued, then another round with an identical structure starts. If there are no further periods the sequence

[8]This should mimic real economy cycles, as dividend are high when economy is in a boom phase and low when we are in a downturn. Moreover, the positive correlation between income and dividend should help participants understanding consumption smoothing across periods.

ends.[9]

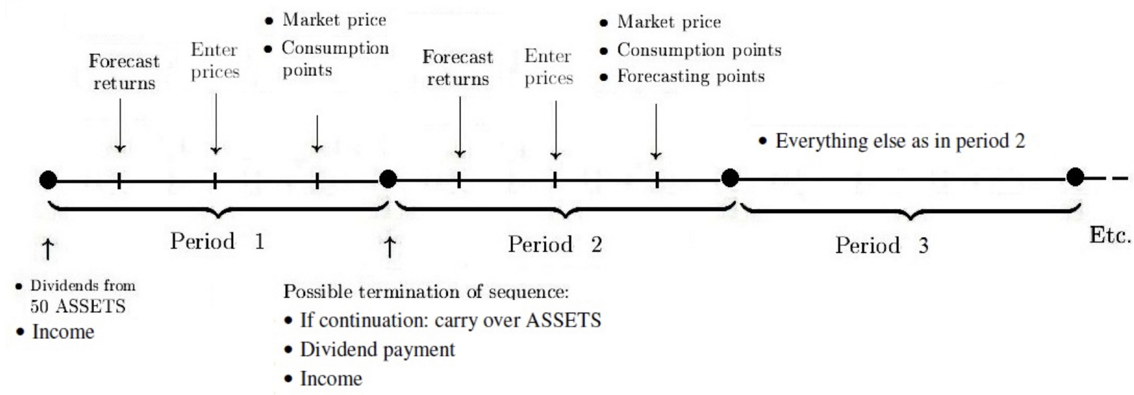


Figure 3.1: Structure of a sequence

3.3.2 Stating the returns expectation

At the beginning of each round, the state of the world is determined, therefore subjects know the cash endowments in experimental currency (Taler) that they have available for trading in that period. The first task they have to perform is forecasting the return of the asset (in percentage) that they are anticipating to realize at the end of the following round, i.e. $E_t^{\mathcal{P}^i}(R_{t+1} \mid \omega^t)$. On one hand, eliciting those beliefs allows me to stay close to the theory, while on the other hand it makes it difficult for subjects to predict the return correctly, as participants need to forecast both the end of period market clearing price and the end of the consecutive period price. To facilitate the task, an intuitive definition of asset returns and some illustrative numerical examples on how to compute the returns were provided in the instructions. See Appendix 3.8 for an English translation of the instructions. Moreover, in line with other asset market experiments, see Hommes et al. (2008), subjects visualize the entire time series of realized returns. In addition to the graphical representation of the realized returns, on the trading screen the entire history of past market clearing prices, dividends and realized returns up to $t-1$ together with their previous round individual asset holdings, S_{t-1}^i , are displayed. Information about other participants' asset holdings or other participants'

[9]Further, there was a protocol in place that ensured that a session did not go over the 2:45 h time limit. After 120 min of the experiment a sequence was put on hold. "*Synthetic*" periods were added to the actually played rounds in which subjects received CP based on their asset holdings at the end of the last played period. No FP could be earned for these synthetic periods. This procedure was explained in the instructions and ensured that subjects' behaviour in later rounds were not distorted because subjects expected the session to end due to time limits.

return expectations are not disclosed, as the information set of each agent includes only her own past predictions, the market price and market outcomes.

Participants' beliefs are incentivised via a scoring function that attributes more points, the closer the individual prediction is to the realized return for the correspondent period. The smaller is the forecast error for each individual prediction, the higher is the number of forecasting points the participant gets. In particular, forecasting points are attributed as follows:

$$FP = max\{20 - f, 0\} \tag{3.12}$$

where $f =\mid E_t^{\mathcal{P}^i}(R_{t+1}) - R_{t+1} \mid$ is the forecast error in percentage terms, i.e. a positive number of forecasting points is associated with individual forecast smaller than twenty per cent, while the maximum number of points (20) corresponds to no forecast error. Since the precision of the forecast cannot be evaluated in the first period of each sequence due to the fact that the first return realizes at the end of the second period played, these rounds were excluded for payment.

3.3.3 Trading the asset

Once participants have entered their predictions for next round return of the asset, they can observe graphically the time series of the market clearing prices and must specify three positive price thresholds. First, the one at which they want to sell all of the assets (*"Sell-all"* point, SA), then the one at which they are indifferent between buying and selling (*"Indifference"* point, IND), finally the one at which they are willing to buy as much as they can given their individual resources (*"Buy-all"* point, BA). The SA price is the lowest price at which a participant is willing to sell all her stocks on the market, the IND price is the one at which she does not want to participate in the market, i.e. neither buying nor selling, while the BA price represents the highest price at which she wants to use all her available cash to buy as many stocks as she can. In other words, the price at which a participant is willing to exhaust all the resources for the current round, that is to use the income she got at the beginning of the round and the dividend paid on her previous round asset holdings to buy stocks, knowing that each round the subject has to consume at least $\underline{C} = 1$.[10] The latter three thresholds define the individual excess demand schedule that, for simplicity, I assume to be piecewise linear with a kink in correspondence of the indifference point. To have consistent demand and supply schedules, participants were asked to enter price thresholds respecting the following ordering: $P_{SA} > P_{IN} > P_{BA}$, i.e. the price participants have to enter at the SA point needs to be at least 0.1 units higher than the one at the indifference point that in turns needs to be at least 0.1 higher than the one at the BA point. In case this ordering was not respected, an error message was displayed on the screen and a new price needed to be specified.[11]

When everyone has specified the extremes of their schedule, a market clearing price can be determined. Since all participants are willing to supply stocks above the maximum indifference price, while above the minimum indifference price everyone demands, then the market clearing price would be between these indifference price thresholds, i.e. $P_t \in (P^{min}_{IN,t},\ P^{max}_{IN,t})$. Given that one can only buy/hold/sell a unit of stock and not fractions of it, multiplicity of market clearing prices is possible with this clearing mechanism. If the price is not unique, then the mean of the prices is considered to be as the one clearing the market. However, it can also be the case that a price clearing the market does not exist as supply and demand schedules do not match exactly. In the latter case, the switching point where excess supply turns into excess demand would be used to determine the market clearing price for the round. At that point rationing of demand (if demand exceeds supply) or of supply (if supply exceeds demand) is taking place, so a rule to specify how to attribute the extra unit available is deemed necessary. The extra units of assets were then randomly assigned to the participants that, at that particular price, had demand for the asset or were willing to supply the asset on the market. This clearing mechanism is close to that used in experimental call markets, see Van Boening et al. (1993). Differently from the other experimental work on testing the Lucas (1978) asset pricing where double auction is adopted, this study follows Haruvy et al. (2007) approach to the market microstructure and implements a call market, as it is better suited for the purpose of belief elicitation.[12] The call market as defined above was programmed in zTree (Fischbacher (2007)).

[10]The lowest value for consumption corresponds to the dividend paid by one stock in the low state of the world.

[11]Tolerance level of 0.1 corresponds to the unit of the grid defined for the interpolation in between the points.

[12]A double auction makes beliefs about future returns more difficult to elicit, since a "period price" is not unambiguously defined. For pros and cons of the two types of clearing mechanisms, see Sunder (1995).

3.3.4 Result of a period

Once a market clearing price P_t was defined, participants were informed about the resulting return of the asset (if the round was not the first of a sequence), their individual end-of-period balances were determined as from their individual budget constraint, their end of period cash and individual stock holdings.

At this point, each individual cash endowment was converted to consumption points and then disappeared from the economy.

In line with Crockett and Duffy (2013), consumption points were attributed via induced-utility method. Using a concave payment function for rewarding consumption decision has a twofold goal: on one side it should facilitate consumption smoothing, on the other it induces risk aversion to those participants that by nature would be risk neutral or slightly risk lover, while making the risk averse participants even further risk averse.

Differently from their approach, consumption values denominated in Taler are converted into consumption points via a CRRA specification, where the risk aversion coefficient (γ) is set to be equal to 0.7. [13]

$$CP = U(C_t^i) = \frac{(C_t^i)^{1-\gamma}}{1-\gamma} = \frac{1}{0.3} \cdot (C_t^i)^{0.3} \tag{3.13}$$

The conversion was explained to participants intuitively in the instructions, both via the formula itself and a table converting the most common Taler values to CP. See Appendix 3.8 for details.

3.3.5 Length of a sequence

In line with previous experiments (Crockett and Duffy (2013) and Asparouhova et al. (2016)) the infinite horizon of the Lucas (1978) model is approximated via indefinite horizon. At the end of each round of trade, a random number is drawn from a uniform distribution between 0 and 1. If the selected number is above 0.972 then the sequence stops. In all other cases, another round is played, i.e. in expectation in 1 out of 36 cases the sequences comes to an end. Should a sequence continue with another round, then the individual asset holdings

[13] A $\gamma = 0.7$ is consistent with Holt and Laury (2002) measure for risk aversion and with an intertemporal elasticity of substitution bigger than one, as required by the model.

are carried over to the next round, while if the sequence ends, the asset became worthless. Since the scope of this paper is to study the cyclicality of asset market prices, an asset has an expected life of 35 rounds, way longer than the above-mentioned experimental papers, where the continuation probability was five sixths. Hommes et al. (2008) have shown that prices in an experimental asset market display a second boom phase around the 40th round played, which should ensure that participants experience at least a boom and a bust phase within the same sequence. This complex procedure is explained to the subjects intuitively by means of a dice example and participants are asked to answer a test question about it before the beginning of the experiment to make sure that they understood fully the constant continuation probability.

Moreover, to be consistent with the original Lucas (1978) framework, stationarity of the economy needs to be ensured. To do so, at the beginning of the experiment it was announced that the experiment lasts until a pre-specified time (i.e. two lecture blocks, approximately 3 hours) and that there would have been as many replications (sequences) of the economy as possible during this time, similarly to Asparouhova et al. (2016). If a sequence ended and more than 30 minutes are left, then a new sequence started. Otherwise it was announced to the participants that the experiment was over. On the contrary, if a sequence was still running by closing time, then the sequence was kept on hold. In order to achieve stationarity, 35 synthetic periods were added to the individual consumption to ensure stationarity of the economy. In case artificial consumption periods were considered, participants were getting credit for their expected consumption in each period, that is the expected income (150 Taler) and expected dividend paid on their individual asset holdings in the last round played. Hence, in case these synthetic periods were to be selected for the final payment, participants received their expected number of consumption points assuming no trade took place from the last round played. Forecasting periods were instead drawn for the periods participants have effectively played.

3.3.6 Subjects' payments

Participants could earn money from both tasks they performed, i.e. from the forecasting task and from trading. Additionally, participants receive a 7 Euro show-up fee. Since both tasks were incentivised as explained earlier in this Section, to the avoid the hedging problems pointed out inBlanco et al. (2010), I randomly selected 10 rounds for payment. Of those, 5 were randomly selected for forecasting and 5 different ones for consumption.

Consumption points, as attributed via induced-utility measure, and forecasting points, as from the scoring rule, were converted into Euro at a unique exchange rate: $1CP = 1FP = 0.15\ Euro$. The exchange rate was computed based on the no-trade average equilibrium for consumption and the average trial sessions forecast error, taking into account that a participant should earn at least 9 *Euro* per hour. On average participants have earned 23 *Euro*.[14]

3.4 Results

The experiment was run in September 2013 in the experimental lab of the University of Mannheim. Five repetitions of the experiment took place, with participants being mostly undergraduate students of the same university. Each session involved 12 subjects with no prior experience of my experimental design (60 subjects in total) and no individual participated in more than one session. Each session lasted approximately 3 hours, including the time reading the instructions and the time for participants to familiarize with the trading interface. Table 3.1 provides details of the five experimental sessions, with each session composed of several sequences of different lengths. In total 13 sequences (313 periods) were played by 60 subjects. The longest sequence was played in the third session, while the shortest one lasted only one period during the first session.

Session	**Number of Sequences**	**Number of Periods (Total by Session, Min within Session, Max)**	**Subjects**
1	4	(66, 1, 52)	12
2	3	(76, 9, 38)	12
3	1	(64, 64, 64)	12
4	2	(57, 24, 33)	12
5	3	(50, 7, 28)	12
Overall	**13**	**(313, 1, 64)**	**60**

Table 3.1: Summary data of all experimental sessions

In the following sections I turn to the analysis of the experimental results, first presenting the overall patterns in market prices and turnover, then analysing the elicited beliefs. For many rounds, the market price is above the fundamental value of the asset, defined as the

[14]On average participants earned a little less than a 27 Euro targeted due to high volatility of the realized returns, that made forecasting a relatively difficult task.

REE price and it is about 3 times more volatile than the fundamental. Mean and dispersion of the expected return distribution can explain a substantial fraction of those deviations, once I control for session and sequence-specific effects. Moreover, heterogeneity in beliefs does not vanish over time, but rather comes as a reaction to past price changes reflected into different individual demand schedule. In such a complex context adaptive learning as suggested by theory seems to take place for a limited fraction of participants. Interestingly, when the fraction of adaptive learners is relatively higher, market price displays a weak form of momentum, as the theory would predict.

3.4.1 Price and quantity dynamics

Figure 3.2 illustrates the time series of the market clearing price and the fundamental value of the asset in each period, in every session. Each panel corresponds to one session, where the transaction price is displayed along with its fundamental value. Since multiple sequences were played in one session, a vertical dashed line identifies the end of a sequence and the beginning of a new one. Despite the similarities with Crockett and Duffy (2013) set-up, undershooting of the fundamentals is observed only in the second session where the market clearing price is half as much as the fundamental value. Instead, it is the case that the asset tends to be overvalued for the majority of the rounds played. Prices exceed fundamentals in the low (41.5 Taler) as well as in the high state (154.8 Taler), though they tend to get closer to the REE price towards the last rounds played, without fully converging to it. The highest transaction price levels are reached in the fourth session, peaking at 1249.5 Taler. Since no short selling was allowed, at this level no trade could occur given the endowments defined in the set-up; the stock was too expensive and no participants could afford buying any unit of the asset. In this regard, trade occurred infrequently and price was not informative of a match between demand and supply. This problem was particularly severe in the fourth session, and for this reason session four is discarded from most of the analysis.

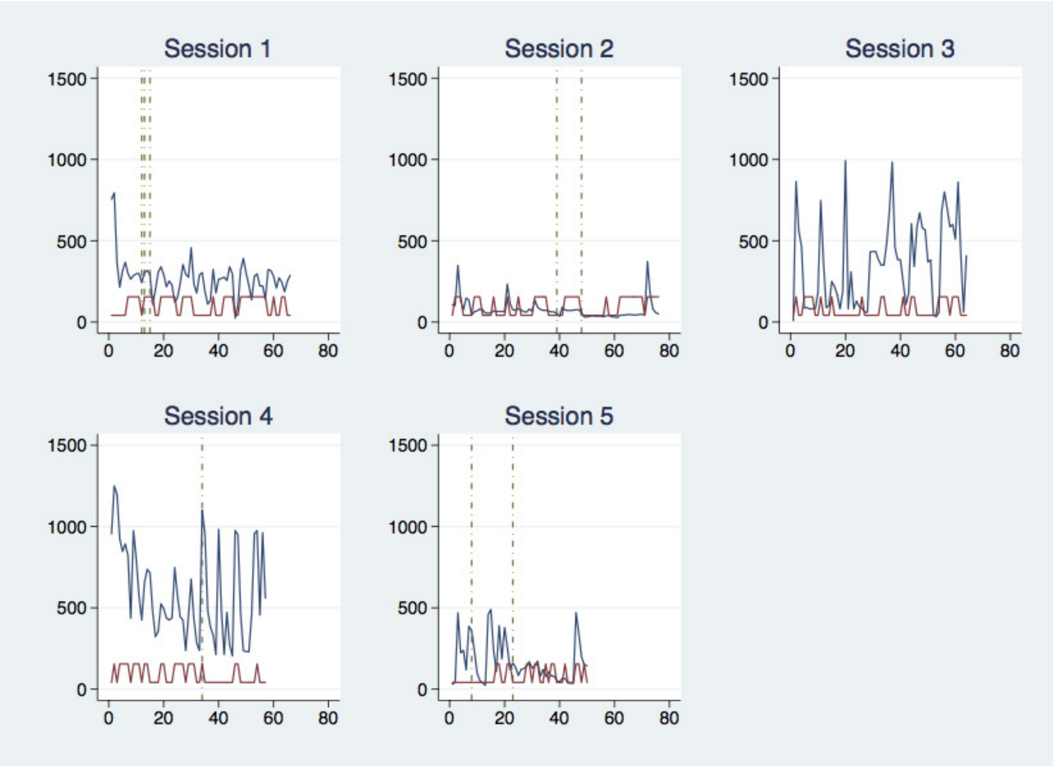


Figure 3.2: Market clearing price and fundamental value of the asset

Market clearing price (blue) and fundamental value of the asset (red). Dashed vertical lines (green) indicate the end of a sequence.

However, the overvaluation of the asset does not correspond to peaks in the quantity exchanged. Since the market price is determined based on the price thresholds each participant enters, it is possible that market clearing occurs at price levels at which no trade can take place, either because stocks are not affordable or because there is no supply at that level. In this sense, the asset is not in a *bubble*, as high prices are not associated with excessive trading, but rather low. Volumes of trade are actually very high for prices close to the fundamental value of the asset or below it, as the market is very liquid. A simple measure of trading volumes is represented by the turnover index, i.e. the ratio of the stocks exchanged over the total outstanding. Figure 3.3 shows the time series of the index for all sessions.

Figure 3.3: Turnover index

Turnover is expressed as number of stocks exchanged over the ones outstanding, expressed in percentage. Dashed vertical lines (green) indicate the end of a sequence.

The magnitude of the asset overvaluation is assessed in Table 3.2. I report by column the average transaction price and fundamental value by sequence, together with the Relative Absolute Deviation (RAD) and the Relative Deviation (RD) as proposed by Stöckl et al. (2010). The last two measures allow the comparison between the extent of the mispricing and the overvaluation (undervaluation) across sequences. The RAD measures the average mispricing by averaging the absolute deviations of the price from the fundamental and rescaling them by the average fundamental value for that session, while the RD measures the overvaluation (undervaluation) of the asset relying on the raw price deviations. In most of the sessions, the two indices point to mispricing as overvaluation of the stock that is diminishing towards the end of the session, without vanishing completely.[15] For example, in the fifth session, the price differs from the average fundamental value by 427%. Such difference shrinks to 238% in the second sequence and drops to 78% in the last session. In contrast, in the second session, the dynamics are reversed, i.e. the transaction price starts close to the fundamentals and

[15] A formal test of convergence of the price to the REE price is presented in Appendix 3.7.1. Strong convergence of the market price to fundamentals is not rejected for the first and the last session in the experiment.

ends halving the REE price. A *t-test* of equality of the market price to the fundamentals at sequence level leads to accepting the alternative hypothesis that the average market clearing price is statistically different from the fundamental value of the asset. In particular the difference between the two is strictly positive (*t = 13.408, p-value: 0.00*).

	Sequence	Number of Periods	Average Price	Average Fundamentals	RAD	RD
Session 1	1	11	386.93	93.04	3.15	3.15
	2	1	242.2	41.51	4.83	4.83
	3	2	311.9	154.88	1.01	1.01
	4	52	246.02	106.91	1.34	1.30
Session 2	1	38	90.48	83.27	0.59	0.08
	2	9	68.82	117.09	0.52	-0.41
	3	29	57.84	100.14	0.59	-0.42
Session 3	1	64	355.44	76.93	3.81	3.61
Session 4	1	33	611.75	106.78	4.72	4.72
	2	24	564.15	60.40	8.33	8.33
Session 5	1	7	215.45	41.51	4.27	4.19
	2	15	229.07	71.74	2.38	2.19
	3	28	127.43	86.04	0.78	0.48

Table 3.2: Measures of mispricing

By column: number of sequences by session and number of periods by sequence, average market clearing price and correspondent fundamental value by sequence. The last two columns contain a measure of mispricing, the Relative Absolute Deviation (RAD) and one of overvaluation, the Relative Deviation (RD). See Stoeckle et al. (2010) for a precise definition of these indices.

Moreover, transaction prices appear significantly more volatile than fundamentals, up to 6 times more. This excess volatility displayed in Table 3.3 is also found in a similar set-up by Asparouhova et al. (2016). A Wilcoxon signed-rank test confirms it by rejecting the null hypothesis of equality of average standard deviations of the market clearing price and the fundamentals (*z = 2.657, p-value: 0.0079*). Similarly to the average price pattern, there is no convergence to the volatility of the fundamentals at the end of a sequence, but volatility seems to be a rather persistent phenomenon.

	Sequence	Number of Periods	Stand. Dev. Price	Stand. Dev. Fundamentals
Session 1	1	11	188.12	56.66
	2	1	0	0
	3	2	6.02	0
	4	52	80.82	56.05
Session 2	1	38	54.88	54.74
	2	9	15.26	53.69
	3	29	64.49	56.73
Session 3	1	64	261.61	52.58
Session 4	1	33	260.24	56.10
	2	24	313.30	42.32
Session 5	1	7	156.05	0
	2	15	151.59	50.27
	3	28	91.02	55.45

Table 3.3: Volatility market clearing prices and fundamentals

By column: number of sequences by session and number of periods by sequence, standard deviation of the market clearing price and of fundamental value by sequence. Volatility of zero corresponds to the case of flat fundamentals.

3.4.2 Beliefs dynamics

At the beginning of each round of trade, beliefs about the future returns of the asset are elicited. In Table 3.4, the mean of the expected returns distribution (third column) and the realized returns by sequence (fourth column) are reported.

