

Cash inflow and trading horizon in asset markets

Michael Razen, Jürgen Huber, Michael Kirchler

Working Papers in Economics and Statistics

2016-06

University of Innsbruck
Working Papers in Economics and Statistics

The series is jointly edited and published by

- Department of Banking and Finance
- Department of Economics
- Department of Public Finance
- Department of Statistics

Contact address of the editor:
Research platform "Empirical and Experimental Economics"
University of Innsbruck
Universitaetsstrasse 15
A-6020 Innsbruck
Austria
Tel: + 43 512 507 7171
Fax: + 43 512 507 2970
E-mail: eeecon@uibk.ac.at

The most recent version of all working papers can be downloaded at
<http://eeecon.uibk.ac.at/wopec/>

For a list of recent papers see the backpages of this paper.

Cash Inflow and Trading Horizon in Asset Markets

Michael Razen, Jürgen Huber, and Michael Kirchler*

This version: October 17, 2016

Abstract

It is conjectured that one of the major ingredients of historic financial bubbles was the inflow of money in various forms. We run 36 laboratory asset markets to investigate the joint effect of cash inflow and trading horizon on price efficiency. We show that markets with cash inflow *and* long trading horizon exhibit bubbles and crashes. We also observe that markets with extended trading horizon but without cash inflow and markets with shorter trading horizon do not trigger bubbles. Finally, we report that beliefs about prices and, importantly, about (constant) fundamentals follow bubble patterns as well.

JEL: C92, D84, G10

Keywords: Experimental finance, cash inflow, trading horizon, backward induction, asset market, price efficiency.

*Razen: University of Innsbruck, Department of Banking and Finance, Universitätsstrasse 15, 6020 Innsbruck. Phone: +43 512 507 73012, E-mail: michael.razen@uibk.ac.at. Huber: University of Innsbruck, Department of Banking and Finance, Universitätsstrasse 15, 6020 Innsbruck. Phone: +43 512 507 73002, E-mail: juergen.huber@uibk.ac.at. Kirchler: Corresponding author. University of Innsbruck, Department of Banking and Finance, Universitätsstrasse 15, 6020 Innsbruck, and University of Gothenburg, Department of Economics, Centre for Finance, Vasagatan 1, 40530 Gothenburg, Sweden. Phone: +43 512 507 73014, E-mail: michael.kirchler@uibk.ac.at. We are grateful for comments by Brice Corgnet, Martin Halla, Jörg Oechssler, David Porter, Stefan Palan, Utz Weitzel, and two anonymous referees. We thank participants at the ESA meeting 2015 in Heidelberg and seminar participants at the Experiment a BIT Workshop Trento 2015 and the eeecon workshop at the University of Innsbruck 2015 for helpful suggestions. Financial support by the Austrian Science Foundation (START-grant Y617-G11 Kirchler) and the Austrian National Bank (OeNB-grant 14953 Huber) is gratefully acknowledged.

1 Motivation

It is conjectured that one – if not *the* – major ingredient of historic financial bubbles was the inflow of money. This can, for instance, be caused by the expansion of credit by lenders, more frequent trading with leverage, expansive central bank policy, the increase in the monetary base of investors through additional income or the inflow of new investors. Moreover, it is assumed that bubbles in real markets usually formed in long-lived assets (stocks, real estate), not in short-lived ones (options and other derivatives). To gain insights on both conjectured bubble drivers, we investigate the joint effect of cash inflow and trading horizon (i.e., speculation horizon) on price efficiency in laboratory asset markets.

The narratives of Galbraith (1994) and Kindleberger and Aliber (2011) the expansion phase of many historic bubbles was fuelled by money inflows after a positive shock in the economy – like the emergence of new technologies or financial deregulation. For instance, it is assumed that the South Sea Bubble 1720 was driven by an increase in the monetary base in the economy, the mania in real estate and asset markets in Japan from 1985 to 1989 was fuelled by huge amounts of cash floating into the markets and the strong price rallies in real estate in the US, Britain, Spain and Iceland around mid 2000 were supported by the expansion of bank credit. Schularick and Taylor (2012) take an empirical macro approach and investigate the development of money, credit, and macroeconomic indicators for the time span 1870-2008 for 14 developed countries. They demonstrate that lagged credit growth is a clear predictor of financial crises. They also find support for the notion that financial stability risks increase with the size of the financial sector and that boom-and-bust episodes in stock markets become more problematic in more developed economies.¹ Mian and Sufi (2014) focus on the recent financial crisis in the United States and identify the increase in the debt to GDP ratio as the major driver. Also during the period 2006 to 2008 the effect of the inflow of new investors has strongly contributed to the Chinese Warrants Bubble (Xiong and Yu, 2011). The most recent example of financial turmoil was the mania in Chinese stock markets in 2014 and 2015 and its subsequent crash in summer 2015. By May 2015 the Shenzhen Composite Index had nearly tripled within one year. At the same time stocks in ChiNext, composed mainly of tech-industry startups, had an average P/E-ratio of 140. Again, it is conjectured that leverage, new money and trader inflows fuelled the bubble substantially.²

¹In macroeconomics literature it is also conjectured that expansive central bank policy fuels overpricing in asset markets. Because returns on alternative investments such as fixed income decrease, additional inflow of cash and investors into more risky asset classes such as stocks is expected. For instance, Buch et al. (2014) investigate the risk-taking of banks following monetary policy changes. They show that banks increase their exposure to risk following expansive monetary policy shocks.