In about half of the sequences played (in 7 out of 13 sequences), participants tend to overestimate the return of the asset if compared to the return that realizes in the correspondent round, though as the experiment progresses, their predictions tend to become more precise. On average, though, the average forecast error does not converge to zero, except in Session 1 and 5. A formal test of strong convergence as performed in Bao et al. (2013) reveals that the average expected return converges to the long run expected value of the realised returns for these sessions. In other words, the average forecast error in these sessions shrinks and approaches zero, hinting at a possible presence of adaptive learning dynamics. See Appendix 3.7.1 for an econometric specification of the test.

	Sequence	Number of Periods	Mean Expected Return	Mean Realized Return
Session 1	1	11	3.09	-3.45
	2	1	34.08	.
	3	2	9.5	5.49
	4	52	11.07	18.07
Session 2	1	38	6.15	14.83
	2	9	12.08	18.96
	3	29	50.41	29.74
Session 3	1	64	20.96	200.06
Session 4	1	33	9.95	2.66
	2	24	359.84	29.69
Session 5	1	7	15.89	203.64
	2	15	81.34	131.07
	3	28	59.63	43.13

Table 3.4: Expected and realized returns

By column: number of sequences by session and number of periods by sequence, mean expected returns and mean of the realized returns by sequence.

Moreover, participants' excessive optimism about returns appears to be time-varying. In particular after an unexpectedly high (low) realized return, not only the mean of the expected return increases (decreases), but also the dispersion of the beliefs distribution. The latter is essentially never vanishing, i.e. beliefs heterogeneity is present at every round of trade. In line with previous literature, the degree of beliefs heterogeneity is proxied by the standard deviation of the expected return distribution. As observed in Figure 3.4 a high degree of beliefs dispersion is common to all sessions.[16] Moreover, it rises when the market clearing price is far away from the fundamental value of the asset. On the one hand, high disagreement between participants is associated with high demand for the asset which raises the market clearing price and pushes it further away from the fundamental value. On the other hand, a high degree of beliefs dispersion might provide evidence of an heterogeneous reaction to realized returns. The latter aspects are further investigated in the coming sections.

[16] An extremely high volatility of the realized returns is observed in the third session, though this results from several consecutive rounds where no trade took place.

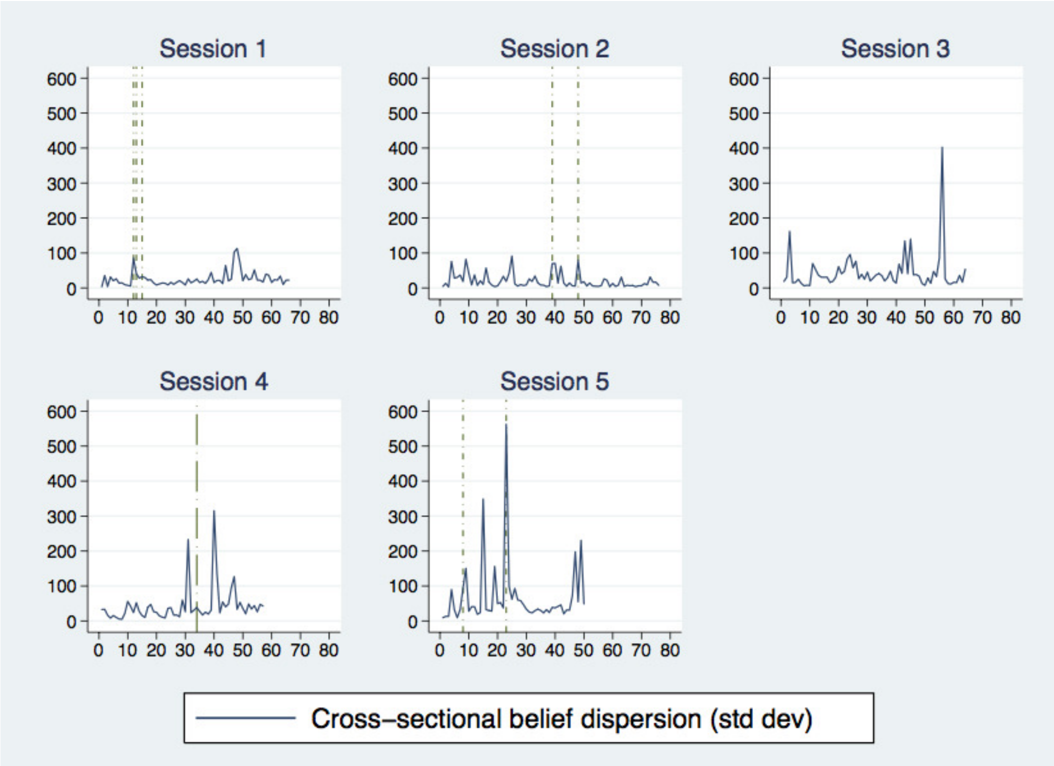


Figure 3.4: Cross-sectional belief dispersion by session

Beliefs heterogeneity by session, measured by the time series of the standard deviation of the expected return distribution (blue). Dashed vertical lines indicate the end of a sequence (green).

3.4.3 Explaining price deviations

As pointed out previously, the price observed on the market deviates substantially from the fundamental value of the asset. Hence, understanding these deviations might shed further light on the nature of the asset overvaluation. Since in the lab returns expectations at individual level are elicited in every round played, it is interesting to consider whether these divergences can be attributed to beliefs. To explore the link between beliefs and mispricing from fundamentals, I run several regression specifications with the time series of the deviation of the market clearing price from the fundamental value (computed at period level) as dependent variable and the mean and variance of the expected returns distribution as independent variables, controlling for sequence-specific effects.

Table 3.5 summarises the results, with each column corresponding to a different specification. First, I consider a specification where the sequence dummies are the only regressors, then the set of regressors is enriched by including the average expected return for the the correspondent period (second column), then the dispersion measure is included (third column), and finally both moments of the expected return distributions are included (fourth column).[17] Due to a substantial degree of mispricing from fundamentals across sessions, a high fraction of the deviations is explained by the time dummies, as acknowledged by an R-squared of 0.47 in the first specification. Once the mean and the variance of the expected returns distribution are inserted as independent variables, then the goodness of fit improves till about 0.50, i.e. even in the presence of big differences across sessions, beliefs seem to have some explanatory power. Aligned with theoretical predictions, the deviations from fundamentals are increasing when beliefs are more optimistic and more dispersed. This relates to the fact that more optimistic participants might want to increase their stock endowments, therefore demand more of the asset. Since stocks are in fixed supply, then demand will push the price up, further away from the rational expectations outcome. Moreover, when the beliefs are more dispersed, i.e. there is disagreement about the profitability of the asset, then price divergence from fundamentals increases. Dispersion of beliefs seems to matter more than the degree of optimism, as confirmed also by smaller values of both information criteria, Akaike and Bayesian, in correspondence of the third specification, indicating it as sightly more preferable than the others.

	(1) ΔFV	(2) ΔFV	(3) ΔFV	(4) ΔFV
Mean Expectation		0.187^{***}		0.121^{**}
		(0.05)		(0.04)
Stand. Dev. Expectation			0.544^{**}	0.465^{**}
			(0.22)	(0.23)
Sequence dummies	√	√	√	√
Session dummies	√	√	√	√
Obs.	253	253	253	253
R-squared	0.476	0.484	0.491	0.494
AIC	3326.884	3325.040	3321.719	3322.233
BIC	3348.085	3349.774	3346.453	3350.500

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3.5: OLS regression deviation from fundamentals

ΔFV (distance market clearing price from fundamental value computed) regressed on the mean and standard deviation of the expected return distribution controlling for sequence specific fixed effects. Every variable is constructed at period level. Robust standard errors are reported in brackets. Session 4 and the second and third sequence in Session 2 are excluded from the sample.

[17] The sequence dummies are such that the first sequence dummy is one if the sequence corresponds to the first one played in each session and zeros otherwise, the second sequence dummy is one in the second session played and zeros otherwise etc. This allows me to control for the within session trends.

Understanding the source of beliefs heterogeneity emerges as key to explain the overpricing of the asset. The latter can stem from heterogeneity in processing the information embedded in past prices (or returns), so from an individual-specific adjustment of the individual demand schedule, or from an heterogeneous reactions to price changes, hence from an individual-specific adjustment of the beliefs about the future profitability of the asset.

Both elements determining the feedback loop beliefs-prices are considered separately in the following sections aiming at disentangling the two components of the self-reinforcing price dynamics. In Section 3.4.4, to gain further understanding of the belief heterogeneity, I first assess how subjects adjust their demand-supply schedule as a reaction to price changes (beliefs-demand side). Subsequently, in Section 3.4.5, I focus on the individual expectations revision, analysing how beliefs are revised once trading took place (price-beliefs revision).

3.4.4 Explaining beliefs heterogeneity: link beliefs-demand

If theory predictions were verified, one should observe a positive correlation between individual expectations and asset holdings, i.e. more optimistic subjects demand more of the asset at a given price. To explore the relationship between expectations and subsequent trading decisions, I rank subjects in each period according to their expectations on future asset returns, from the lowest to the highest, assigning the mid-rank should two subjects enter identical expected returns. Each participant is ranked in each period played so that larger ranks indicate higher optimism about the return for the correspondent period. This ranking procedure have a twofold goal: providing a measure of optimism that is not sensitive to session specificities, since the range of ranks is constant and extreme outliers would have no effect on mean and standard deviation.

The rank of each subject is considered to connect individual expectations with individual trading decisions to assess first if there is a positive link between beliefs and net purchases, then to study the relationship of beliefs and share holdings, while controlling for sequence-specific effects. The results of these regressions at session level and the pooled ones controlling for sequence specific effects are reported in Table 3.6.

	Net Purchases	Sequence Dummies	Share Holdings	Sequence Dummies
Session 1	0.055^{***}	$\surd$	1.348^{***}	$\surd$
	(0.01)		(0.29)	
Session 2	0.107^{**}	$\surd$	0.575	$\surd$
	(0.03)		(0.35)	
Session 3	0.018	$\surd$	-1.134^{**}	$\surd$
	(0.02)		(0.41)	
Session 4	0.0006	$\surd$	0.342	$\surd$
	(0.003)		(0.28)	
Session 5	0.079^{**}	$\surd$	0.034	$\surd$
	(0.02)		(0.22)	
Pooled	0.0435^{**}	$\surd$	0.1877	$\surd$
	(0.02)		(0.16)	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3.6: OLS regression net purchases and share holdings

Net purchases regressed on the ranking of subjects in the expected return distribution and sequence dummies in the first two columns, share holdings regressed on the ranking of subjects in the expected return distribution and sequence dummies in the third and fourth column. Pooled regressions controlling for sequence fixed effects are reported in the last two rows of the table. Regressions run at period level.

In three out of five sessions considered, the ranking of the beliefs is a significant predictor of net purchases, with more positive beliefs associated with greater net purchases. The pattern is also confirmed at pooled level. If I consider the total share holdings at the beginning of a period instead, the ranking of the beliefs display a positive correlation with the share holdings only in one session in the experiment, hinting at optimistic behaviours in correspondence of those participants with high stock endowments in the first session.

To check the robustness of beliefs as determinants of individual behaviours, a regression where net sales are depending on the ranking in the beliefs distribution is also considered in Appendix 3.7.2. The results suggest that beliefs influence more the buying than selling decisions. The latter asymmetry might be related to the fact that purchases involve anticipation of future resale, while the profitability of a sale, once concluded, is not affected by future returns.

To further investigate the relevance of beliefs on demand, I then consider the relationship between beliefs and the demand schedule participants specified in each trading period. In my set-up, a higher demand for the asset translates into an upward shift of the price thresholds, conditionally on the past prices. In Table 3.7 the results of a panel regression with individual fixed effects are reported, with the three price thresholds as dependant variables. The latter are regressed on the individual ranking of the beliefs, the last market clearing price, the first lag of the respective price threshold, as the price thresholds display persistence over time, the dividend to capture state-specific dynamics and the change in the asset holdings with respect to the previous trading period.

A marginal increase of the individual degree of optimism is associated with an increase in the three price thresholds, although with different magnitudes. Given the way individual demand-supply function is determined, this corresponds to an outwards shift of the schedule, i.e. a relatively more optimistic subject is willing to buy/sell stocks at a higher price. The same type of reasoning can be applied for the reaction to the last market clearing price observed and changes in the asset holdings from one period to the next one. A difference in the magnitude of the reaction between the sell-all and the buy-all price is remarkable and confirms a relatively smaller influence of beliefs on individual sale decisions.

	P^{SA}	P^{IND}	P^{BA}
Ranking Beliefs	2.942**	3.668**	4.805**
	(1.19)	(1.79)	(2.04)
1st lag market price	0.178***	0.317***	0.408***
	(0.03)	(0.04)	(0.04)
1st lag dep. variable	0.359***	0.269***	0.302***
	(0.07)	(0.05)	(0.04)
Dividend	9.589***	11.864***	15.532***
	(2.29)	(2.68)	(3.28)
Asset change	1.166***	2.580***	3.980***
	(0.26)	(0.45)	(0.71)
Individual Fixed Effect	√	√	√
Sequence Fixed effect	√	√	√
Obs	3596	3596	3596
R-squared	0.513	0.525	0.491

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3.7: Panel regression price thresholds

Price thresholds regressed on the average expected return, first lag of the market clearing price, first lag of the price threshold, dividend and change in asset holding, sequence dummies and individual specific fixed effects. Entire sample.

3.4.5 Explaining beliefs heterogeneity: learning

A closer look at the individual data will shed further light into a second dimension of the cross sectional beliefs heterogeneity: the reaction to realized returns. To analyse whether adaptive learning is taking place, I follow Bao et al. (2013) and classify participants according to the way they process the information embedded in the price. Differently from their specification, realized returns are considered as independent variables and not prices, in line with the theory that assumes participants are learning about the realization of the returns rather than prices. For each participant, the two specifications were run as follows:

$$E_t^{\mathcal{P}^i}(R_{t+1}) = R_t^i + \lambda_i(R_t - E_t^{\mathcal{P}^i}(R_t)) \tag{3.14}$$

$$E_t^{\mathcal{P}^i}(R_{t+1}) = R_t + \gamma_i(R_t - R_{t-1}) \tag{3.15}$$

where $E_t^{\mathcal{P}^i}(R_{t+1})$ indicates the expected return of subject i as asked at the beginning of period t for the end of period $t+1$, $E_t^{\mathcal{P}^i}(R_t)$ indicates the expected return of subject i had at the beginning of period $t-1$ for the end of period t, while R_t, R_{t-1} stands for the realized return respectively at time $t$and at $t-1$.

For each subject I estimate the learning specifications and assign a type to each participant in the experiment depending on the model with the highest explanatory power. A subject can therefore be considered an adaptive learner or following a trend extrapolating rule. In the latter case, the participant will be considered: a contrarian if $\gamma_i < 0$ or a trend follower if $\gamma_i > 0$ or '*Other*' should the coefficients of both specifications not be statistically significant. Results follow in Table 3.8, where each cell contains the number of subjects per type and the last column contains the observed autocorrelation of the realized returns, as a measure of cyclicality of asset returns.

	Adaptive learner	Trend follower	Contrarian	Other	Autocorrelation Realized Return
Session 1	4	2	4	2	0.073
Session 2	0	6	0	6	-0.152
Session 3	1	5	1	5	-0.065
Session 4	1	5	3	3	-0.161
Session 5	3	2	4	3	-0.089

Table 3.8: Categorization of participants and autocorrelation of returns

Categorization of participants by type for each Session and corresponding autocorrelation of the realized returns.

Though no causal inference can be drawn from this classification of individuals according to the reaction of their expectations to past realized returns, a balanced mixed of adaptive learners and contrarians is associated with a weak form of momentum. On the contrary, if one excludes the fourth session, as earlier in the analysis, the absence of adaptive behaviours is associated with a limiting case of mean reversion. In line with the findings by Bao et al. (2013), the price seems to be more stable, the more subjects follow adaptive behaviours, hence it is easier for participants to predict future returns. In my set-up this would correspond to realized returns that are positively autocorrelated, i.e. a high return in the past would be an indication of future returns moving in the same direction. In particular, it is interesting to note that in the first and the fifth session strong convergence of beliefs to their long run equilibrium is also observed. However, given that the latter pattern occurs only in two of the sessions, more replications of the experiment would be required to prove the robustness of this phenomenon.

3.5 Discussion and Conclusion

This paper presents a new experimental design for testing the cyclicality of asset market booms and busts. In line with recent experimental contributions bringing the Lucas (1978) model to the laboratory, I design an experiment where the price feedback mechanism emerging in a consumption-based asset pricing by beliefs dynamics can be studied. Both the beliefs-demand side and the price-beliefs side can be analysed in a set-up that combines the previous experimental literature of the *learning-to-forecast* with the *learning-to-optimize*.

My results show that the market price tends to deviate from the the fundamental value of the asset. Despite the high heterogeneity across experimental sessions, beliefs can account, even though marginally, for those deviations. Unlike theoretical predictions, market returns are rarely cyclical, but rather tend to display mean reversion. Weak cyclicality is displayed in sessions where the fraction of participants revising their expectations adaptively is balanced with respect to those revising their expectations as contrarians, whilst mean reversion seems to be associated with a limiting case where no adaptive subject was classified.

The contribution of beliefs in explaining price deviations from fundamentals seems, however, rather mild when compared to finite horizon experiment, as Haruvy et al. (2007). To a certain extent, this might be related to a higher complexity of my experimental set-up resulting from bringing to the lab Lucas (1978) model, preserving all its main features so as to study price-beliefs feedback. Moreover, as pointed out by Bao et al. (2013), when participants have to perform both an optimization and a forecasting task, i.e. when *learning-to-forecast* and *learning-to-optimize* set-ups are combined, the observed price dynamics are relatively more unstable than when they are asked to solve either one or the other task. The latter issue might be even more severe in my experimental design since subjects have to think in two different measurement units: first think in returns (while forecasting), then in prices (when trading). Favouring either a *learning-to-forecast* or a *learning-to-optimize* approach, however, would impede the study of the price-beliefs feedback highlighted in Adam et al. (2014).

My experiment provides a first attempt to test experimentally the price-expectation feedback mechanism highlighted in the adaptive learning literature accounting for cyclical deviations of prices from fundamentals. While the proposed experimental design might be functional for testing this mechanism, it might be too complex for some participants, hence leading, in some cases, to trading behaviours that are unrelated to their future return expectations. This could eventually break the link expectations-price, making it generally difficult to observe optimistic beliefs associated with the higher asset demand. Further research is encouraged in the field to confirm these results in a possibly simpler experimental set-up.

3.6 Appendix I: derivations price thresholds

At P_t^{SA}, an agent prefers selling all the stock holdings and consume at time t, to keeping her stock holdings and consuming at time $t+1$. Therefore, in period t consumption is equal to $C_t^i = S_{t-1}^i P_t + (\alpha + S_{t-1}^i) D_t$, while consumption in $t+1$ can never be higher than Y_{t+1} . Hence, substituting the latter into the first order condition and using the definition of expected return, P_t^{SA} can be derived as

$$\begin{aligned} P_t^{SA} &\geq \delta E_t^{\mathcal{P}^i} \left\{ \left[\frac{Y_{t+1}}{S_{t-1}^i P_t^{SA} + \left(\alpha + S_{t-1}^i\right) D_t} \right]^{-\gamma} \left(P_{t+1} + D_{t+1}\right) \right\} && (3.16) \\ &= \delta E_t^{\mathcal{P}^i} \left\{ \left[\frac{Y_{t+1}}{S_{t-1}^i P_t^{SA} + \left(\alpha + S_{t-1}^i\right) D_t} \right]^{-\gamma} \left(\frac{P_{t+1} + D_{t+1}}{P_t^{SA}} \right) P_t^{SA} \right\} && (3.17) \\ &= \left[\frac{1}{S_{t-1}^i P_t^{SA} + \left(\alpha + S_{t-1}^i\right) D_t} \right]^{-\gamma} P_t^{SA} \delta E_t^{\mathcal{P}^i} \left\{ Y_{t+1}^{-\gamma} \underbrace{\left(\frac{P_{t+1} + D_{t+1}}{P_t^{SA}} \right)}_{R_{t+1}} \right\} && (3.18) \end{aligned}$$

$$\left[S_{t-1}^i P_t^{SA} + \left(\alpha + S_{t-1}^i\right) D_t\right]^{-\gamma} \geq \delta E_t^{\mathcal{P}^i} \left\{Y_{t+1}^{-\gamma} R_{t+1}\right\} \quad (3.19)$$

Applying Jensen's inequality,

$$\begin{aligned} S_{t-1}^i P_t^{SA} + \left(\alpha + S_{t-1}^i\right) D_t &\leq \delta^{-\frac{1}{\gamma}} E_t^{\mathcal{P}^i} \left[\left(Y_{t+1}^{-\gamma} R_{t+1}\right)^{-\frac{1}{\gamma}} \right] && (3.20) \\ \Rightarrow P_t^{SA} &\leq \frac{\delta^{-\frac{1}{\gamma}} E_t^{\mathcal{P}^i} \left[Y_{t+1} R_{t+1}^{-\frac{1}{\gamma}} \right] - \left(\alpha + S_{t-1}^i\right) D_t}{S_{t-1}^i} && (3.21) \\ &= \frac{\delta^{-\frac{1}{\gamma}} E_t^{\mathcal{P}^i} \left[\alpha D_{t+1} R_{t+1}^{-\frac{1}{\gamma}} \right] - \left(\alpha + S_{t-1}^i\right) D_t}{S_{t-1}^i} && (3.22) \end{aligned}$$

P_t^{SA} is then a function of the asset holdings and expectations of future returns, i.e. it can be interpreted as a measure of how pessimistic an agent is at time t about the return of the asset in period $t+1$.

Similarly, the highest price at which an agent is willing to use her entire income in order to buy assets is determined. At P_t^{BA}, an agent prefers to buy stocks today (t) and bring her consumption to its lowest level $\underline{C}$, than consuming in period $t+1$. Consumption in period $t+1$ can never be higher than $C_{t+1}^i = (P_{t+1} + D_{t+1}) \cdot \left[\frac{S_{t-1}^i (P_t + D_t) + Y_t - \underline{C}}{P_t} \right] + Y_{t+1}$. Substituting the latter one with equality in the first order condition we get that

$$
\begin{aligned}
C_t^{-\gamma} &\geq \delta E_t^{\mathcal{P}^i}\left\{\left[\left(P_{t+1}+D_{t+1}\right)S_t^i+Y_{t+1}\right]^{-\gamma}R_{t+1}\right\} && (3.23)\\
&= \delta E_t^{\mathcal{P}^i}\left\{\left[\left(P_{t+1}+D_{t+1}\right)\left(\frac{Y_t-\underline{C}+\left(P_t^{BA}+D_t\right)S_{t-1}^i}{P_t^{BA}}\right)+Y_{t+1}\right]^{-\gamma}R_{t+1}\right\} && (3.24)\\
&= \delta E_t^{\mathcal{P}^i}\left\{\left[R_{t+1}\left(Y_t-\underline{C}+\left(P_t^{BA}+D_t\right)S_{t-1}^i\right)+Y_{t+1}\right]^{-\gamma}R_{t+1}\right\} && (3.25)
\end{aligned}
$$

$$
C_t \leq \delta^{-\frac{1}{\gamma}}\left\{E_t^{\mathcal{P}^i}\left\{\left[R_{t+1}\left(Y_t-\underline{C}+\left(P_t^{BA}+D_t\right)S_{t-1}^i\right)+Y_{t+1}\right]^{-\gamma}R_{t+1}\right\}\right\}^{-\frac{1}{\gamma}} \quad (3.26)
$$

Applying Jensen's inequality,

$$
\begin{aligned}
C_t &\leq \delta^{-\frac{1}{\gamma}}\left\{E_t^{\mathcal{P}^i}\left\{\left[R_{t+1}\left(Y_t-\underline{C}+\left(P_t^{BA}+D_t\right)S_{t-1}^i\right)+Y_{t+1}\right]^{-\gamma}R_{t+1}\right\}\right\}^{-\frac{1}{\gamma}} && (3.27)\\
&= \delta^{-\frac{1}{\gamma}}E_t^{\mathcal{P}^i}\left\{R_{t+1}^{1-\frac{1}{\gamma}}\left(Y_t-\underline{C}+\left(P_t^{BA}+D_t\right)S_{t-1}^i\right)+Y_{t+1}R_{t+1}^{-\frac{1}{\gamma}}\right\} && (3.28)\\
&= \delta^{-\frac{1}{\gamma}}E_t^{\mathcal{P}^i}\left\{R_{t+1}^{1-\frac{1}{\gamma}}\left(Y_t-\underline{C}+D_tS_{t-1}^i\right)+Y_{t+1}R_{t+1}^{-\frac{1}{\gamma}}\right\}+\delta^{-\frac{1}{\gamma}}E^{\mathcal{P}^i}\left\{R_{t+1}^{1-\frac{1}{\gamma}}P_t^{BA}S_{t-1}^i\right\} && (3.29)
\end{aligned}
$$

$$
\begin{aligned}
\delta^{-\frac{1}{\gamma}}E_t^{\mathcal{P}^i}\left\{R_{t+1}^{1-\frac{1}{\gamma}}P_t^{BA}S_{t-1}^i\right\} &\geq C_t-\delta^{-\frac{1}{\gamma}}E_t^{\mathcal{P}^i}\left\{R_{t+1}^{1-\frac{1}{\gamma}}\left(Y_t-\underline{C}+D_tS_{t-1}^i\right)+Y_{t+1}R_{t+1}^{-\frac{1}{\gamma}}\right\} && (3.30)\\
\Rightarrow P_t^{BA} &\geq \frac{C_t-\delta^{-\frac{1}{\gamma}}E_t^{\mathcal{P}^i}\left\{R_{t+1}^{1-\frac{1}{\gamma}}\left(Y_t-\underline{C}+D_tS_{t-1}^i\right)+Y_{t+1}R_{t+1}^{-\frac{1}{\gamma}}\right\}}{\delta^{-\frac{1}{\gamma}}S_{t-1}E_t^{\mathcal{P}^i}\left\{R_{t+1}^{1-\frac{1}{\gamma}}\right\}} && (3.31)
\end{aligned}
$$

Once again, the price P_t^{BA} is also a function of the asset holdings and of the expectations of future returns and dividends, i.e. it can be interpreted as a measure of an agent's optimism at time t about the return of the asset at time $t+1$.

3.7 Appendix II: additional analysis

3.7.1 Expectations convergence tests

Convergence of the average expected return to the long run average of the realized returns is tested following the Section 2.1 of Duffy (2008). The test was run for each session, considering all periods when a realisation of the return was available.

The following AR(1) model is estimated

$$y_{j,t} = \alpha_{j,t} y_{j,t-1} + \beta_j + \epsilon_{j,t}$$

with $y_{j,t}$ being the time series of the average expected return for session j, $y_{j,t-1}$being its first lag and β_j being a session specific constant.

For strong convergence to take place, the estimate of the long run coefficient $\frac{\widehat{\beta_j}}{1-\widehat{\alpha_j}}$ should not be significantly different from the long run average of the REE returns for the session. For weak convergence, instead, $\widehat{\alpha_j}$ needs to be significant smaller than the unit. To note that strong convergence implies weak convergence, but the opposite is not true.

The table below report the long run average of the returns in the rational expectation equilibrium and the p-value of the test having as a null hypothesis that the long run estimate of the average expected returns is equal to the long run average of the realised returns. In other words, under the null the average forecast error should tend to zero.

	$\widehat{\beta}$	$\widehat{\alpha}$	Long Run REE Returns	P-value	Strong Convergence
Session 1	6.456	0.342	1.177	0.001	$\surd$
Session 2	13.213	-0.025	1.248	0.108	-
Session 3	21.237	-0.005	1.383	0.126	-
Session 4	164.977	-0.150	1.314	0.280	-
Session 5	39.354	-0.002	1.381	0.047	$\surd$

Table 3.9: Test of convergence to REE return

By column: long run average of the REE return, p-value of the test and strong convergence check.

3.7.2 Beliefs as determinant of selling decisions

In Table 3.10 the results of a linear regression of ranking of subjects in the expected return distribution on the net sale of the assets in the correspondent period are summarised. The sign of the relationship is correct, though the effect appears to be insignificant at session level, while a pooled regression indicate a small negative correlation between selling behaviours and the degree of optimism of subjects.

	Net Sales	Sequence Dummies
Session 1	-0.017	$\surd$
	(0.03)	
Session 2	-0.149^{**}	$\surd$
	(0.73)	
Session 3	-0.069	$\surd$
	(0.04)	
Session 4	-0.008	$\surd$
	(0.008)	
Session 5	-0.090	$\surd$
	(0.05)	
Pooled	-0.077^{**}	$\surd$
	(0.029)	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3.10: OLS regression net sales

Net sales regressed on the ranking of subjects in the expected *return* distribution and sequence dummies by column. Pooled regressions controlling for sequence fixed effects are reported in the last two rows of the table. Regressions run at period level.

3.7.3 Categorizations of players: estimation of forecasting strategies

Players are assigned a category depending to the forecasting rule that better fits (higher R-squared) their forecasting strategies as illustrated in Section 3.4.5. In case the coefficients of chosen specification are not statistically significant, the alternative specification is preferred. The reported coefficient indicates the estimated value of $\widehat{\lambda_i}$ if should a subject's forecasting rule be the adaptive rule specified in Equation 3.14 or of $\widehat{\gamma_i}$ should the subject's forecasting rule be the extrapolative one specified in Equation 3.15. If neither $\widehat{\lambda_i}$ nor $\widehat{\gamma_i}$ is statistically significant at least at 10 percent level in none of the two specifications, the subject is assigned to the 'Other' category.

	Participant	Coefficient	P-value	R-squared	Type
Session 1	1	0.244	0.000	0.189	A
	2	0.147	0.001	0.194	A
	3	-	-	-	O
	4	0.178	0.001	0.254	T
	5	-0.210	0.055	0.656	C
	6	-0.315	0.057	0.279	C
	7	-0.273	0.002	0.6145	C
	8	0.067	0.030	0.115	A
	9	0.251	0.000	0.258	A
	10	0.142	0.012	0.460	T
	11	-0.278	0.006	0.553	C
	12	-	-	-	O

Table 3.11: Categorization of players Session 1

Categorization of players depending on their forecasting rule in the first Session. By column: the estimated coefficient for the selected forecasting rule, its p-value, the R squared of the selected model and the correspondent type assigned.
In the Type column, A means adaptive, C means contrarian, T trend extrapolation rule, while O means 'other'.

	Participant	Coefficient	P-value	R-squared	Type
Session 2	1	0.060	0.003	0.211	T
	2	0.062	0.088	0.168	T
	3	-	-	-	O
	4	-	-	-	O
	5	0.141	0.000	0.410	T
	6	-	-	-	O
	7	-	-	-	O
	8	0.092	0.000	0.391	T
	9	0.039	0.000	0.082	T
	10	-	-	-	O
	11	-	-	-	O
	12	0.108	0.027	0.069	T

Table 3.12: Categorization of players Session 2

Categorization of players depending on their forecasting rule in the second Session. By column: the estimated coefficient for the selected forecasting rule, its p-value, the R squared of the selected model and the correspondent type assigned.
In the Type column, A means adaptive, C means contrarian, T trend extrapolation rule, while O means 'other'.

	Participant	Coefficient	P-value	R-squared	Type
Session 3	1	0.001	0.020	0.014	T
	2	0.006	0.000	0.166	T
	3	-	-	-	O
	4	0.010	0.000	0.196	T
	5	0.001	0.003	0.036	T
	6	-	-	-	O
	7	0.009	0.000	0.485	T
	8	-0.052	0.000	0.521	C
	9	-	-	-	O
	10	-	-	-	O
	11	0.008	0.000	0.020	A
	12	-	-	-	O

Table 3.13: Categorization of players Session 3

Categorization of players depending on their forecasting rule in the third Session. By column: the estimated coefficient for the selected forecasting rule, its p-value, the R squared of the selected model and the correspondent type assigned.
In the Type column, A means adaptive, C means contrarian, T trend extrapolation rule, while O means 'other'.

	Participant	Coefficient	P-value	R-squared	Type
Session 4	1	-1.030	0.000	0.461	C
	2	-0.353	0.000	0.630	C
	3	0.085	0.036	0.096	T
	4	0.074	0.072	0.051	T
	5	0.224	0.000	0.300	T
	6	-0.313	0.000	0.391	C
	7	-	-	-	O
	8	0.150	0.000	0.345	T
	9	0.060	0.072	0.137	T
	10	0.369	0.026	0.335	A
	11	-	-	-	O
	12	-	-	-	O

Table 3.14: Categorization of players Session 4

Categorization of players depending on their forecasting rule in the fourth Session. By column: the estimated coefficient for the selected forecasting rule, its p-value, the R squared of the selected model and the correspondent type assigned.
In the Type column, A means adaptive, C means contrarian, T trend extrapolation rule, while O means 'other'.

	Participant	Coefficient	P-value	R-squared	Type
Session 5	1	-	-	-	O
	2	0.035	0.054	0.012	T
	3	-0.179	0.014	0.403	C
	4	0.020	0.010	0.027	A
	5	-0.318	0.049	0.569	C
	6	0.014	0.016	0.159	A
	7	-0.189	0.001	0.568	C
	8	0.042	0.003	0.270	T
	9	-0.288	0.001	0.590	C
	10	0.010	0.001	0.221	A
	11	-	-	-	O
	12	-	-	-	O

Table 3.15: Categorization of players Session 5

Categorization of players depending on their forecasting rule in the fifth Session. By column: the estimated coefficient for the selected forecasting rule, its p-value, the R squared of the selected model and the correspondent type assigned.
In the Type column, A means adaptive, C means contrarian, T trend extrapolation rule, while O means 'other'.

3.8 Appendix III: Instructions (English translation)

Welcome

Thank you for taking part in this experiment. The experiment lasts approximately 3 hours and you will be paid cash directly at the end of the experiment.

It is very important that you do not talk to the other participants during the entire experiment. If you still have questions after reading the instructions, please raise your hand. An experimenter will come to you and answer directly to your question.

General explanations

Today's experiment consists of one or more sequences. Each sequence is composed of one or more periods. The exact number of periods and sequences is random and therefore it is not known beforehand. At the end of each period randomness decides whether there will be another period in the same sequence or not.

In this experiment you can earn two types of points. The number of points you earn in this experiment determines how much you will earn at the end of the experiment (for more details see section **Payment**). You earn points for two different tasks.

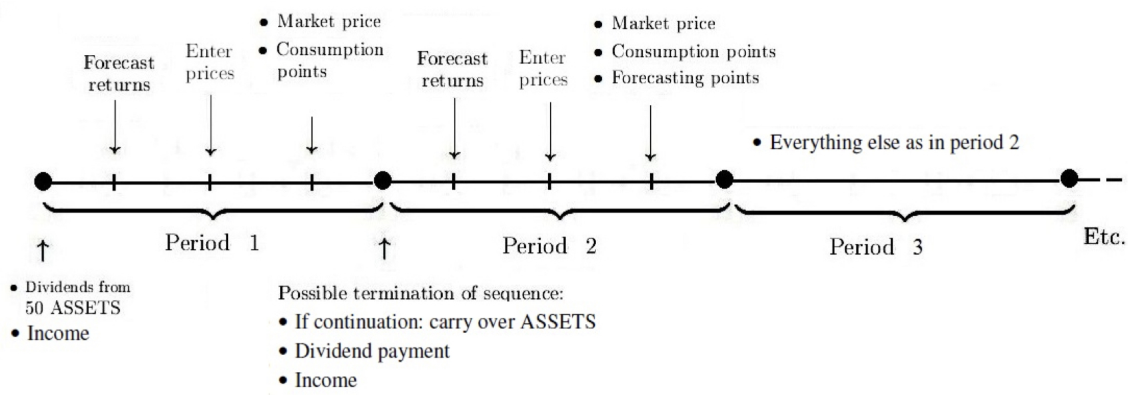
In every period you will be asked to perform two tasks. First, we will ask you to state your expectations about the future return of a stock. Second, you will have the opportunity to trade this stock with other participants.

At the beginning of each sequence you are endowed with a certain number of stocks and at the beginning of each period you receive also some cash. While you can use cash only within a period, you can keep stocks for the entire duration of a sequence, i.e. for multiple periods, if you do not sell the stocks. You cannot carry cash over from one period to the next.

In each period you get points for the return expectation you state (see more details in the section **Stating your Return Expectations**) and for the result of your trading (see more details in the section **Trading of the Stocks**). In each period you can use cash to buy additional stocks or you can sell your stocks and get cash from your sale. The cash you have at the end of a period, after buying or selling stocks, is converted into consumption points.

Structure of one period

Each period is composed by three parts. First, we ask you to state your stock return expectations. Then, you can use your cash to trade your stocks with other participants. Finally, you know how many stocks you bought/sold in this period and how many points you earned.



At the beginning of each sequence you receive 50 stocks. Additionally, you receive cash at the start of each period. The currency in this experiment is called Taler. The number of Taler you get depends on (1) how many stocks you own and (2) how high the dividend is.

At the beginning of each period you receive a dividend for every stock you own. This dividend is either **1** or **5** Taler per stock. In the first period of a sequence both dividends are equally probable.

In every subsequent period, the dividend is also random, but the probability of one of the two possible dividends depends on the size of the dividend in the previous period. If the dividend in the first period was 5 Taler, then the probability that the dividend is again at 5 Taler in the second period is 70%. That is in 7 out of 10 cases the dividend is again 5 Taler and in 3 out of 10 cases (30% probability) the dividend is 1 Taler.

Example:

If the dividend was 1 Taler in the previous period, than the dividend in the next period would be again at 1 Taler in 7 out of 10 cases (70%). In 3 out of 10 cases (30%) the dividend will be 5 Taler. On the contrary, in the first period of a sequence both dividends are equally probable.

In each period you receive an additional income, independent of the number of stocks you own. In periods where the dividend is 1 you get **100** Taler, while if the dividend is 5 you receive an income of **500** Taler.

*You own 50 stocks. If the dividend is one Taler you receive 150 Taler in total: 50*1 Taler as from dividend payment and additionally an income of 100 Taler. In the next period the dividend will be in 7 out of 10 cases again 1 Taler, in 3 out of 10 cases 5 Taler.*

Both, income and dividend are paid at the **beginning** of each period. This means in every period you earn cash for each stock you own at the start of the period. Therefore there are two reasons to hold stocks: (1) you earn additional money in each period via the dividend and (2) you can possibly sell the stock in a later period and earn other cash.

Stating your return expectations

In each period we will ask you to state your expectations about the future return of the stock. A stock return measures how profitable it would be to buy a stock in this period and sell it in the next period. The return is computed as follows:

$$Return \quad = \quad \frac{Dividend\, in\, the\, next\, period + Price\, change\, from\, this\, to\, the\, next\, period}{Price\, in\, this\, period}$$

Returns are stated in percent. If the return of the stock is positive, then the price change plus the dividend will be positive. If you buy a stock in this period and sell it in the next, you earn some money. The higher your expected return is, the larger is the gain you expect from buying a stock.

If the return is negative in a certain period, then the price decrease will be larger than the size of the dividend. If you had bought a stock in a period like this one and had sold the stock one period later, you would have lost money.

Two examples on how to calculate the return are following. ***All stock prices in these calculations are only examples****. They are not suggestions on how to act in the experiment.*

For example, if you expect that the price of the stock in this period is 1850 Taler, the dividend next period 5 Taler and the price of the stock will increase to 2150, then your expected return is +16.5%.

$$Expected\,Return \quad = \quad \frac{5 + 2150 - 1850}{1850} \cdot 100 = 16.5$$

If you expect instead that the dividend in the next period will be 1 Taler and the stock price will be 1600 Taler, your expected return is -13.5%.

$$Expected\,Return \quad = \quad \frac{1 + 1600 - 1850}{1850} \cdot 100 = -13.5$$

You have to enter your expected return in percentage, in steps of 0.1% point. When you state your expectations you know the dividend in this period. You do not know neither this period stock price, nor the price or the dividend for the next round. You do not know this period stock price yet, since it is determined by the trading of the stock, which will take place after you have stated you expectation.

At the end of the **following** period you receive points depending on the precision of your expectations. The closer you predicted the return, the higher is the number of points you receive. The number of points you will get is calculated as follows:

$$Points\,for\,return\,expectations \quad = \quad \max\{20 - f, 0\}$$

where f indicates the absolute error of your prediction expressed in percentage points. That is, if $f = 8.5$, then your expectation was 8.5% higher or lower compared to the realized return.

Examples for the calculation of points for the return expectation:

Assume that you stated an expectation of 8% in the previous period. If the market price, which is determined by the buy and sell orders of all subjects, is 2.1 Taler, the dividend is 1 Taler and the market price at 1 Taler, then the realized return is-4.8%*. This means your expectation overstates the realized return by 12.8 percentage points:*$f = |8 - -4.8| = 12.8$*. Hence you receive* $2–12.8 = 7.2$ *points for your expectation.*

If your expectation is exactly the true return, then you receive 20 points. The larger is the difference between your expectation and the true return, the lower is the number of points you receive for you guess. If you state a return that is higher/lower than 20 percentage points, then you do not receive any points for your expectation.

There is a difference in the first period of each sequence. Since in this period there is no previous market price you cannot earn any points for your expectation in the first period of each sequence. The expectation you state in the first period determines your payout in the second period (and the expectation you state in the second period determines you possible payout in the third period and so on).

Trading the stock

Once you have stated your return expectations, you have to state the prices at which you are willing to buy additional stocks or sell some.

You can use all your available Taler to buy stocks. The Taler available for purchasing stocks are those you have in a period minus one Taler. This Taler represents your minimal consumption. This means you must at least consume this Taler at the end of each period, therefore you cannot use it for buying additional stocks.

You have to state three prices:

(a) First, the price at which you are willing to **sell** ALL stocks you currently own.

(b) Second, the price at which you are neither willing to sell one of your stocks, nor are willing to buy additional stocks.

(c) Third, the price at which you are willing to **buy** as many stocks as possible.

All these prices are prices per unit of stock, which means that all prices are relevant for buying/selling **one** stock.

You have to specify a price at which you are willing to sell all your stocks (a) higher than the price at which you are neither willing to buy nor sell any stocks (b). This price (b) must also be larger than the price at which you are willing to buy as many stocks as possible (c). So, price (a) > price (b) > price (c).

Assume that this period market price is between the price (a), at which you are willing to sell all your stocks, and (b), the price at which you are neither willing to buy nor to sell any of your stocks. It means that at this market price that you are willing to sell some, but not all of your stocks. The higher the market price is, the higher is the number of stocks are you willing to sell.

If the market price of the stock in this period equals the price (a) you stated or it is above, then the computer tries to sell as many of your stocks as possible to other participants. If the market price is between the price (a) and the price at which you neither want to buy nor sell stocks (b), then the computer tries to sell some, but not all of your stocks. The closer is the market price to the price (a), at which you want to sell all your stocks, the more stocks the computer tries to sell. The closer the price is to the price (b), the fewer of your stocks are going to be sold.

Conversely, a market price that is lower than the price (b) you stated means that you are willing to buy more stocks. Exactly as in the case of a market clearing price that are larger than (b), for all prices between (b) and (c), the price at which you are willing to buy as many stocks as possible, the computer tries to buy more stocks from other participants the closer the market price is to (c). The lower the market price is, the more stocks you are willing to buy.

Clearly, you can only sell as many stocks as you own in this period and you can only buy as many stocks as you can afford. All prices can be stated in steps of 0.1 Taler.

After every participant stated these three prices the computer computes the stock market price. By doing this, it tries to find the price at which some participants state to sell as many stocks as some other participants want to buy. Therefore it searches for the price at which the number of stocks demanded and the number of stocks supplied are equal. This market price determines if you buy or sell stocks in this period.

Assume you would like to sell all your stocks at a price of 2400.0 Taler (a). At a price of 1850 Taler you neither want to buy nor sell any stocks (b) and at a price of 1719.2 you are willing to buy as many stocks as possible (c). If now the price of the stock is above 1850 Taler, for example at 2008.5 Taler, than the computer will compute how many stocks you can and want to sell at this price. If the price is below 1850 Taler, for example at 1747.3 Taler, the computer calculates how many stocks you want and can buy in this case. Note that the numbers used in this and other examples are only indicative. They do ***not*** *provide any information about the prices or your suggested actions in the experiment.*

The exact calculation of the market price is not given here, due to space constraints. It is only important for you that the number of stocks you buy or sell depends on the prices thresholds you state, the amount of stocks you own, the amount of Taler you hold and depends on other participants' stated inputs.

Result of a period

All transactions within a period take place at the same market price. As soon as this market price is computed for the stock, you visualize the realized price on the screen. The market price will be shown together with the number of stocks you bought or sold in this period and the return, which derives from this market price.

You see how many points you earned for your expectation in the previous period. You also see how many points you earned for your consumption. You consume all Taler, which you have left after buying and selling stocks. The higher the amount of Taler you own at the end of a period, the higher the number of consumption points you earn. Taler will be converted into consumption points with a formula. More Taler always result in more consumption points, but the difference between the consumption points is larger between low values e.g. 10 and 20 Taler, than the difference between higher amounts, e.g. 90 and 100 Taler.

How many Taler you have at the end of a period depends on how many stocks you bought or sold at a certain market price. Table 1 indicates how some values in Taler are converted into consumption points. All the other possible Taler values not stated in the table are converted using the same formula. So, for example, the number of consumption points you receive for 56,57 etc. Taler is above the number for 50 Taler but below the one corresponding to 60 Taler.

Taler	Consumption Points	Taler	Consumption Points
1	3.3	400	20.1
2	4.1	500	21.5
3	4.6	600	22.7
5	5.4	700	23.8
10	6.7	800	24.8
20	8.2	900	25.7
30	9.2	1000	26.5
40	10.1	1100	27.2
50	10.8	1200	28.0
60	11.4	1300	28.6
70	11.9	1400	29.3
80	12.4	1500	29.9
90	12.9	1600	30.5
100	13.3	1800	31.6
110	13.7	2000	32.6
120	14.0	2200	33.5
130	14.4	2400	34.4
140	14.7	2600	35.3
150	15.0	2800	36.1
170	15.6	3000	36.8
190	16.1	3500	38.6
200	16.3	4000	40.1
220	16.8	4500	41.6
240	17.3	5000	42.9
260	17.7	5500	44.2
280	18.1	6000	45.3
300	18.5	6500	46.3

Determining the number of periods and sequences

As mentioned above, the experiment consists of one more multiple sequences, and each sequence consists of one or more periods. At the end of each period the computer randomly determines whether there is an additional period in the same sequence. In 35 out of 36 cases (about 97.2%) there is another period in the same sequence. In one out of 36 cases the sequence ends after this period.

This is the same as a situation in which you throw two six-sided dice at the end of each period. If **BOTH** dice show the number 6, then this is the last period of this sequence. If one or both of the dice show a different number, then there is another period within the same sequence.

In case a sequence ends, a message is displayed on your screen. All stocks you hold at that point are worthless. The next period is then the start of a new sequence. This means you receive again 50 stocks, independently from how many stocks you owned at the end of the previous sequence.

If the sequence does NOT end this period, a new period follows automatically. In the new period you own the amount of stocks you had in the previous period. This means within a sequence you carry over all your stocks from one period to the next.

Please note that the probability that a sequence ends does not depend on the number of periods you have already played in the same sequence. The procedure is as if you throw two dice after each period and only if both dice show a six there is no additional period in the same sequence. This means at the end of each period the chance that there is another period in the same sequence is the same.

There will be as many sequences as possible within the 3 hours of the experiment. Therefore after a sequence ends, we always start a new sequence, as long as the first sequence has started less than 90 minutes before.

In the unlikely event that the last sequence does not end within the 3 hours planned for the experiment, we will put the last sequence on hold. In this case the sequence does not end, but we add the expected number of periods to this last sequence which would most likely be played if the sequence had not put on hold. The stocks you own in the last period are therefore not worthless.

Since these periods are not played due to time restrictions, for each period we add the expected number of consumption points. The amount of consumption points is determined by the number of stocks you own. The expected consumption is higher if you own more stocks, since on average you would have earned more from dividend payments. We act as if the sequence continued and in each additional period you would consume your entire income plus all dividends and you would neither buy nor sell any stocks.

Payment

Your payment in this experiment consists of two parts. First, you get **7 Euro** show-up fee for participating in the experiment. Additionally, you receive some money based on your performance.

After the end of the last sequence the computer randomly selects **10** periods for payment. You are paid in 5 periods for your consumption and in 5 different ones for your stated expectations. Clearly the first period within a sequence can never be selected for the payment of your expectations, since no stock return in this period is defined.

If the last sequence was not completed due to time constraints, the additional periods can only be selected for the payment of consumption points. These periods do not contribute to determine the payment for your expectations.

The points you earned in these selected periods are converted into Euros. The exchange rate is **15 cents** per point, independently from the fact that the point was earned for consumption or forecasting.

*If you have earned for example a total of 90 points for your consumption and 75 points for forecasting in the selected periods, you will receive a total of 31,75 Euro. ((90+75) points * 0.15 Euro/point + 7 Euro = 31,75 Euro).*

You will now familiarize with the computer interface and conduct a test period. When you finish reading the instructions, please click trough the introductory period. The remarks on the screen explain you the different parts of the interface. After all participants have completed this introductory period, we will ask you some questions to make sure you have understood. You can answer to these questions directly on the computer. In case you have some questions after completing the introductory period or need help with the understanding questions, please raise your hand. Then we will clarify your question personally.

Chapter 4

Determinants of Asset Price Volatility: An Experimental Approach

This chapter is based on a joint project with Timo Hoffmann.
Continued guidance and support by Klaus Adam, Dirk Engelmann and Stefan Penczynski are acknowledged.

4.1 Introduction

The behaviour of stock prices has been a prominent subject of interest in financial economics. Explaining asset price movements and identifying the mechanism driving those has been at the core of the macro-finance literature, starting from the early contributions by Lucas (1978) and Grossman and Shiller (1981). Consumption-based asset pricing models became workhorse models, serving as major reference for understanding asset price dynamics. Though very popular, their baseline variant with standard time-separable consumption preferences performs very poorly when it comes to matching stylized facts about asset prices. In particular, the model implications under rational expectations are at odds with the observed high persistence and volatility of the price-dividend ratio, the high volatility of stock returns, the long-term predictability of excess returns and the risk premium.[1] However, a recent contribution by Adam et al. (2016) shows that a simple consumption-based asset pricing model is able to quantitatively explain the observed price volatility patterns, once the assumption that agents know perfectly how prices are formed in the market is relaxed.

In a baseline Lucas (1978) model, an investor has to solve a simple investment decision, i.e. she has to choose how much to save and how much to consume. Under rational expectations, the basic asset pricing equation resulting from the first-order optimality condition of that investment decision implies that price volatility in equilibrium results from two different sources: a volatile stochastic discount factor (SDF) and volatile future asset payoffs. Understanding which of these two factors drives asset price fluctuations is particularly challenging with field data as it requires assessing the individual intertemporal consumption decisions together with individual future asset return expectations. A laboratory instead provides an ideal setting where one can keep track of individual trading decisions and expectations in a stationary environment. We therefore conducted a lab experiment in which only one of the two theoretical sources is present in each treatment so to assess which of the two theoretical sources of volatility can explain the observed volatility better and gain further understanding on the reasons why Lucas asset pricing model predictions are not met.

Experimental economics has extensively studied asset market price dynamics, both in finite and infinite horizon models, starting from the seminal paper by Smith et al. (1988). Their experimental design of a finite 15 period asset market became the benchmark for several

[1] See Campbell (2003) for a review of consumption-based asset pricing models, both in its original version and later modifications resulting from relaxing its assumptions.

other finite horizon asset market experiments, such as Dufwenberg et al. (2005) and Haruvy et al. (2007). In the latter study, participants trade an asset living 15 periods and they are asked to forecast the price of the asset for all the remaining trading periods. Haruvy et al. (2007) find that short terms beliefs about future prices are adaptive and informative of future price movements. Beliefs are then shown to play a crucial role in explaining the price deviation from fundamentals, with fundamentals being defined by the theoretically defined rational expectation equilibrium price.

Recently, infinite horizon asset pricing models, which before have only been very popular in the theoretical literature, have become of interest to experimentalists. Crockett and Duffy (2013), Asparouhova et al. (2016) and Donini (2016) brought the Lucas (1978) asset pricing model to the lab in order to study intertemporal consumption smoothing, cross-sectional predictions (e.g. equity premium puzzle) or the cyclicality of asset market booms and busts. Differently from the earlier asset market experiments based on Smith et al. (1988) design, this strand of the literature considers an asset which lives for an uncertain number of periods. So to implement the equivalence of an indefinite asset market into the lab, at the end of each round a random draw determines whether the market ends or another period follows. Subjects carry their asset holdings (the *"tree"* in Lucas (1978) terminology) from period to period, while the their cash balances (the *"fruits"* in Lucas (1978) terminology) experimental currency are out of the economy at end of each period, i.e. they are consumed. Similarly to the finite horizon asset market experiments, the infinite horizon experiments have shown that the trading price differs substantially from the fundamental value of the asset and it is usually excessively volatile. Moreover, the mentioned papers provide evidence that subjects adjust their asset holdings across states of the world, i.e. they smooth their consumption intertemporally. These results point at a key finding of the adaptive learning literature that considers belief dynamics to be responsible for market price deviations from fundamentals, see e.g. Branch and Evans (2011). Moreover, they validate Adam et al. (2016) results by showing that the market clearing prices are consistent with internally rational agents whose price beliefs are only approximately correct.

In this paper we follow the path of the latter experiments with the main goal of identifying the role of the stochastic discount factor and the payoff volatility on the observed asset price volatility. In order to discern the two theoretical sources of volatility, we design two treatments, in which either only the stochastic discount factor varies (SDF treatment) and the expected asset payoffs are constant or the other way around (PAYOFF treatment). In the SDF treatment the volatility of asset prices comes solely from a volatile stochastic discount factor, while in the PAYOFF treatment price fluctuations are only due to the volatility of the future asset payoff. We also elicit subjects' beliefs about future returns of the asset, as in Bottazzi et al. (2011) and Donini (2016), and can therefore explore the relationship between individual return expectations and trading decisions.

In the experiment we find that market clearing prices are substantially less volatile than the fundamental value of the asset, i.e. *negative excess volatility.* The latter pattern is puzzling since over a sufficiently long horizon the price should reflect fundamentals and their volatility. Average trading prices are co-moving with the state of the world, but less than the theory would predict. In particular, price volatility is higher in the PAYOFF treatment than in the SDF, pointing at subjects having difficulties in understanding (or applying) the optimal intertemporal trading strategy. If subjects were to behave optimally, then in high states of the world, prices should be higher than in the low states due to both a wealth effect, since participants have more money to spend in high states than in low states, and for intertemporal consumption smoothing motives, i.e. since consumption has a decreasing value, then participants should be willing to postpone consumption to future periods. Moreover, the latter pattern should be emphasized by the dynamics of individual expectations, with more optimistic participants being even more willing to buy asset in high states of the world aligned with their valuations of the asset. However, subjects seem to have difficulty in understanding the optimal trading strategy and expectations dynamics are shown to have a milder effect on individual asset allocation decisions in the experimental framework than predicted in theory. The latter difficulty reveals particularly in the SDF treatment, where the price clears the market most of the times at a value in between the two state dependent fundamental values.

The remainder of the paper is organized as follows: next section describes the theoretical set-up, while Section 4.3 presents the experimental design and the hypotheses we test. In Section 4.4 we discuss the experimental results and Section 4.5 concludes.

4.2 Theoretical model

We consider a simple version of the consumption based asset pricing model à la Lucas (1978) with time-separable consumption preferences. The economy is populated by a unit mass of infinitely living risk-averse agents ($i = 1, 2, 3...I$) endowed with a stock (S_t).[2] This stock is traded at an ex-dividend price P_t on a competitive market and pays every period t a perishable consumption good D_t, i.e. the dividend.[3] Moreover, each agent receives an additional perishable endowment Y_t, chosen to be proportional to the dividend $Y_t = \alpha D_t,\ \alpha > 0$.[4]

Each agent i is an expected utility maximizer with time-separable preferences over consumption C_t^i. Every period, she has to take an investment decision of the following type:

$$\max_{C_t^i > 0, S_t^i \in [0, \bar{S}]} E_t^{\mathcal{P}^i} \sum_{t=0}^{\infty} \delta^t \cdot \frac{(C_t^i)^{1-\gamma}}{1-\gamma} \tag{4.1}$$

subject to

$$C_t^i + P_t S_t^i = (P_t + D_t) S_{t-1}^i + Y_t \tag{4.2}$$

$$S_t^i \geq 0 \ \forall t \tag{4.3}$$

$$S_t^i \leq \bar{S} \ \forall t \tag{4.4}$$

$$C_t^i \geq \underline{C} \ with \ \underline{C} > 0 \ \forall t \tag{4.5}$$

$$S_{-1}^i \quad given \tag{4.6}$$

where δ denotes a common discount factor, C_t^i individual consumption demand at time t, S_t^i the individual stock holdings and S_{-1}^i being a given individual initial endowment, Y_t the exogenous additional income, $\bar{S}$ the total number of outstanding shares and $\mathcal{P}^i$ indicates the subjective probability measure of each agent i, as in Adam et al. (2016). In particular, we consider each agent to be *internally rational* in Adam and Marcet (2011) sense, i.e. she takes fully optimal decisions, given her system of beliefs about price realizations and future dividends, i.e. about $\omega = \{P_t, D_t\}_{t=0}^{\infty}$, where $\omega \in \Omega$, element of the space of all possible realizations.[5]

Hence, an agent makes contingent consumption plans C_t^i subject to a budget constraint (2), two asset limits constraints, i.e. a no-short selling constraint (3) and an upper bound on holdings (4) and a positive lower bound for consumption $\underline{C}$ (5). All these constraints have to

[2] Time sub-index always indicates beginning-of-period variables.

[3] The dividend process is defined depending on the treatment.

[4] Proportionality of the exogenous income has a twofold goal, on one side, it is mimicking the real economy cycle, on the other it allows us to have a stochastic discount factor independent of the initial stock endowment of participants.

[5] See Adam and Marcet (2011) for further discussions of the underlying probability space.

hold for all t almost surely in $\mathcal{P}$. Since the objective function is concave and the feasible set is convex, the agent's optimal consumption plan is characterized by the following first order condition:

$$\left(C_t^i\right)^{-\gamma} \cdot P_t \quad = \quad \delta \cdot E_t^{\mathcal{P}^i}\left(\left(C_{t+1}^i\right)^{-\gamma}(P_{t+1} + D_{t+1})\right) \tag{4.7}$$

i.e. the marginal loss of utility an investor bears if she buys an additional unit of the asset at time t is equal to the marginal gain she obtains from an extra payoff at time $t+1$.

Solving the above specified infinite horizon investment problem has the following well-defined solution under rational expectations:[6]

$$P_t^{REE} = E_t\left[\sum_{j=1}^{\infty} \delta^j \left(\frac{C_{t+j}}{C_t}\right)^{-\gamma} \cdot D_{t+j}\right] \tag{4.8}$$

$$= \sum_{j=1}^{\infty} \delta^j \left[\underbrace{E_t\left(\left(\frac{D_{t+j}}{D_t}\right)^{-\gamma}\right)}_{\text{contribution}_{SDF}} \cdot \underbrace{E_t\left(D_{t+j}\right)}_{\text{contribution}_{PAYOFF}} + \underbrace{Cov_t\left(\left(\frac{D_{t+j}}{D_t}\right)^{-\gamma},\ D_{t+j}\right)}_{\text{contribution}_{COV}}\right] \tag{4.9}$$

where $\text{contribution}_{SDF}$ is the contribution of the stochastic discount factor to the asset pricing in REE, $\text{contribution}_{PAYOFF}$ is the contribution that future payoffs give to the asset pricing in REE and $\text{contribution}_{COV}$ is the contribution that the covariance between the two factors gives to the asset pricing.

Hence, in equilibrium price volatility comes from three sources of variability: volatile stochastic discount factor (SDF), volatile future payoffs (PAYOFF) and the co-movement between these two (COV). The first factor represents the inter-temporal marginal rate of substitution, the so called pricing kernel. It identifies the rate at which an investor is willing to substitute consumption at time $t+1$ for consumption at time t. In our case, due to the proportionality of income to the dividends, the pricing kernel is simply defined by the expectations at time t of the growth rate of the dividends process. Therefore, in equilibrium, state dependent dividends would contribute to time-varying prices. As a matter of fact, an *iid* dividend process would imply a constant contribution of the PAYOFF factor to the pricing

[6] See the Appendix 4.6 for a precise derivation of the rational expectation equilibrium prices in the two treatments.

of the asset, i.e. no contribution in terms of price volatility. In this case, SDF would drive price volatility together with the covariance term between SDF and PAYOFF.

The second factor (PAYOFF) identifies how much an investor receives in expectation in the consecutive period from one unit of the asset. In our case, the payoff is defined by the expectations at time t about next period dividend. A dividend process characterized by a time varying mean would therefore transmit into volatile equilibrium prices. Consequently, a dividend process characterized by a constant unitary growth would net out the contribution that the SDF factor gives to price volatility. Hence, PAYOFF would be the driver of asset price volatility together with the covariance term between the SDF and PAYOFF.

The third factor (COV) represents an additional source of volatility of prices that is additive to the latter two. A negative covariance between the stochastic discount factor and the payoff would therefore have a negative impact on the equilibrium price as it will introduce an asset-specific risk correction. As we will argue in the next section in more detail, this third factor can determine asset price volatility to a smaller extent than the other two factors, for the chosen parametrization of the experiment.

4.3 Experimental design

4.3.1 General set-up

The experiment consists of two treatments, each of them composed of rounds and sequences. A sequence contains a random number of rounds and each round consisted of a forecasting and a trading part. The main difference between the treatments is the dividend process, as explained later in Section 4.3.6. In both treatments, 8 subjects participated to each market.

At the start of a sequence (the start of the first round $t = 0$), all participants are endowed with 20 units of stock ($S^i_{-1} = 20 \forall i = 1, 2..., 8$, so $\bar{S} = 160$).[7] Additionally, at the start of every period subjects receive some cash income, denominated in the experimental currency Taler. The income is composed of two parts, which are both paid at the beginning of each period. A part is independent of the number of stocks a subject possessed, but depend on the state of the world. The other part relates to the dividend payments for each stock an individual own and therefore depend on the state of the world and the individual stock holdings at the beginning of the round. Due to the stock independent part of the income it was ensured that

[7] Each session contained two groups of 8 subjects with the exception of session 1 (SDF treatment) where only 7 subjects per market, therefore $\bar{S} = 140$.

subjects could buy the asset, even if they did not receive any dividend income. Similarly to Asparouhova et al. (2016), the total income co-moved with the dividend draw (high income in high-dividend states and low in low-dividend states) to mimic the real economy booms and busts cycles.

Each round is composed by two parts. First, subjects state their expectation for the return of the stock (see Section 4.3.2 for definition of the return) and in the second part of the round the asset could be traded via a double auction mechanism among all participants within a group. When making the forecast, subjects knew the dividend paid by the stock in this round (as dividends are paid at the beginning of each round), but not the market price of the stock for this round, since the market price is determined in second part of the round by the trading of subjects. The number of stocks outstanding, $\bar{S}$ remained constant during the entire experiment and the structure of a round was identical in both treatments (see Figure 4.1). The timing within a round was as follows:

1. A random draw from a known distribution determined the state of the world and therefore the dividend D_t and the income Y_t.
2. Each participant stated a forecast of the expected return of the asset conditional on an information set ω^t , $E_t^{\mathcal{P}^i}(R_{t+1} \mid \omega^t)$, knowing P_{t-1}, D_t, R_{t-1} , S_{t-1}^i and S_t^i.
3. Participants could trade the asset on a computerized double auction market. A trading phase lasted 2 minutes (90 seconds from the sixth period of a sequence onwards).
4. After the trading ended the average market price for the asset (P_t) and her or his individual stocks (S_t^i) and cash holdings were reported to each individual.
5. All cash left the economy and was converted to consumption points (CP) for each individual via an induced utility method. Also subjects received forecasting points (FP) for their return forecast depending on their return statement in the previous round and the realized return of the asset. Participants were only informed of their own CPs and FPs, but not of those of other subjects.
6. A random draw determined whether another round in the same sequence took place. The draw was identical for all subjects in a session, meaning it was equivalent for both groups within a session.[8] If the sequence continued, then another round with an identical structure was started. If there was no further period the sequence ended.[9]

[8] This ensured that the experiment lasted the same amount of time for all subjects in a session.

[9] Further, there was a protocol in place that ensured that a session did not go over the 2:45 h time limit. After 120 min of the experiment a sequence was put on hold. "*Synthetic*" periods were added to the actually

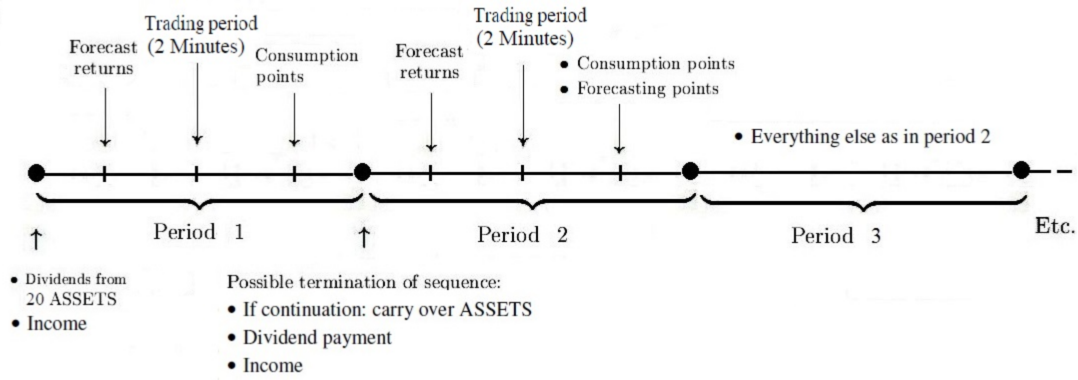


Figure 4.1: Structure of a sequence for both treatments

4.3.2 Stating the returns expectations

At the beginning of each round, the state of the world was determined by a random draw, hence subjects got to know the dividend and their corresponding income available for trade and consumption. The first task they performed was to forecast the return of the asset from this to the next round. The return is defined as follows:

$$R_{t+1} = \left(\frac{P_{t+1} + D_{t+1} - P_t}{P_t} \right) \tag{4.10}$$

where R_{t+1} is the return that will realize at time $t+1$ expressed in percentage points, D_{t+1} is the dividend in period $t+1$, P_t is the average market price in period t and P_{t+1} the average market price in the consecutive period $(t+1)$. The average market price is the average price of all transactions completed in a trading period. In the instructions this formula was given, together with numerical examples and an intuitive definition of asset return.[10] In order to facilitate the task participants were provided with a calculator in which their own estimations of the end of period market price, the expected dividend and expected market price for the consecutive round could be entered and then the corresponding return was displayed.[11] The

played rounds in which subjects received CP based on their asset holdings at the end of the last played period. No FP could be earned for these synthetic rounds. This procedure was explained in the instructions and ensured that subjects' behaviour in later rounds was not distorted because subjects expect the session to end due to time limits.

[10]See Appendix 4.9 for an English translation of the original German version of the instructions.

[11]In line with other asset market experiments, e.g. Hommes et al. (2008), subjects had a visualization of the entire time series of realized returns for the current sequence on their screens when stating their expectation. In addition to this graphical representation all past prices, dividends and realized returns up to $t-1$ within the same sequence were displayed in a table.

screen informed subjects about the dividend in the current round, their available cash and their stock holdings. Subjects stated their expectation in percentages, up to one decimal of precision and could move to part two only after entering a return expectation.

4.3.3 Trading the asset

Trading took place through an anonymous, electronic continuous open book system based on the double auction mechanism in zTree (Fischbacher (2007)). The trading screen was intuitive and enabled subjects to make offers or bids for trading a single stock. Trading took place at integer values and an improvement rule was in place for submitting a new ask or bid.[12] Subjects could accept outstanding bids and asks at any time, given that they possessed the necessary funds to pay the asking price (ask) or owned at least one stock (bid).[13] In each round the trading period lasted 2 minutes (or 90 seconds in rounds 6 and later of a sequence). At the end of the trading period all outstanding asks and bids were cancelled.

4.3.4 Result of a period

After trading ended subjects were informed about P_t, the average trading price in the period, the resulting return of the asset (if the round was not the first round of the sequence) and their end of period cash and stock holdings.

At this point the cash of each individual was converted into consumption points and then disappeared from the economy. Cash was converted into CPs in both treatments using the following induced concave function, with C_t^i being the end of period t cash holdings of subject i:

$$CP = U\left(C_t^i\right) = 100 - 200 \cdot {C_t^i}^{-0.5}. \tag{4.11}$$

As discussed in Crockett and Duffy (2013), the concave payment for consumption results in induced risk aversion for by nature risk neutral and very slightly risk-loving participants and pushes risk aversion even further for by nature risk-averse subjects. The conversion was explained intuitively to subjects in the instructions, which contained also the formula itself and a table converting the most common Taler values to CPs. CPs were converted to Euro at the end of the experiment, see Section 4.3.7 for the detailed payment procedure.

[12] Each new bid had to improve the highest outstanding bid by at least one Taler and each new ask had to be at least one Taler lower than the lowest outstanding ask.

[13] A screen-shot of the trading screen is provided in Figure 4.8 in Appendix 4.8.

4.3.5 Length of a sequence

To introduce the infinite horizon model feature into the lab, we followed previous experiments on the Lucas (1978) asset pricing model (Asparouhova et al. (2016) and Crockett and Duffy (2013)) and approximated the infinite horizon via an indefinite horizon. At the end of each round a random number was drawn from a uniform distribution between 0 and 1. For draws above $\frac{11}{12}$ the sequence stopped. For all other outcomes another round was played, i.e. in 1 out of 12 cases the sequence comes to an end. When the sequence continued, the individual asset holdings were carried over to the next round, while if the sequence ended the assets became worthless.

Furthermore, to ensure a stationary economy, we defined a termination protocol along the lines of Asparouhova et al. (2016) one. At the beginning of the experiment it was announced that the experiment lasts until a pre-specified time (i.e. 2:45 hours) and that there are as many replications (sequences) of the economy as possible during this time. If a sequence ended and more than 30 minutes were left of the two hours and forty five minutes maximum session time, a new sequence started. Otherwise it was announced to the participants that the experiment was over.

In contrast, if a sequence was still running by the closing time, the sequence was kept on hold. 12 synthetic periods were added to the individual consumption to ensure stationarity of the environment. Each subject received her expected income, i.e. dividend plus income payment, based on her stock holdings at the end of the last played round.[14] Therefore in these synthetic consumption periods participants received their expected number of consumptions points assuming no trade.

4.3.6 Treatments

We defined two treatments mainly differing for the dividend process. Each subject participated only in one treatment and in each session only one treatment was conducted. In the SDF treatment the dividend followed an *iid* process, while in the PAYOFF treatment it followed a unit root process.

The dividend in the SDF treatment was randomly selected from a binomial distribution with two equally likely realizations, $D_{low} = 0.25$ and $D_{high} = 0.5$. As stated earlier the

[14] Meaning an individual received the mean income plus the mean dividend payment times the number of her stocks for each of the 12 added periods.

dividend also determined the income a subject received at the beginning of the period. In each state the subject received the respective dividend for each stock she owned and additionally 30 times the dividend. The second part of the income ensured that subjects with no or very few stocks could still participate in the trading of the asset if they wanted.[15]

Subjects were informed about the dividend process since the beginning of the experiment. Due to the *iid* nature of the process, the expected dividend is constant over time and there is no variation in the expected payoffs. Since the expected dividend does not vary over time and it is independent of the state of the world, the payoffs volatility will not be the source of the price volatility. Conversely, the stochastic discount factor clearly depends on the state. Therefore, only the stochastic discount factor would be accountable for any resulting asset price volatility.

In the PAYOFF treatment the dividend process was as follows:

$$D_t = D_{t-1} \cdot \varepsilon_t \tag{4.12}$$

with D_t being the dividend in round t and ε_t being an *iid* shock with equally likely realizations $\varepsilon_{low} = 0.8$ and $\varepsilon_{high} = 1.2$. In the first round in each sequence the dividend process was applied to $D_0 = 0.375$, such that the dividend in the first round was either 0.45 or 0.3 with equal probability.[16]

Differently from the SDF treatment, in the PAYOFF treatment expected payoffs vary from round to round as function of the dividend, i.e. future dividends depend on current dividend and the expected dividend payment varies over time. Consequently, the payoffs are volatile, opposed to a stochastic discount factor that is constant due to a constant unitary growth of the chosen dividend process. Hence, in this treatment, the only source of asset price volatility would therefore be the volatility of payoffs.

4.3.7 Subjects' payments

Subject earned money for both task they performed: predicting the return of the asset and trading the asset. Additionally, they received a show-up fee of 4 Euro. The statement of their expectation about the return of the stock was incentivised such that predictions closer to the

[15] All income payments were rounded up to entire Taler values, since only integer steps were possible during the trading.

[16] If necessary the dividend was rounded to three digits.

realized return yielded higher payments. Since the REE prices of the stock substantially differ between the treatments, the expected asset returns in REE are very different. The scoring rules for the belief payments were adapted in such a way, that entering the REE asset returns yielded similar expected payoffs. This was achieved by changing the parameters of the scoring rule. For each belief statement subjects could earn money (FP) calculated with the following scoring rule:

$$\text{SDF treatment:} \quad FP = \max\{0.01 * (230- \mid f \mid), 0\} \tag{4.13}$$

$$\text{PAYOFF treatment:} \quad FP = \max\{0.046 * (50- \mid f \mid), 0\} \tag{4.14}$$

where f is the forecast error in percentage points. For instance, in the PAYOFF treatment a positive number of forecasting points was associated with individual forecast errors smaller than fifty percent, while the maximum number of points (2.3 FP = 2.3 €) corresponded to exact predictions.

At the end of the experiment 10 rounds were randomly chosen for payment. Since subjects performed two task in each round and possibly could have used their belief statement and their trading behaviour to ensure themselves a payoff if both tasks would have been paid, in each round only one of the two tasks could be chosen for payment to avoid the potential hedging problem described by Blanco et al. (2010). In four of the selected rounds subjects were paid for forecasting and in six different ones for consumption.[17] Each consumption point was converted to 5 Euro cents. Additionally, a zero lower bound was imposed on the payment scheme, so that a subject could not make negative profits with the consumption. If the sum of consumption points for the six selected periods was smaller than zero, the subject received no money for consumption.

4.3.8 Asset prices in REE

Under the assumption of rational expectations, asset prices in equilibrium can be derived from equation (4.9). These REE prices serve as our benchmarks in the empirical analysis.

In the SDF treatment the REE price is given by

[17] Synthetic rounds and the first period of each sequence could not be chosen for forecasting points, since either no return prediction was stated (synthetic rounds) or no return can be calculated (first period of a sequence).

$$P^{REE}_{t,SDF} = \frac{\delta}{1-\delta}\, D_t^{\gamma}\,(2B - C\mu) = \frac{\delta}{1-\delta}\left(\underbrace{D_t^{\gamma} B}_{\text{contribution}_{SDF}} + \underbrace{D_t^{\gamma}(B - C\mu)}_{\text{contribution}_{COV}}\right) \tag{4.15}$$

where B, C and μ are constants depending on the dividend process and the chosen parametrization of the utility function. They are respectively defined as

$$\begin{aligned}
B \equiv & p \cdot (D_H)^{1-\gamma} + (1-p) \cdot (D_L)^{1-\gamma}, \\
C \equiv & p \cdot (D_H)^{-\gamma} + (1-p) \cdot (D_L)^{-\gamma} \text{ and} \\
\mu \equiv & p \cdot (D_H) + (1-p) \cdot (D_L) \text{ i.e. the mean of the dividend process.}
\end{aligned}$$

The dividend process ($D_L = 0.25$ and $D_H = 0.5$ each realisation being equally likely) results in two different state-dependent asset prices that are proportional to the value of the dividend rescaled by the risk-aversion parameter γ. The two prices are reported in Table 4.1 using the parametrization of the utility function used in the experiment with $\delta = 0.917$ and $\gamma = 1.5$.

	Dividend state	
	Low	High
$Cov_t\left(\left(\frac{C_{t+j}}{C_t}\right)^{-\gamma}, D_{t+j}\right) = 0$	2.347	6.639
$Cov_t\left(\left(\frac{C_{t+j}}{C_t}\right)^{-\gamma}, D_{t+j}\right) \neq 0$	2.792	7.896

Table 4.1: REE prices in the SDF treatment

Given that the covariance between the SDF and the stochastic discount factor contribute only marginally to the variance of the fundamental value across states of the world, we consider the REE prices with the zero covariance to be the benchmark for the analysis presented later.[18]

Similarly, REE prices can be derived for the PAYOFF treatment. Differently from the

[18]The volatility of the REE prices across states, measured as standard deviation of the REE prices, is 3.60, while if the covariance term is ignored, it reduces to 3.03.

SDF treatment, in the latter case the chosen dividend process implies a series of REE prices that are dependent on the current dividend realization. Given that the dividend follows an autoregressive process REE prices will vary depending on the previous period dividend realization. For illustration purposes we report the derivation of the REE price in the PAYOFF treatment and the resulting prices for the two possible dividend states in the first period of a sequence in Table 4.2.

$$P_{t,PAYOFF}^{REE} = D_t \left[\frac{\delta\lambda}{1-\delta\lambda} - \frac{\delta(\lambda-\phi)}{1-\delta(\lambda-\phi)} \right] \tag{4.16}$$

$$= \underbrace{D_t \frac{\delta\lambda}{1-\delta\lambda}}_{\text{contribution}_{PAYOFF}} - \underbrace{D_t \left(\frac{\delta(\lambda-\phi)}{1-\delta(\lambda-\phi)} \right)}_{\text{contribution}_{COV}} \tag{4.17}$$

where λ, ϕ, μ are constants depending on the dividend process and the utility function. These constants are defined respectively as

$$\lambda \equiv E\left(\varepsilon_{t+i}^{1-\gamma}\right) = p \cdot (\varepsilon_H)^{1-\gamma} + (1-p) \cdot (\varepsilon_L)^{1-\gamma}$$

$$\phi \equiv E\left(\varepsilon_{t+i}^{-\gamma}\right) = p \cdot (\varepsilon_H)^{-\gamma} + (1-p) \cdot (\varepsilon_L)^{-\gamma}$$

$$\mu \equiv E\left(\varepsilon_{t+1}\right) = p\varepsilon_H + (1-p)\varepsilon_L = 1 \quad \text{i.e. the mean of the shock on the dividend process.}$$

In the PAYOFF treatment the REE price of the asset is proportional to the state-dependent level of the dividend, but differently to the SDF treatment, the REE prices are independent of the risk-aversion parameter. This results in the REE prices for the first period of a sequence listed in Table 4.2.

	Dividend state Low	Dividend state High
$Cov_t\left(\left(\frac{C_{t+j}}{C_t}\right)^{-\gamma}, D_{t+j}\right) = 0$	4.037	6.056
$Cov_t\left(\left(\frac{C_{t+j}}{C_t}\right)^{-\gamma}, D_{t+j}\right) \neq 0$	4.234	6.352

Table 4.2: REE prices in the PAYOFF treatment

Dividend states and prices reported are those corresponding to the first period in a sequence.

Following the same line of reasoning of the SDF treatment, given that the covariance between the SDF and the stochastic discount factor contributes only marginally to the volatility of the fundamental value across states of the world, we consider the REE prices with the zero covariance to be the benchmark for later analysis.[19]

4.3.9 Hypotheses to test

As previously mentioned, the main difference between the two treatments pertains the dividend process. The two dividend processes were chosen such that only one of the two sources of volatility influences the equilibrium price. Therefore the two designed treatments allow us to study whether subjects take the varying stochastic discount factor into account when pricing of the asset. We hypothesize that subjects do not understand the meaning of the stochastic discount factor.

Since the changing stochastic discount factor is the only reason for the different REE prices of the asset in the SDF treatment, if subjects disregard changes in the stochastic discount factor the price should be stable, reflecting the expected dividend value, rather than being dependent on the dividend draw in a given round.

Hypothesis 1. *In the SDF treatment the market price of the asset is independent of the dividend realization and on average between the two REE prices.*

In the PAYOFF treatment the stochastic discount factors is constant, hence it does not influence the equilibrium market price. The volatile dividend results in variations of (expected) payoffs, which affects the equilibrium market price for the asset from round to round. The actual market price of the asset should therefore co-move with the dividend payments independently of whether subjects do or do not understand the stochastic discount factor.

Hypothesis 2. *In the PAYOFF treatment the market price of the asset co-moves with the dividend.*

REE predicts prices that result in a larger price volatility in the treatment SDF, since the expected changes in the stochastic discount factor leads to a lot more volatility in the equilibrium asset prices. But if Hypothesis 1 and 2 are confirmed and subjects do not take into

[19]The volatility, measured as standard deviation, of the REE price across states in the presence of a non-zero covariance is 1.49, while if the covariance term is ignored, the variance of the REE prices across states reduces to 1.42.

account the stochastic discount factor, then only prices in the PAYOFF treatment should be volatile. Consequently, a higher price volatility should be observed in the PAYOFF treatment when compared to the SDF treatment.

Hypothesis 3. *Price volatility in the PAYOFF treatment is larger than in the SDF treatment.*

4.4 Results

The experiment was run between October and December 2014 in the experimental lab of the University of Mannheim. Six repetitions of the experiment took place, three for each treatment, with participants being mostly undergraduate students of the same university. Each session involved 16 subjects (14 in the case of the first session) with no prior experience of this experimental design (94 subjects in total) and no individual participated in more than one session. In each session, we run two markets (groups) with 8 participants each (7 in the case of the first session). The two groups participated simultaneously to the experiment facing different economies characterised by the same number of sequences and periods within a sequence.

The experiment lasted approximately 3 hours, including the time reading the instructions and the time for participants to familiarize with the trading interface. Table 4.3 provides details of the experimental sessions, with each session composed of several sequences of different lengths. In total 21 sequences (358 periods) were played by 94 subjects. The longest sequence was played in the sixth session, while the shortest one lasted only one period during the first (and second) session.

Session Number	Number of Sequences	Treatment	Number of Periods (Total by Session, Min within Session, Max)	Subjects
1	6	SDF	(58, 1, 14)	14
2	5	PAYOFF	(56, 1, 12)	16
3	2	PAYOFF	(50, 12, 13)	16
4	3	PAYOFF	(60, 4, 15)	16
5	3	SDF	(66, 4, 15)	16
6	2	SDF	(68, 5, 29)	16
Overall	21		(358, 1, 29)	94

Table 4.3: Summary data of all experimental sessions (both treatments)

In the following we focus on the analysis of the experimental results, first considering each treatment separately, then a treatment comparison is provided.

The experiment tries to answer to two research questions: first, we are testing whether the Lucas (1978) model actually predicts the trading behaviour of subjects. Based on the previous studies discussed in the introduction, one could presume it not to be the case. Hence, our second and main objective is to test whether the observed asset price volatility is mainly driven by variations in the stochastic discount factor or by the variations in expected payoffs.

To provide an answer to the first question, we compare the observed market prices with the REE prices, while regarding the second question we analyse the co-movement of the transaction prices with the dividend. Since a double auction market delivers multiple prices for each trading period, we consider the *average trading price* per period for later analysis, aligned with other double auction experiments, e.g. Asparouhova et al. (2016). This price is the mean price of all completed transactions within a given period, stated in Taler, the experimental currency used within the experiment.

A look at the summary statistics, see Table 4.12 in Appendix 4.7.1 for details, reveals a lot of heterogeneity across sessions and groups within a treatment. The latter is not surprising, since the value of a stock depends on the dividend paid and the dividend payments are independent between groups. In order to compare prices between groups and sessions within a treatment Tables 4.4 and 4.6 consider the *average trading price* for each session and group in the two states of the world in the SDF treatment (high or low dividend) and for dividends above and below the median in the PAYOFF treatment, where the median is calculated at the group level. We first discuss the average trading prices in the different states separately for the SDF and PAYOFF treatment. The prices observed in the SDF treatment are relevant for testing Hypothesis 1, while the trading prices in the PAYOFF treatment allow to test Hypothesis 2. We then try to compare the importance of the two difference sources for asset price volatility in our experiment so to verify Hypothesis 3, before looking at the volatility and the individual trading behaviour.

4.4.1 Prices in the SDF treatment

The *iid* dividend process defines two different states of the world, each of them dependent on the realized dividend and resulting in two different REE asset prices. In Table 4.4 the average trading price for each group is summarized separately in correspondence of each state of the world. These prices suggest a higher average trading price in the high-dividend state. Testing the difference of the *average per period trading price* between the two states on a group level using a Mann-Whitney-U test (MWU) leads to four significant differences out of six comparisons on the 10% level or lower, as reported in the seventh column in Table 4.4. Performing an MWU test on the pooled data for all 6 groups of the SDF treatment yields to a significant difference at the five percent confidence level (p-value 0.0255). However, this test uses repeated observations within a group and it might therefore be misleading. Alternatively, we run a sign test using the difference between the average trading prices per group. Since in all six groups the higher average trading price is observed in the high state periods, this test results in a significant difference (p-value 0.0313). Hence, the state of the world matters for the pricing of the asset in the SDF treatment.

	Dividend	Average Trading Price Mean	SD	Max	Min	MWU test p-value	Wilcoxon t-test p-value
Session 1							
Group 1	0.25	2.2	0.8	4.1	1.2	0.0075	0.3087
	0.50	3.0	0.7	4.4	2.2		0.0022
Group 2	0.25	6.2	0.8	7.4	4.6	0.0072	0.0010
	0.50	7.0	0.7	7.8	5.1		0.0735
Session 5							
Group 1	0.25	3.4	0.5	4.4	2.6	0.0001	0.0004
	0.50	4.4	0.6	5.6	3.5		0.0003
Group 2	0.25	4.4	0.6	5.4	3.2	0.1719	0.0010
	0.50	4.7	0.6	5.4	3.6		0.0010
Session 6							
Group 1	0.25	2.4	1.4	5.0	0.0	0.0509	0.7676
	0.50	3.1	1.1	5.1	1.9		0.0015
Group 2	0.25	2.9	2.4	10.4	1.2	0.1571	0.4459
	0.50	3.1	2.3	11.3	1.8		0.0032
Pooled data							
	0.25	3.6	1.9	10.4	0	0.0255	0.0000
	0.50	4.1	1.8	11.3	1.8		0.0000

Table 4.4: Average trading price statistics in the SDF treatment

By column: dividend realisation, average trading price statistics by state in the SDF treatment, i.e. mean, standard deviation, maximum and minimum. The MWU test refers to a between-states comparison at group level, while the Wilcoxon signed-rank test refers to a mean comparison to the REE equilibrium. REE price in the low state is 2.347 and in the high state is 6.639. All values besides the p-values are stated in Taler.

The latter finding, though being in line with the REE predictions of two distinct asset prices, contradicts Hypothesis 1 stating that subjects do not take the variation in the stochastic discount factor into account. If the variation in the stochastic discount factor was completely ignored, we should observe no difference between the prices in the two states. At a first sight, the clear conclusion from this observation would be that subjects take the state of the world and therefore the stochastic discount factor into account when trading the asset. However, the difference between the prices in the two states is rather modest once it is compared to the REE predicted prices. The eighth column of Table 4.4 reports for each group the result of Wilcoxon t-tests of the equivalence between the observed average trading prices and the predicted REE price, depending on the state. Only in three out of the 12 cases the difference between the observed trading prices and the REE price predictions is not significant, all cases being in correspondence of the low state of the world.

The graph in Figure 4.2 plots the *average trading price* for all periods and the corresponding rational expectation equilibrium (REE) prices for group 1 of session 1. The vertical lines indicate the start of a new sequence and the lower panel in the graph display the dividend paid in each trading period. The pattern observed for this group is typical for the SDF treatment, i.e. the difference in the REE prices between the two states of the world is larger than the one in the realized trading prices. In rational expectations, a price of 6.6 Taler is defined for the high state of world (dividend of 0.5 Taler), while an equilibrium price of 2.3 Taler for the low state of the world, i.e. a dividend of 0.25 Taler. While the theoretical difference between the REE prices in the two states is 4.3 Taler, the actual difference between the means is only 0.8 Taler for this group, while in the pooled data it is even smaller at 0.5 Taler. In several periods the *average trading price* is in between the theoretical equilibrium prices and in all other periods it is even lower than the REE price in the low state. Moreover, the *average trading price* reduces along the course of the session and in the last sequence played the *average trading price* is below the REE prediction in all 14 periods of the sequence.

Besides the stochastic discount factor, a second factor might lead to a difference in the *average trading prices* between the two states in this treatment, i.e. the different liquidity in the two states of the world. The income a subject receives independently of the dividend payments is proportionally to the state, i.e. in the high state a subject receives an additional income of 15 Taler and in the low state individuals receive 8 Taler. It follows that even an individual with no stocks would be able to buy more stocks in the high-dividend state than in a low-dividend state, while for subjects owing a positive amount of stocks the liquidity difference is even larger due to the dividend payments.

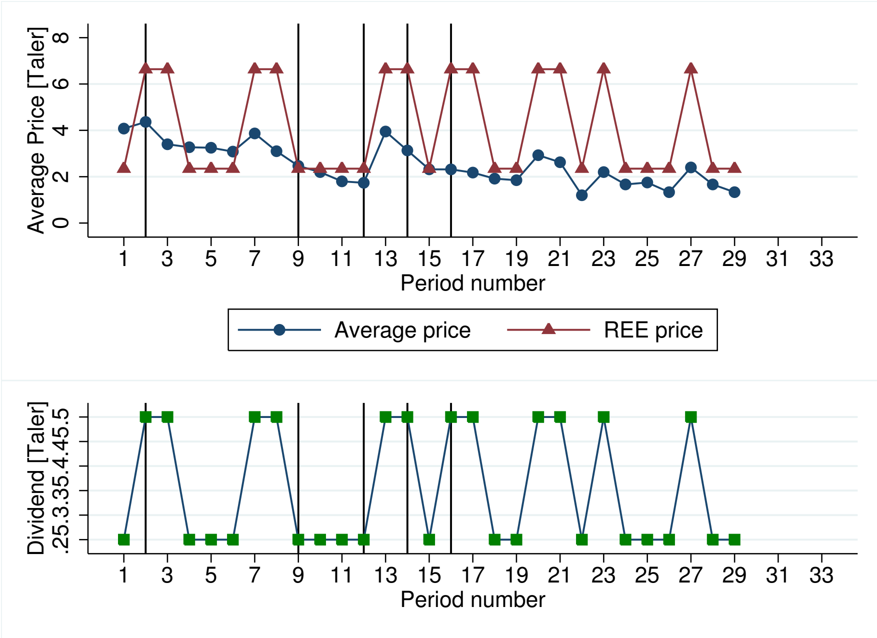


Figure 4.2: Price and dividend dynamics in the SDF treatment

The graph reports price and dividend dynamics for Session 1 Group 1 in the experiment. All values are stated in Taler.

Even if subjects do not take the stochastic discount factor into account and consequently have state independent asset valuations, if subjects asset valuations are heterogeneous, this liquidity difference could lead to the different *average trading prices.* On the one hand, in the high state all subjects have more money available, therefore subjects that value the asset more can buy more stocks in these periods. On the other hand, individuals that value the asset less and therefore are more likely to sell stocks, instead of buying them, can always sell independently of the state. Selling, differently from buying, is not influenced by the available liquidity. Hence, it could be the case that a higher *average trading price* emerges in high states even if the stock valuation for all subjects is independent of the dividend. The higher liquidity in the high state compared to the low state could result in an increased demand for the stock in this state, while the supply remained constant in the two states.[20]

If our reasoning was to be verified in the data, then we should observe a difference in the trade volumes depending on the state. The higher liquidity in the high-dividend state should result in more completed transactions. Given the small difference in the *average trading price* documented earlier, we should observe this difference in trading volumes despite the increased

[20]Clearly, price increases in the high-dividend state are not purely liquidity driven. Instead this could be interpreted as the price increases are possible even if subjects do not take the SDF into account, hence the equilibrium arguments for higher asset prices in the high state do not apply.

price, since the liquidity per subject more than doubles in the high state compared to the low state, while the price increase is in the neighbourhood of thirty percentage points. Hence, the liquidity effect should outweigh any price effect on trade volumes.

	Dividend	No. of periods	Number of trades Mean	SD	Min	Max	MWU test p-value
Session 1							
Group 1	0.25	17	10.76	6.47	3	22	0.2046
	0.50	12	14.17	6.86	5	28	
Group 2	0.25	19	6.05	1.27	4	8	0.0029
	0.50	10	8.50	2.64	3	13	
Session 5							
Group 1	0.25	16	7.38	3.63	3	15	0.0031
	0.50	17	10.59	2.81	6	16	
Group 2	0.25	19	16.16	5.87	10	35	0.0461
	0.50	14	19.50	6.38	12	36	
Session 6							
Group 1	0.25	21	4.00	2.61	0	11	0.0011
	0.50	13	7.77	2.65	2	11	
Group 2	0.25	18	12.61	3.79	7	21	0.1316
	0.50	16	14.44	3.22	9	20	
Pooled data							
	0.25	110	9.4	5.96	0	35	0.0000
	0.50	82	12.68	5.84	2	36	

Table 4.5: Number of trade statistics in the SDF treatment

By column: dividend realisation, number of trades (per period) statistics by state in the SDF treatment, i.e. mean, standard deviation, maximum and minimum. MWU test p-values refers to across states comparison at group level.

Table 4.5 shows that in periods with a high dividend on average more trades took place than in periods with a low dividend. On average 12.7 trades were executed in a period with a dividend of 0.5, while only 9.4 transaction took place in a period with a low dividend. Similarly to Table 4.4, the MWU on the pooled data is problematic due to the repeated use of observations within in a group. Performing a sign rank test with the group differences yields a significant difference at the five percent confidence level (p-value 0.0313, for all six groups more trades are completed in the high-dividend state). Using a MWU test on the individual groups yields a significant difference (at five percent confidence level or higher) for four out of the six groups. These comparisons support our presumption that more trades might take place in the high state of the world due to the higher liquidity.[21]

As additional evidence for the influence of the available liquidity we perform an OLS regression of the number of completed transactions on the dividend and several control variables, i.e. period, sequence number, average trading price and group fixed effects. The regression reported in Table 4.13 in Appendix 4.7.2 shows that for the SDF treatment the number of trades is larger in the high-dividend states. Moreover, the larger liquidity available in periods with a higher dividend partially explains the observed differences in the average prices.

To summarise, four are the main results for the SDF treatment. First, the *average trading price* is larger in the high-dividend state than in the low state contradicting Hypothesis 1. Second, this difference is considerably smaller than in the REE predictions. Third, the price difference seems to be at least partially be driven by the difference in liquidity in the two states and fourth, we do not observe an overvaluation of the stock, since in most periods the *average trading price* is between the two REE prices or in certain occasion below the lowest REE price.

4.4.2 Prices in the PAYOFF treatment

In the PAYOFF treatment the unit root dividend process results in a constantly changing dividend, since the dividend is either 80% or 120% of the dividend in the previous period, with equal probability. Table 4.6 summarizes the *average trading prices* for all periods splitting the sample in period with a dividend above and periods with a dividend below the median of the dividend. The median of the dividend is defined at group level, so that this classification allows us a similar state-dependent analysis as in the SDF treatment. Similarly, we can therefore test whether the *average trading price* depends on the dividend state. According to Hypothesis 2 higher dividends should result in higher asset prices. Consequently, the average trading price for periods with a dividend above the median should be larger than the average trading prices for periods with a dividend below the median.

[21] These results are qualitatively unchanged if the first five or ten periods of each session are excluded from the analysis to check whether the difference goes away over time. The role of the varying liquidity is discussed in more detail when we analyse the individual trading behaviour.

	Dividend	Average trading price Mean	SD	Max	Min	MWU test p-value
Session 2						
Group 1	below median	2.73	0.43	3.45	1.89	0.0927
	above median	3.25	0.78	4.85	2.20	
Group 2	below median	1.43	0.89	3.00	0.00	0.0033
	above median	2.52	0.37	3.34	1.94	
Session 3						
Group 1	below median	1.21	0.60	2.74	0.43	0.0002
	above median	2.63	0.75	4.15	1.50	
Group 2	below median	8.66	1.18	11.00	6.11	0.2208
	above median	8.30	0.50	9.17	7.29	
Session 4						
Group 1	below median	2.60	1.40	6.40	1.53	0.0618
	above median	2.87	1.41	7.67	1.85	
Group 2	below median	0.85	0.63	2.15	0.00	0.0001
	above median	2.28	0.65	3.67	0.82	

Table 4.6: Average trading prices in the PAYOFF treatment

By column: average trading prices statistics by dividend in the PAYOFF treatment, i.e. mean, standard deviation, maximum and minimum. MWU test p-values refers to across dividend comparison at group level (below versus above median dividend).
All values besides p-values are expressed in Taler.

Table 4.7 reports the mean dividend for all groups and sequences of the PAYOFF treatment. There is a large variation in the dividends paid between the groups and also between different sequences of the same group. The dividend payments in the PAYOFF treatment varied between 0.06 Taler and 1.55 Taler, with an average dividend of 0.40 Taler. Using the above described classification for periods and testing whether the *average trading price* is larger in periods with a high dividend yields significant differences for all but one group at ten percent confidence level. This clearly shows the importance of the dividend of the pricing of the asset. In periods with a higher dividend the stock is traded at higher prices. Also the absolute difference in the pooled data (0.8 Taler) is larger than in the SDF treatment (0.5 Taler), while the *average trading prices* seem generally to be lower.

	Sequence	No. of periods	Dividend Mean	SD	Max	Min		Dividend Mean	SD	Max	Min
Session 2											
Group 1	1	1	0.30	-	0.30	0.30	Group 2	0.30	-	0.30	0.30
	2	12	0.41	0.11	0.29	0.65		0.52	0.11	0.36	0.72
	3	1	0.30	-	0.30	0.30		0.45	-	0.45	0.45
	4	2	0.27	0.04	0.24	0.30		0.50	0.06	0.45	0.54
	5	12	0.35	0.09	0.23	0.55		0.22	0.10	0.13	0.45
	Pooled	28	0.37	0.10	0.23	0.65		0.38	0.17	0.13	0.72
Session 3											
Group 1	1	13	0.15	0.07	0.06	0.30	Group 2	0.49	0.10	0.35	0.69
	2	12	0.90	0.33	0.45	1.55		0.77	0.33	0.43	1.48
	Pooled	25	0.51	0.45	0.06	1.55		0.62	0.27	0.35	1.48
Session 4											
Group 1	1	4	0.24	0.04	0.19	0.30	Group 2	0.60	0.14	0.45	0.78
	2	11	0.28	0.08	0.16	0.45		0.26	0.04	0.21	0.35
	3	15	0.28	0.11	0.15	0.54		0.25	0.14	0.09	0.54
	Pooled	30	0.27	0.09	0.15	0.54		0.30	0.16	0.09	0.78
All sessions											
	Pooled	166	0.40	0.26	0.06	1.55					

Table 4.7: Summary statistics dividend in the PAYOFF treatment

By column: summary statistics of the dividend in the PAYOFF treatment at sequence level by group, i.e. mean, standard deviation, maximum and minimum. All values a part from the number of periods are expressed in Taler.

As highlighted earlier for the SDF treatment, however the difference in the *average trading prices* can be partially due to the difference in the aggregate state-dependent liquidity. In general the argument also holds in the PAYOFF treatment, with two differences with respect to the SDF treatment. First, the difference in liquidity from period to period is not as big as in the SDF treatment, since the dividend process leads to a smaller variation in the dividend. Second, while in the SDF treatment the *iid* process leads to comparable average dividends across groups, due to the path dependency of the dividend in the PAYOFF treatment this is not the case. Nevertheless, the OLS regression of the number of completed transactions reported in the second column of Table 4.13 in Appendix 4.7.2 shows a similar influence of the dividend on the number of trades. Hence, also in the PAYOFF treatment more trades take place in periods with a higher dividend, hinting at that higher liquidity in these periods also influencing the *average trading price*.

Following the earlier analysis, Figure 4.3 shows price and dividend movements for a representative group for the PAYOFF treatment. The REE price seems to move more than the *average trading price*, whilst the realized prices are generally below the REE predictions. However, the difference between the theory prediction and the actual realized trading price appears to be very large only for periods with relatively high dividends. The general movements in the dividend and in the realized *average trading price* seem to be very similar, in most of the groups in the PAYOFF treatment.

To consider whether dividends and price movements are aligned, Table 4.8 classifies each period of the PAYOFF treatment according to the dividend change in regard to the previous period. The column *Down* means that the dividend decreased from the last period to this period and *Up* lists all periods with a dividend increase.[22] Therefore if the *average trading price* follows the dividend we should observe most periods to be in the (*Up, Up*) or (*Down, Down*) cell. While a Fisher's Exact probability test yields a significant difference at the one percent confidence level (p-value 0.004) between the two columns, which supports the claim that the average trading price moves together with the dividend. To note that the test uses multiple observations from each group leading to dependent observations and therefore the result should be taken with care.[23]

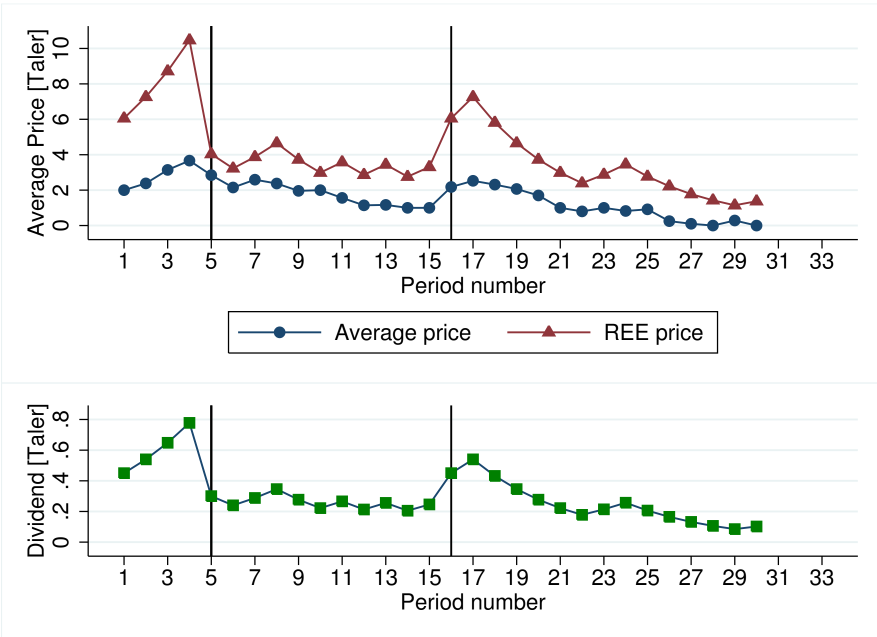


Figure 4.3: Price and divided dynamics in the PAYOFF treatment

The graph reports price and dividend dynamics for Session 4 Group 2 in the experiment. All values are stated in Taler.

[22]Since the dividend changes between every period only the first period of a sequence cannot be classified.
[23]A Chi squared test yields the identical result, p-value 0.004, but also assumes independent observations.

To sum up, three conclusions can be drawn from the analysis of the PAYOFF treatment. First, the *average trading price* is larger in periods with lager dividends, confirming Hypothesis 2. Second, the number of transactions increases in periods with a higher dividend, which hints that at least part of the price increase could be driven by the higher liquidity being in the market in high-dividend periods. Finally, the movements of the dividend and the *average trading price* seem to be highly correlated.

Average trading price change	Dividend change		
	Down	Up	Total
Down	56	34	90
Up	21	35	56
Total	77	69	146

Table 4.8: Dividend and direction of the price changes in the PAYOFF treatment

4.4.3 Treatment comparison

We now compare the influence of the dividends on prices for the two treatments directly. We further analyse whether there is a treatment difference with regard to the asset price volatility between the treatments by means of a regression whose results reported in Table 4.9. We run an OLS regression of the *average trading price* separately for both treatments on several explanatory variables so to gain understanding of the effect of the dividend payments on the trading price. The main independent variable is *Dividend* which is the dividend paid in the respective period expressed in Taler. Furthermore the regressions include a dummy for the first period of a sequence (*New sequence*), the period number (*Period*) and the sequence number (*Sequence*).[24] Both regressions also include group fixed effects to account for the between-group heterogeneity and the dependence of repeated observations within a group.[25]

[24]Period number counts periods over sequences within a session, so if the first sequence lasted 5 periods, period 3 of sequence number two has the period number 8.

[25]In order to increase the readability of the table, these group fixed effects are not reported in Table 4.9. The estimated group fixed effects vary a lot between groups, indicating high degree of heterogeneity between the groups.

	(1) SDF Treatment	(2) PAYOFF Treatment
Dividend	2.04**	2.36***
	(0.60)	(0.34)
New Sequence	0.35	0.29
	(0.28)	(0.26)
Period	−0.06	−0.10***
	(0.04)	(0.02)
Sequence	0.00	0.21
	(0.12)	(0.14)
Group FE	√	√
Obs.	192	166
R-squared	0.93	0.97

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4.9: OLS regression average trading price

Average trading price regressed on dividend, new sequence dummy, period, sequence and group fixed effect for both treatments. Standard errors clustered at group level are reported in brackets.

The first column reports the results for the SDF treatment, while the second column, the results for the PAYOFF treatment. For both regressions the coefficient of *Dividend* is significantly positive (at the 5%-level for the SDF and at the 1%-level for the PAYOFF treatment). These coefficients confirm an earlier finding that the average market price reacts to the dividend, i.e. a higher dividend leads to, on average, higher market prices for the asset in both treatments.

The estimated coefficient values are both around 2, which means that a dividend increase of 1 Taler translates in an average trading price that is about 2 Taler larger. However, an increase of 1 Taler for the dividend is basically impossible in the used set-up. In the SDF treatment, the dividend varies between 0.25 and 0.5 Taler. The increase of the dividend is therefore limited to 0.25 Taler, therefore the coefficient on the *Dividend* corresponds to an increase in the asset price of 0.51 Taler ($2.04 \cdot 0.25 = 0.51$). The detailed derivation of the REE price in Appendix 4.6, in particular equation (4.26) shows that an increase of one Taler in the dividend should result in an increase in the average trading price by 4.977 Taler. Clearly, the regression results in a much smaller coefficient confirming the findings from above that prices co-move with the dividend, but to a smaller extent than predicted by theory.

Similarly, for the PAYOFF treatment the coefficient on *Dividend* yields a coefficient of 2.36. But also in this treatment the expected dividend changes are much smaller. In Appendix 4.6 the predicted relationship between the dividend and the REE price is derived, see equation

(4.38). For an increase of the dividend of one Taler the REE price should increase by 13.45 Taler. Clearly, the estimated coefficient of 2.36 is much smaller than the theoretical value the regressor should have. Therefore the regression confirms the finding that also for the PAYOFF treatment the dividend has a significant influence on the asset price, but that the change in the asset price is much smaller than predicted.

Therefore in both treatments the average market price co-moves with the dividend, indicating that subjects in the respective treatments took the stochastic discount factor (SDF treatment) or the volatility of payoffs (PAYOFF treatment) into account and in both treatments the REE predicts a stronger reaction of the market price than the one observed in the experiment.

The only other significant coefficient besides *Dividend* is *Period* in the PAYOFF treatment. This negative coefficient confirms the downward time trend observed in Figure 4.3 above for one group for the entire PAYOFF treatment. On the contrary, the time trend coefficient in the SDF treatment is not significant.

These results contradict Hypothesis 1, and rather confirm Hypothesis 2.

While regarding Hypothesis 3, which predicts that the co-movement of dividend and trading price should be stronger in the PAYOFF than in the SDF treatment, the regression does not yield a very clear result. While both the SDF and the expected payoff influence the dividend, the REE predicts a stronger movement of the REE price as reaction to a dividend change in the PAYOFF treatment than in the SDF treatment. However, the OLS regression shows very similar effects of the dividend in both treatments, but mainly because the effect of the stochastic discount factor is stronger than assumed in Hypothesis 1. Given that the size of the coefficients and that the prediction was a stronger effect for the PAYOFF treatment our data does not support Hypothesis 3.

We now focus our analysis on the asset price volatility observed in the experimental sessions. In line with previous experiments, we first measure price volatility as the standard deviation of the average market clearing price ($\sigma_{Price_{jk}}$) for group (j) for sequence level (k). In the following tables we report the volatility of the market price and the one of the correspondent rational expectation price computed for each treatment at sequence level. As stated in Table 4.10, in the SDF treatment, market clearing prices are substantially less volatile than the fundamentals, as confirmed by a Wilcoxon sign-test.

	Sequence	No. of periods	Volatility Trading Price	Volatility FV		Volatility Trading Price	Volatility FV
Session 1							
Group 1	1	1	-	-	Group 2	-	-
	2	7	0.47	2.29		0.36	2.29
	3	3	0.33	0		0.59	2.48
	4	2	1.56	3.03		0.22	3.03
	5	2	0.58	3.03		0.14	3.03
	6	14	0.51	2.24		0.84	1.88
Session 5							
Group 1	1	4	0.58	2.14	Group 2	0.55	2.14
	2	15	0.72	2.22		0.62	2.22
	3	14	0.64	2.22		0.44	2.20
Session 6							
Group 1	1	5	0.23	1.92	Group 2	3.37	2.35
	2	29	1.16	2.19		0.70	2.18

Table 4.10: Summary statistics average market price volatility in the SDF treatment

Summary statistics volatility of the average market price volatility versus volatility of fundamentals (FV) in the SDF treatment. All values are rounded to two digits.

	Sequence	No. of periods	Volatility Trading Price	Volatility FV		Volatility Trading Price	Volatility FV
Session 2							
Group 1	1	1	-	-	Group 2	-	-
	2	12	0.58	1.45		0.38	1.47
	3	1	-	-		-	-
	4	2	0.10	0.57		0.50	0.85
	5	12	0.31	1.25		0.72	1.32
Session 3							
Group 1	1	13	0.75	0.95	Group 2	1.19	1.35
	2	12	0.81	4.50		0.49	4.43
Session 4							
Group 1	1	4	1.64	0.60	Group 2	0.75	1.90
	2	11	0.69	1.09		0.66	0.56
	3	15	0.39	1.50		0.88	1.86

Table 4.11: Summary statistics average market price volatility in the PAYOFF treatment

Summary statistics volatility of the average market price versus volatility of fundamentals (FV) in the PAYOFF treatment. All values are rounded to two digits.

A similar picture emerges for the PAYOFF treatment, as summarized in Table 4.11. We observe *negative excess volatility,* i.e. the realised price volatility is significantly lower than the theoretical one in both treatments. So to understand the driving forces of the latter excess volatility, we construct a treatment-invariant measure of volatility that takes into account the different theoretical volatility participants were facing in the two different set-ups. We rescale the standard deviation of the average trading price at sequence level with the corresponding one of the fundamentals, as

$$P_{ex-vola} = \frac{\sigma_{Price j_k} - \sigma_{FV_{jk}}}{\sigma_{FV j_k}} \tag{4.18}$$

where $\sigma_{Price_{jk}}$ is the standard deviation of average trading price for group j in sequence k and $\sigma_{FV_{jk}}$ is the standard deviation of the average fundamental value for the same group and sequence.[26]

We then compare the rescaled volatility measure across treatments and find that a Mann-Whitney test indicates no statistical different between the two. Whilst the difference is not statistically significant, it appears to be the case that the price volatility in PAYOFF treatment is higher than in SDF.[27] Hence, even if mildly, the stochastic discount factor seems to have a more limited effect in predicting the volatility of prices than the payoffs. This can arise from the difficulty associated with understanding the stochastic discount factor itself that needs some further investigation by means of the individual trading data.

4.4.4 Individual trading

The analysis so far concentrated on aggregate data for the two treatments. In this section instead, we investigate the individual trading behaviour of subjects. One way to determine the individual valuation of subjects for the asset is to use the detailed trading data from the double auction market. We use the offered or executed bid prices to construct a *willingness-to-pay (wtp)* measure for each subject in each period. The *willingness-to-pay* of a subject is the highest bid she made during a period that was either executed, standing at the end of the period or deleted because the subject made another trade.[28] In order to determine if subjects had a different valuation for the asset in the SDF treatment depending on the state of the

[26]We exclude those sequences that lasted only one period and the ones where the fundamentals were constant.

[27]The latter result is confirmed also if we exclude the first periods or the first sequence, with similar level of significance.

[28]Subjects could make multiple offers for buying/selling the stock, but execution of one order deleted all the other standing asks/bids. This procedure excludes cancelled bids. If the highest *wtp* of a subject in a period was a bid that was deleted, then a seller accepted a lower bid from the same subject. Otherwise, the deleted bid would not be the highest, hence not the bid being used to determine the *wtp* .

world we perform MWU tests separately for each individual of the SDF treatment, testing whether the *wtp* of subjects was different in high-state periods versus low-state periods. Ten subjects out of 46 have a significantly different *wtp* in the two states (at the 5% level). Therefore, only 22% of all participants to the SDF treatment seem to take the stochastic discount factor variation significantly into account when trading the asset.

We also perform a similar analysis for the PAYOFF treatment, using the median dividend at the group level to sort periods into high and low-dividend periods. Seventeen of the 48 subjects in the PAYOFF treatment have a significantly different *wtp* in the two "states" (again 5% significance level). This value indicates that the dividend value seems to be important for more subjects' asset valuation in the PAYOFF treatment when compared to the SDF treatment. However, still only 35% of the participants to the PAYOFF treatment show a significant difference in their *wtp*.

To further assess whether subjects actually realise the importance of the stochastic discount factor in the SDF treatment is to analyse their consumption behaviours. With the actual asset prices described in the previous sections a subject that is aware of the stochastic discount factor should consume relatively more in the low state of the world and less in the high state. In the SDF treatment average prices are below REE prices in the high state of the world and above the REE in the low one. Therefore, the asset is undervalued if the dividend is high, while it is overvalued if the dividend is low. A subject understanding the role of the stochastic discount factor should therefore consume relatively more in low states than in high states, while she should buy the assets in the high state of the world.

In order to check how many subjects followed such an optimal strategy we rank subjects within their trading group according to their relative consumption.[29] A subject that follows the outlined trading strategy be ranked relatively high with regard to consumption in the low-dividend state (since the stock price is likely above REE and therefore the subject should sell), but rank low in high-dividend states, since the subjects buy the undervalued asset.

Only ten out of 46 subjects in the SDF treatment (22%) can be classified as following such a strategy. We use individual consumption in a given period to classify subjects according to their ranking within their group, then use all position rank of a subject to test whether there is a difference between the position ranks the participant was assigned in the low versus high dividend states. The difference in ranks is significant for 14 subjects (using a two sided

[29]Essentially, we rank subjects in each period within their trading group since they all face the same sequence of dividends. Between groups or between treatments comparison is not considered.

t-test), but only for 10 the consumption is higher in the high state.[30] Using this (very broad) classification 80% of subjects do not fully take the stochastic discount factor into account in their consumption behaviour.

The analysis of the individual trading behaviour shows that only a small fraction seems to fully understand the role of the stochastic discount factor. Both approaches, using the stated individual *willingness-to-pay* or the relative rank of a subject with respect to consumption, result in about 80% of subjects in the SDF treatment that do not follows trading strategies that are in line with fully understanding the stochastic discount factor. However, their "*imperfect*" reaction to the changes in the stochastic discount factor and the 20% of subjects that seem to take the stochastic discount factor into account result in average trading prices that lead to a rejection of Hypothesis 1.

4.4.5 Beliefs

We now have a look at the individual expectations about the future asset returns. At the beginning of each trading period, subjects were asked to predict the future asset return, i.e. the return that they believe will realize at the end of the consecutive period of trade.

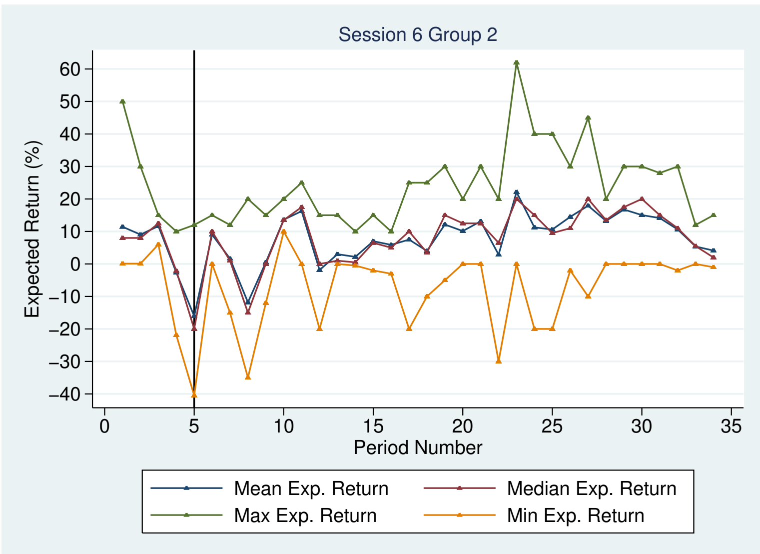


Figure 4.4: Expected returns statistics in the SDF treatment

The graph reports mean, median, maximum and minimum of the elicited beliefs for Session 6 Group 2 in the experiment. All values are stated in percentage points.

[30]In the other four cases, the difference in the average rank is significant, but they consume relatively less in the high state than in the low state. Therefore their trading behaviour is exactly the opposite of the described strategy.

In the following, we report the evolution over time of the first moment of the expected return, together with the median, the highest and the lowest expected return. We use the interval with the upper bound of the most optimistically stated future expected return and the lower bound of the most pessimistic one to measure the dispersion of individual beliefs. The latter is possible since our experimental design allows us to keep track of the entire cross-sectional belief distribution in every market, for each period traded. One representative group of each treatment has been chosen for illustrative purposes.

In the SDF treatment, we notice a substantial degree of heterogeneity of beliefs in the first period played that persists during the experiment, but shrinks towards the end of it. Less polarized beliefs at the end of last sequence played point at a common agreement about the profitability of the asset. The latter occurs once the market price has stabilized and volumes of trade are very low. Moreover, median and mean of the distribution are pretty stable over the entire length of the experiment, hinting at no time variation of the degree of optimism.

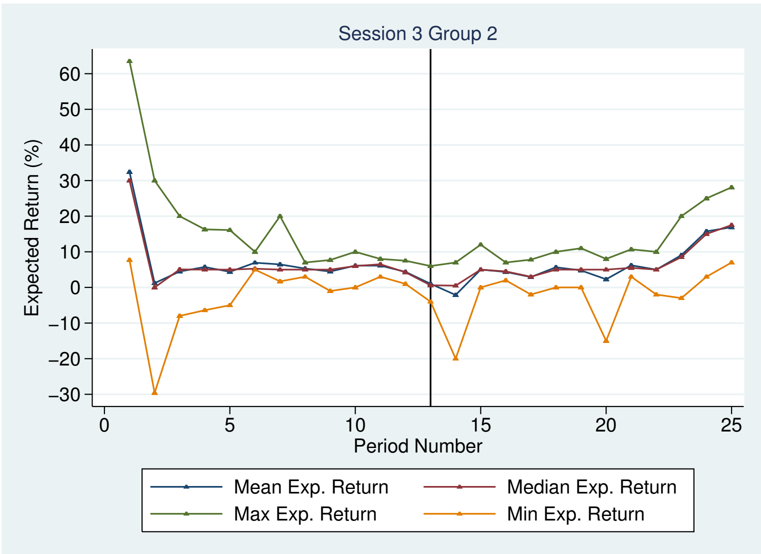


Figure 4.5: Expected returns statistics in the PAYOFF treatment

The graph reports mean, median, maximum and minimum of the elicited beliefs for Session 3 Group 2 in the experiment. All values are stated in percentage points.

A similar picture is displayed for the PAYOFF treatment. Interestingly, the dynamic of expected returns is characterized by more dispersed beliefs at the beginning of a sequence played that vanishes along the way once market price is steady, as in the SDF treatment. Furthermore, even though more stable than in the SDF treatment, also in the PAYOFF treatment the mean and the median of the cross-sectional distribution are mostly identical, i.e. the time variation of fundamentals does not go hand in hand with the expectations. Essentially, in our set-up there is room for adaptive learning dynamics and expectations feedback into prices only at the beginning of the experiment.[31]

Only a weak link between beliefs and prices is observed in our set-up. Differently from Donini (2016) where beliefs are shown to affect price dynamics by shifting individual demand schedules, in our experiment we observe a rather mild link between individual demands and stated return expectations. We relate this to the complexity of the experiment itself that might induce the stating of wrong beliefs or a general difficulty of participants to relate returns with intertemporal trading decisions.

4.5 Discussion and Conclusion

This paper presents a new experimental set-up for testing which of the two theoretical sources, the stochastic discount factor or the payoff volatility, is accountable for the observed price volatility in (experimental) asset markets. In line with recent experiments bringing the Lucas asset pricing model to the laboratory, we design two treatments where only one source of price volatility is in place in each of them. In the SDF treatment, the theoretical source of volatility is identified by the stochastic discount factor, whilst in the PAYOFF treatment the volatility of payoffs is responsible for the theoretical price volatility.

Our results show that, while both sources lead to variation in the asset prices, in both treatments the observed price volatility is much smaller than predicted by the REE. In particular, in the SDF treatment most observed prices are in between the two state dependent fundamental values. Therefore, while subjects seem to take the stochastic discount factor into account, the resulting price changes of the asset imply that subjects do not fully internalize the effect of the stochastic discount factor in our setting.

The results in the PAYOFF treatment are similar with regard to the observation that subjects react in their pricing behaviour to the changes in the volatility of payoffs, but as in the SDF treatment the resulting market clearing price volatility is much smaller than predicted by theory.

Hence, we find that both sources of price volatility lead to asset prices that change with the dividend, which implies that the stochastic discount factor as well as the volatility of prices are important for the observed price volatility in asset markets. The fact that subjects find

[31] The average expected returns in comparison to the realised returns are plotted in Appendix 4.7.3.

difficulties in applying the concept of intertemporal consumption smoothing in our setting is at odds with previous experiments by Asparouhova et al. (2016) and Crockett and Duffy (2013). However, our set-up differs substantially from the latter studies and the benchmark of a rational no-trade equilibrium in our experiment might be harder to obtain in our framework.

Possibly due to the complexity of the environment or the fact that subjects had to solve two tasks (predicting returns and trading the asset), as highlighted in Bao et al. (2013), we do not find evidence for a significant link between expected asset returns and trading behaviour of individual subjects. Given the observed dynamics of the beliefs about future return of the asset, the belief-price feedback loop that should amplify price oscillation around fundamentals is almost absent in our set-up since the price stabilizes relatively quickly and beliefs become very homogeneous after the first few periods played.

Our experiment provides a first approach to shed some light on the sources of the observed asset price volatility in experimental asset markets. We are able to show that both the stochastic discount factor, as well as the volatility of payoffs matter for the pricing of the asset, but which is the major driver for the volatility remains unclear. While the used environment might be too complex for some participants, hence lead to noisy trading that complicate the identification of the different sources of volatility, a likely conclusion from our results is that both sources matter, with a slightly higher probability that the volatility of payoffs might matter more. Given that we find a lower volatility of prices than expected and therefore no price bubbles occur in our experimental market, it is possible that the combination of both sources for price volatility results in a bigger effect than the two effects separately. Further research should be done in order to confirm our results in a possibly simpler experimental set-up, focusing on the role of the interaction effect between the two theoretical sources of asset price volatility.

4.6 Appendix I: REE prices in the two treatments

In the following we report the detailed calculations of the rational expectations equilibrium (REE) prices in the two treatments.

4.6.1 REE price in SDF treatment

$$
\begin{aligned}
P_{t,SDF}^{REE} &= E_t\left[\sum_{j=1}^{\infty}\delta^j\left(\frac{C_{t+j}}{C_t}\right)^{-\gamma}\cdot D_{t+j}\right] && (4.19)\\
&= \sum_{j=1}^{\infty}\delta^j\left[E_t\left(\left(\frac{D_{t+j}}{D_t}\right)^{-\gamma}\right)\cdot E_t\left(D_{t+j}\right)+Cov_t\left(\left(\frac{D_{t+j}}{D_t}\right)^{-\gamma},\, D_{t+j}\right)\right] && (4.20)\\
&= \sum_{j=1}^{\infty}\delta^j D_t^{\gamma}\left[E_t\left(D_{t+j}^{1-\gamma}\right)+Cov_t\left(D_{t+j}^{-\gamma},\, D_{t+j}\right)\right] && (4.21)\\
&= \sum_{j=1}^{\infty}\delta^j D_t^{\gamma}\left[E_t\left(D_{t+j}^{1-\gamma}\right)+\left(E_t\left(D_{t+j}^{1-\gamma}\right)-E_t\left(D_{t+j}^{-\gamma}\right)E_t\left(D_{t+j}\right)\right)\right] && (4.22)\\
&= \frac{\delta}{1-\delta}D_t^{\gamma}\cdot\left[E_t\left[\sum_{j=1}^{\infty}(D_{t+j})^{1-\gamma}\right]+\left(E_t\left[\sum_{j=1}^{\infty}(D_{t+j})^{1-\gamma}\right]-E_t\left[\sum_{j=1}^{\infty}(D_{t+j}^{-\gamma})\right]\cdot E_t\left[\sum_{j=1}^{\infty}(D_{t+j})\right]\right)\right] && (4.23)\\
&= \frac{\delta}{1-\delta}D_t^{\gamma}\left(2B-C\mu\right) && (4.24)\\
&= \frac{\delta}{1-\delta}\left(\underbrace{D_t^{\gamma}B}_{\text{contribution}_{SDF}}+\underbrace{D_t^{\gamma}(B-C\mu)}_{\text{contribution}_{COV}}\right) && (4.25)
\end{aligned}
$$

where B, C and μ are constants defined as

- $B \equiv p\cdot(D_H)^{1-\gamma}+(1-p)\cdot(D_L)^{1-\gamma}$
- $C \equiv p\cdot(D_H)^{-\gamma}+(1-p)\cdot(D_L)^{-\gamma}$
- $\mu \equiv p\cdot(D_H)+(1-p)\cdot(D_L)$, mean of the dividend process

An alternative formulation of the REE price, that states the REE price for the SDF treatment only as function of the dividend is given below

$$P^{REE}_{t,SDF} = \underbrace{\frac{\delta}{1-\delta}B}_{A} \cdot D_t^{\gamma} \tag{4.26}$$

where A for the chosen parametrization is 18.77.

For a change in the dividend from 0.25 to 0.5 (low to high state) this formula implies a change in the REE price of:

$$\Delta P^{REE}_{t,SDF} = \gamma \ A \ D_t^{\gamma-1} \ \Delta D_t \tag{4.27}$$

$$= 1.5 \cdot 18.77 \cdot 0.5^{0.5} \cdot 0.25 \tag{4.28}$$

$$= 4.977 \tag{4.29}$$

4.6.2 REE price in PAYOFF treatment

$$P^{REE}_{t,PAYOFF} = E_t\left[\sum_{j=1}^{\infty}\delta^j\left(\frac{C_{t+j}}{C_t}\right)^{-\gamma}D_{t+j}\right] \tag{4.30}$$

$$= \sum_{j=1}^{\infty}\delta^j\left[E_t\left(\left(\frac{D_{t+j}}{D_t}\right)^{-\gamma}\right)\cdot E_t\left(D_{t+j}\right) + Cov_t\left(\left(\frac{D_{t+j}}{D_t}\right)^{-\gamma}, D_{t+j}\right)\right] \tag{4.31}$$

$$= \sum_{j=1}^{\infty}\delta^j\left[E_t\left(\varepsilon_{t+j}^{-\gamma}\cdot\left(D_t\cdot\prod_{i=1}^{j}\varepsilon_{t+i}\right)\right) + Cov_t\left(\varepsilon_{t+j}^{-\gamma}, \left(D_t\cdot\prod_{i=1}^{j}\varepsilon_{t+i}\right)\right)\right] \tag{4.32}$$

$$= D_t\cdot\left[\sum_{j=1}^{\infty}\delta^j E_t\left(\prod_{i=1}^{j}\varepsilon_{t+i}^{1-\gamma}\right) + \left[\sum_{j=1}^{\infty}\delta^j\left(E_t\left(\varepsilon_{t+j}^{-\gamma}\cdot\prod_{i=1}^{j}\varepsilon_{t+i}\right) - E_t\left(\varepsilon_{t+j}^{-\gamma}\right)E_t\left(\prod_{i=1}^{j}\varepsilon_{t+i}\right)\right)\right]\right] \tag{4.33}$$

$$= D_t\cdot\left[\sum_{j=1}^{\infty}\delta^j\left(\prod_{i=1}^{j}E_t\left(\varepsilon_{t+i}^{1-\gamma}\right)\right) + \sum_{j=1}^{\infty}\delta^j\left(\left(\prod_{i=1}^{j}E_t\left(\varepsilon_{t+i}^{1-\gamma}\right)\right) - E_t\left(\varepsilon_{t+i}^{-\gamma}\right)\cdot\prod_{i=1}^{j}E_t\left(\varepsilon_{t+i}\right)\right)\right] \tag{4.34}$$

$$= D_t\cdot\left[\sum_{j=1}^{\infty}\delta^j\cdot\lambda^j - \sum_{j=1}^{\infty}\delta^j\cdot(\lambda-\phi\cdot 1)^j\right] \tag{4.35}$$

$$= D_t\cdot\left[\frac{\delta\lambda}{1-\delta\lambda} - \frac{\delta(\lambda-\phi)}{1-\delta(\lambda-\phi)}\right] \tag{4.36}$$

$$= \underbrace{D_t\cdot\frac{\delta\lambda}{1-\delta\lambda}}_{\text{contribution}_{PAYOFF}} + \underbrace{D_t\cdot\left(-\frac{\delta(\lambda-\phi)}{1-\delta(\lambda-\phi)}\right)}_{\text{contribution}_{COV}} \tag{4.37}$$

where λ, ϕ, μ are constant defined as follows,

- $\lambda \equiv E\left(\varepsilon_{t+i}^{1-\gamma}\right) = p\cdot(\varepsilon_H)^{1-\gamma} + (1-p)\cdot(\varepsilon_L)^{1-\gamma}$
- $\phi \equiv E\left(\varepsilon_{t+i}^{-\gamma}\right) = p\cdot(\varepsilon_H)^{-\gamma} + (1-p)\cdot(\varepsilon_L)^{-\gamma}$
- $\mu \equiv E\left(\varepsilon_{t+1}\right) = p\varepsilon_H + (1-p)\varepsilon_L = 1$, mean of the shock on the dividend process

with $\mid \delta\cdot\lambda \mid < 1$ and $\mid \lambda - \phi \mid < 1$.

An alternative formulation of the REE price, that states the REE price for the PAYOFF treatment only as function of the dividend is given below

$$P^{REE}_{t,PAYOFF} = \underbrace{\frac{\delta\lambda}{1-\delta\lambda}}_{F}\cdot D_t \tag{4.38}$$

where F for the chosen parametrization is 13.45.

For a change in the dividend from 0.3 to 0.36 this formula implies a change in the REE price of:

$$\Delta P_{t,PAYOFF}^{REE} = F \, \Delta D_t \tag{4.39}$$
$$= 13.45 \cdot 0.06 \tag{4.40}$$
$$= 0.807 \tag{4.41}$$

4.7 Appendix II: additional analysis

4.7.1 Average trading prices

Table 4.12 summarizes the average trading prices for all sessions and groups by sequence.

SDF treatment				PAYOFF treatment			
Sequence	No. of periods	Average trading price		Sequence	No. of periods	Average trading price	
Session 1				**Session 2**			
		Group 1	Group 2			Group 1	Group 2
1	1	4.077	6.429	1	1	2.190	3.000
2	7	3.477	7.157	2	12	3.599	2.580
3	3	2.156	7.190	3	1	3.455	2.684
4	2	2.843	6.988	4	2	2.839	2.321
5	2	2.726	6.900	5	12	2.477	1.171
6	14	1.955	5.878				
Session 5				**Session 3**			
		Group 1	Group 2			Group 1	Group 2
1	4	4.919	3.938	1	13	1.338	8.665
2	15	3.847	4.342	2	12	2.609	8.262
3	14	3.735	4.890				
Session 6				**Session 4**			
		Group 1	Group 2			Group 1	Group 2
1	5	4.821	7.520	1	4	5.810	2.798
2	29	2.304	2.162	2	11	2.484	1.799
				3	15	2.100	1.064

Table 4.12: Summary statistics average trading price in both treatment

By column: average trading price in all sessions, both in the SDF and in the PAYOFF treatment. All values except the number of periods composing a sequence are expressed in Taler.

4.7.2 Trading volumes

An OLS regression where the dependent variable is the number of completed trades within a period is reported in table 4.13. In both treatments, more trades took place in correspondence of higher dividend values and trade decreased over time.

	(1) SDF Treatment	(2) PAYOFF Treatment
Average price	-1.36^{*}	-1.65
	(0.55)	(1.81)
Dividend	13.38^{***}	11.78^{**}
	(2.42)	(4.04)
Period	-0.35^{**}	-1.06^{***}
	(0.11)	(0.10)
New Sequence	-0.06	-0.48
	(0.66)	(1.77)
Period	-0.06	-0.10^{***}
	(0.04)	(0.02)
Sequence	-0.93^{**}	0.00
	(0.34)	(1.73)
Constant	18.96^{***}	21.48^{***}
	(2.31)	(5.98)
Group FE	$\surd$	$\surd$
Obs.	191	165
R-squared	0.644	0.728

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4.13: OLS regression trading volumes

Trading volumes regressed on average price, period, new sequence dummy, dividend and group specific fixed effects. Standard errors clustered at group level are reported in brackets.

4.7.3 Beliefs

Figures 4.6 and 4.7 report realized returns for the same sessions and sequences considered in section 4.4.5. In both groups the realized returns are much more volatile then the state return expectations. One possibility for this finding is that subjects converged to the same mean belief when they realized that they are unable to match the true return. Therefore returns converge quickly on a value that is roughly between the realized returns.

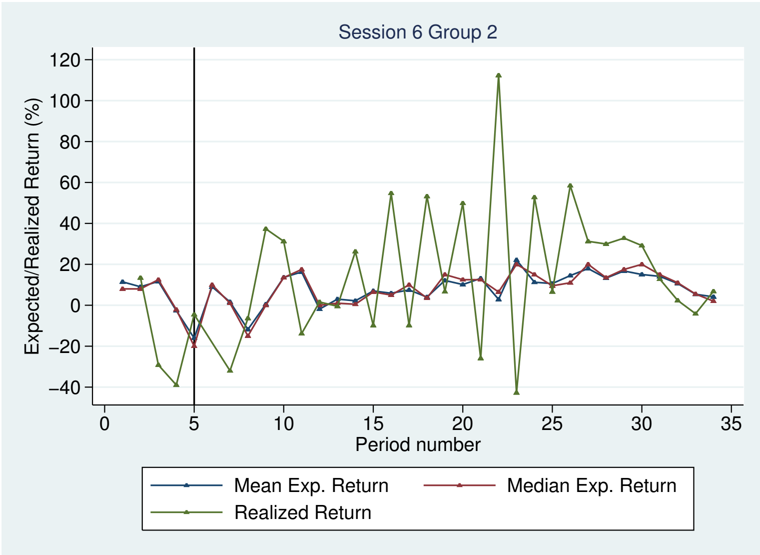


Figure 4.6: Expected and realised returns in the SDF treatment

The graph reports mean and median of the elicited beliefs together with the realised return for Session 6 Group 2 in the experiment. All values are stated in percentage points.

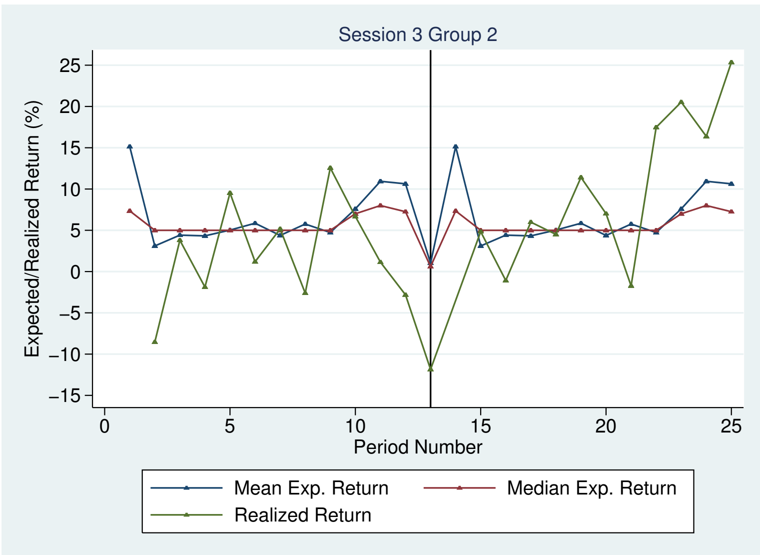


Figure 4.7: Expected and realised returns in the PAYOFF treatment

The graph reports mean and median of the elicited beliefs together with the realised return for Session 3 Group 2 in the experiment. All values are stated in percentage points.

4.8 Appendix III: Screen-shots trading screen

Below you see a screen-shot of the trading screen used in the experiment (in German). The shown screen is for the first period of a sequence. In later periods the history of the average market prices for the asset in the same sequence was shown.

Figure 4.8: Screen-shot of trading screen

4.9 Appendix IV: Instructions (English translation)

These are the translations of original instructions in German for the SDF treatment. The instructions for the PAYOFF treatment are equivalent with a different description of the dividend process and the payment rule for the return belief. The instructions are available from the authors upon request.

Welcome

Thank you for your decision to take part in this experiment. The experiment will take up to 2 hours and 45 minutes and you will receive your payment directly after the experiment in cash. It is very important that you do not talk to other participants during the entire experiment. In case you have questions after reading the instructions, please raise your hand. An experimenter will come to you and answer your question in private.

General instructions

The experiment today consists of one or multiple sequences. Each sequence consists of one or multiple periods. The exact number of periods and sequences is random and therefore not previously known. At the end of each period a random draw decides whether there will be another period or not.

In each period we ask you to perform two tasks. On the one hand we will ask you to make prediction of the return of a stock. On the other hand you have the possibility to trade this stock with other participants. You can earn money with both tasks.

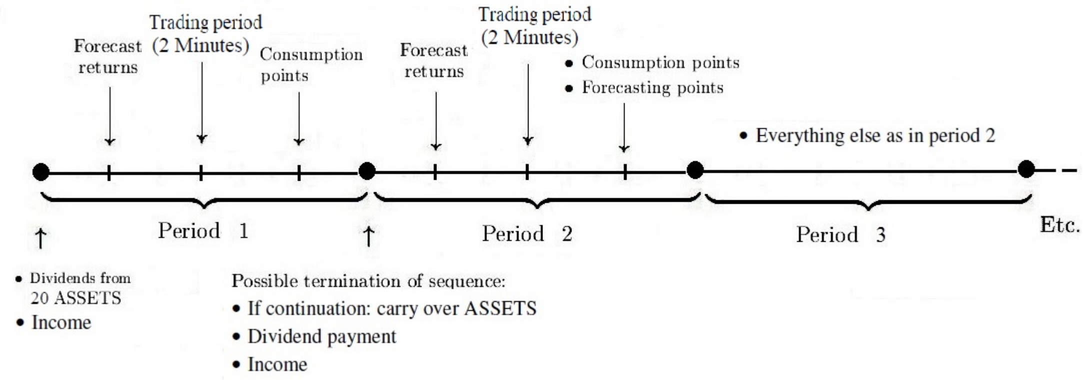
At the start of each sequence you receive a fix number of stocks and at the start of each period you receive some cash. While cash can only be used in the given period, you keep the stocks for the entire sequence, meaning for several periods, if you do not decide to sell the stocks. Money you cannot transfer from one period to the next.

In this experiment there are two groups. The set-up and procedures are the same for each group. A random move determines in which group you are.

We will now describe the details of the experiment. In case you still have questions after reading the instructions, please raise your hand.

Structure of a period

Each period consists of three parts. First, we ask you for your expectation regarding the return of the asset. Then, you can use your cash and stocks to trade those with other participants. Finally, you receive the information about how many points you earned in the given period.



At the start of each sequence you receive 20 stocks. Additionally, at the start of each period you receive additional money. The money in this experiment is called Taler. How many Taler you receive depends on (1) how many stocks you own and (2) on the magnitude of the dividend.

At the start of each period you receive for each stock you own a dividend payment. The dividend is either 0.5 or 0.25 Taler per stock. In each period each dividend payment is equally likely. Additionally you receive in each period an income of 15 or 8 Taler. This income is independent of the number of stocks you own, but it depends on the dividend. If the dividend is 0.5 Taler you receive 15 Taler and if the dividend is 0.25 Taler you receive 8 Taler as income.

Example:

You own 20 stocks. If the dividend is 0.25 Taler you receive a total of 13 Taler: 20*0.25 Taler as dividend and additionally an income of 8 Taler. Income and dividend are paid at the start of each period. This means you receive a dividend payment for each stock you own at the start of a period. Therefore there are two reasons to hold stocks: (1) You receive some additional money through the dividend payment for each stock you own. (2) You can possibly sell the stock in a later period.

(1) Prediction of the return

In each period you will be asked for your expectation about the return of the asset. The return of the stock captures how profitable it would be to buy a stock in this period and sell it in the next. The return consists of the price change of the stock from this to the next period and from the height of the dividend in the next period.

$$\text{Return} = \frac{\text{Dividend in next period} + \text{Price change from this to next period}}{\text{Price in this period}} * 100$$

Returns are measured in percent. If the return of a stock is positive, than the sum of the price change and the dividend was positive. When you buy a stock in this period and sell it in the next, than you make money if the return is positive. The higher your expected return is, the higher is the profit you expect from buying a stock.

If the return in a period is negative, then the price of the stock decreased by more than the dividend payment. If you buy a stock in this period and sell it in the next, then you would loss some money.

When you state your return expectation you can test with the calculator which prices and dividends result in which returns. For this task there will be a "return calculator" on the screen. We will show you this calculator in a trial round after all participants have read the instructions.

You state your return expectation in percent, with increments of 0.1% steps. When you state your return expectation you always know the dividend of this period. You do not know the price of the stock in this or the next period and you do not know the dividend of the next period. You do not know the price for the stock in this round, since the price will be determined by the trading which follows after entering the return expectation. At the end of the next period you receive money for the precision of your predictions. The closer you match the return, the more points you will receive. Your payment for the prediction is calculated in the following way:

$$\text{Points for return prediction} = \max\{0.01 * (230 - |f|), 0\}$$

f is the absolute deviation of your prediction from the realized return in percentage points. If $f = 13$, then your prediction was either 13% points higher or smaller compared to the realized return.

If your prediction exactly matches the realized return you receive 2.3 Euro. The larger the deviation between your prediction and the realized return is, the fewer points you will receive. If you make a prediction that is more than 230 percentage points larger or smaller than the true return you do not receive a payment for the prediction in that period.

An exception is the first period in each sequence. Since there is no market price from a previous period you do not receive a payment for your return prediction in the first period of a sequence. The return prediction you state in the first period determines your payment in the second period (and your statement in the second period determines your payment in the third period etc.).

(2) Trading the stocks

After all participants have stated their expectations the trading period starts. Each trading period lasts 2 minutes. During this time each participant can use her stocks and cash to buy or sell stocks. (After the first five periods in a sequence the trading period is shortened to 90 seconds.)

All participants can make bids to buy or asks to sell one stock. Each participant can make an offer for selling a stock by stating a Taler amount in the field "ask price" at which he or she is willing to sell one stock and then clicking on "make ask". The offer then appears in the column "Sell offers" and can be seen by all participants. If a participant wants to make a bid for buying a stock he or she states the price he or she is willing to pay for one stock in the field "bid price" and clicks on "make bid". The offer is then shown in the column "Buy offers" for all participants. [The entire screen will be shown and explained to you again before the start of the first period].

Please note that all bids/asks are for buying/selling one stock. It is not possible to buy or sell multiple stocks in one transaction. Also the bids/asks need to be an improvement of the existing bids/asks. This means a participant can only make an offer to sell a stock at a lower price than the currently lowest ask price. Similarly, each bid to buy a stock has to be higher than the currently highest bid price from other participants.

Each participant can accept each displayed buy or sell offer, except for own offers. The own offers will therefore be shown in BLUE, while all other offers are shown in BLACK. Each participant only sees which offers are made by him- or herself. He or she cannot distinguish the offers made by other participants. A participant accepts an offer by selecting the appropriate offer in the column "Buy offers" with the mouse and then clicking on "selling" at the lower end of the column. By doing this, one stock of the participant is transferred to the participant who made the bid and simultaneously the seller receives the offered Taler amount.

Buying a stock can be done in a similar way by marking a sell offer in the column "Sell offers" and then clicking on the button "buying". By accepting an offer, all other asks and bids of the same participant are removed from the list. However you can make new offers.

You can sell and buy as many stocks within a trading period as you wish, as long as you have sufficient money to buy the offered stocks or you own at least one stock to accept a bid. You can also "cancel" asks/bids you made, but which have not been accepted by another participant. To do this select the ask/bid and click on the appropriate button.

WARNING: By "cancelling" ALL your outstanding bids and asks are deleted. It is not possible to cancel a single bid/ask. After cancelling your bids/asks you can make new bids/asks.

The number of stocks and Taler you own are always shown to you. Also the average prices and returns from previous periods are displayed in a table and a graph with the average prices in all previous periods is shown.

As said before, we will show you the trading screen before the first period and explain it again.

(3) Result of a period

If multiple trades are completed within one period, it is possible that these trades results in buying/selling stocks at different prices. To determine a market price for the stock, which we need for the calculation of the return, we will calculate an average market price at the end of each period.

At the end of each period you will see the average market price, the number of Taler and stocks at the end of the trading period as well as the return of the stock in this period (except for the first period of a sequence). It is also displayed how many Euro you received for your prediction of the return in the previous period and you can see how many points you earned from you consumption. You consume all Taler, which you own after buying or selling stocks. This means you cannot transfer Taler to the next period. But all stocks you own at the end of a period are transferred to the next period.

You always have to consume at least one Taler, therefore one Taler of your income will always be excluded from your trading budget. You cannot use this Taler to buy stocks. The more Taler you own at the end of the period, the higher is the number of consumption points you receive in a given period. More Taler always result in more consumption points. However, the difference in consumption points for smaller Taler amounts, e.g. 10 and 20 Taler, is larger than between larger Taler amounts, e.g. 40 and 50 Taler. The table below shows you for several Taler amounts how Taler are exchanged for consumption points. Also all not Taler amounts that are not displayed, are exchanged for consumption points using the same formula. E.g. the number of consumption points you receive for 51, 52 etc. Taler is larger than the number of consumption points you receive for 50 Taler, but less than for 55 Taler.

Taler	**Consumption points**	**Taler**	**Consumption points**	**Taler**	**Consumption points**
1	-100.0	17	51.5	33	65.2
2	-41.4	18	52.9	34	65.7
3	-15.5	19	54.1	35	66.2
4	0.0	20	55.3	36	66.7
5	10.6	21	56.4	38	67.6
6	18.4	22	57.4	40	68.4
7	24.4	23	58.3	42	69.1
8	29.3	24	59.2	44	69.8
9	33.3	25	60.0	46	70.5
10	36.8	26	60.8	48	71.1
11	39.7	27	61.5	50	71.7
12	42.3	28	62.2	55	73.0
13	44.5	29	62.9	60	74.2
14	46.5	30	63.5	70	76.1
15	48.4	31	64.1	80	77.6
16	50.0	32	64.6	90	78.9

The exact conversion formula is: Consumption points $= 100 - 200 * (Taler)^{-0.5}$. At the end of a period if you have a number of points that is not listed in the table, then your points will be calculated with this formula.

Note: You can never consume less than one Taler. In case you have less than zero consumption points for all paid periods you receive 0 Euro for your consumption. Therefore you can **not** make any loses.

How the number of periods and sequences is determined

As stated above, the experiment consists of one or multiple sequences, while each sequence consists of one or multiple periods. At the end of each period the computer determines whether there will be another period. On average there will be another period in 11 out of 12 cases ($\sim 91.7\%$) in the same sequence. In one of 12 cases the sequence ends with this period.

This is identical to a situation in which you throw a dice at the end of each period with a twelve-sided dice. If the result is a 12, then this period was the last period in this sequence. If anything but a 12 shows up, then a new period in the same sequence starts.

In case a sequence ends, you will be informed about its end on your screen. Then all stocks you own at that point become worthless. The next period is then the start of a new sequence. This means you receive again 20 stocks at the start of this new sequence, independently of the number of stocks you owned at the end of the previous sequence.

If the sequence does NOT end with this period, after the end of the period automatically a new period starts. In this period you own the number of stocks you owned at the end of the previous period. This means within a sequence you carry all your stocks from one period into the next.

Please note that the chance that a sequence ends after a given period does not depend on the number of previously completed periods. This is like throwing the dice again after each period and only if the result is a twelve there is no additional period in the same sequence. This means, at the end of each period the chance of this being the last period is equally large.

There will be as many sequences as possible in the 2:45 hours of experiment time. Therefore after the end of a sequence there will always start a new sequence as long as the start of the first sequence is less than 75 minutes ago.

In the unlikely event that the last sequence takes so long to finish, that the experiment cannot be concluded in the planed 2:45 hours, we will put this last sequence on hold. In this case the sequence does not end, but we add to this last sequence the expected number of periods, which would most likely been played without the time limit. The stocks you own in this last played period are not worthless. Since these periods cannot be conducted due to time reasons we will add the expected number of consumption points for each of these periods. The number of consumption points you receive for these added periods depends on the number of stocks you owned at the end of the last conducted period. Your expected consumption is higher, if you own more stocks at the end of this last period, since your expected dividend income is higher. We simply assume that the sequence would have continued and in each additional period you would have consumed your income and the entire dividend payments and you would not have traded any stocks.

Payment

Your payment in this experiment consists of two parts. In any case you receive 4 Euro for your participation. Additionally to this you receive a payment dependent on your performance which is calculated as follows.

At the end of the last sequence the computer randomly selects 10 periods for payment. In six of these periods you will be paid for your consumption and in 4 other periods you will be paid for your return predictions. Clearly the first period of a sequence can never be selected for the payment of your prediction, since in this period there is no stock return.

If the last sequence was not completed due to time constraints, then the additional periods can only be used for the payment of consumption points. These periods will not be used to determine your payment for the return predictions.

If the sum of all six selected periods for the consumption payment is negative, then your payment for the consumption part is zero. This means you cannot lose money with the consumption. The points you earned in the selected periods will be exchange to Euro. The exchange rate is 5 Cents for each point.

If in the selected period you earned a total of 300 points for your consumption and 6 Euro for your predictions, then you receive a total of 25 Euro for the experiment: 300 points * 0.05 Cent/point + 4 Euro + 6 Euro = 15 Euro + 10 Euro = 25 Euro.

We will now show you the program and conduct a trial period. When you are finished with reading these instructions, please click through the trial period. The explanations on the screen provide you with details about the different elements. Afterwards we will ask you several understanding questions. These can be answered directly at the computer. In case you still have questions after the trial period or need help with the understanding questions, please raise your hand. We will clearly your questions directly with you. After all participants have completed the trial period the actual experiment will start.

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Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig angefertigt und mich keiner anderen als den in ihr angegebenen Quellen und Hilfsmitteln bedient zu haben. Insbesondere sind sämtliche Zitate aus anderen Quellen als solche gekennzeichnet und mit Quellenangaben versehen.

Mannheim, November 2016 *Alessandra Donini*

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