²According to Credit Suisse 6-9 percent of China's market capitalization was based on leverage, nearly five times the average in the industrialized world. Furthermore, more than 12 million new trading accounts had been opened in April 2015 alone, putting additional money into the market. See

Turning to our second treatment variable, trading horizon, the literature is much scarcer and nothing is reported on the interplay of cash inflow with trading horizon. In the theoretical bubble literature one necessary requirement for ruling out bubbles is this particular ability and willingness to engage in backward induction (Brunnermeier, 2009; Brunnermeier and Oehmke, 2013). While in infinite horizon settings with rational investors bubbles can emerge which grow at a certain rate ad infinitum (Blanchard and Watson, 1982), in finite horizon models bubbles cannot form under the requirement that rational investors are not restricted from selling the desired number of shares (Tirole, 1982). Since a bubble cannot grow after time T , there cannot be a bubble in $T-1$, which rules out a bubble for any point earlier in time. However, experimental studies show that individuals in finite horizon settings have difficulties with backward induction (see, for instance, Hirota and Sunder (2007), or Burks et al. (2009) on the Hit-15 game requiring backward induction). McKelvey and Palfrey (1992) show in an experimental study on the centipede game that subjects start playing this game, violating the backward induction principle. This finding questions whether the theoretical assumption of perfect backward induction is a good proxy for human behavior in asset markets with finite horizons. As we deem the trading horizon a potential driver of bubbles, as a longer horizon provides scope for speculation and makes the ending fundamental value less salient, we investigate whether total time until maturity of the asset (defined here as “trading horizon”) has an impact on traders’ ability to backward induct and thus influences markets’ proneness to bubbles. Assuming the same cash inflow in markets, we expect that longer trading horizons after the final cash inflow might provide traders with more time to engage in speculative activities, rendering backward induction less important and less salient in the beginning of the market. Conversely, shorter trading horizons in combination with the same cash inflows let traders focus more on the end of the market rendering backward induction more salient and letting subjects refrain from engaging in speculative activities.

The challenges with identifying the origins of historic bubbles are that i) bubbles can hardly be measured empirically because of the indeterminacy of fundamental values and that ii) different bubble drivers might have contributed simultaneously blurring the exact role of cash inflow and failure of backward induction. In this paper we tackle these problems and investigate the impact of cash inflow and trading horizon on price efficiency. We run a laboratory experiment as it offers the advantages of controlling and isolating the effects of cash inflow and trading horizon and allowing us to investigate speculative behavior in markets. In particular, we formulate the following research questions:

<http://www.economist.com/news/finance-and-economics/21652337-economic-dangers-chinas-manic-bull-market-goring-concern> for further information.

- RQ1: Does the inflow of cash trigger price inefficiencies?
- RQ2: Does the extension of trading horizon increase markets' proneness to price inefficiencies?
- RQ3: Does the joint effect of cash inflow and extended trading horizon trigger price inefficiencies?

To answer both research questions we set up a 2x2 treatment design with the variables “Cash Inflow” (either YES or NO) and “Trading Horizon” (either MEDIUM with 8 periods or LONG with 14 periods). We refrain from running markets with short horizons of one or two periods because, for instance, Plott and Sunder (1982, 1988) and Stöckl (2014) have shown that such markets do not exhibit bubble and crash patterns. The reason for selecting 8 and 14 periods is that we allow for cash inflow at the beginning of periods 3, 5, and 7. Therefore, in markets with 14 periods subjects know that another eight periods follow after the last cash injection into the market, providing more time for engaging in speculative activities compared to markets with 8 periods. In the latter markets substantial cash inflows that could potentially facilitate speculation emerge towards the end of maturity (in periods 5 and 7) and might therefore be too late to affect bubble formation. We use the market design of Kirchler et al. (2015) with a constant fundamental value of the asset and heterogeneous information of traders.

We find a strong interaction between cash inflow and trading horizon. First, markets with medium trading horizon do not show substantial overpricing and price rallies no matter whether there is cash inflow or not. Second, markets with long trading horizon but without cash inflow do not exhibit significantly higher levels of overpricing and price amplitude compared to markets with medium maturity. However, the probability of “price mirages” (Camerer and Weigelt, 1991) increases as traders coordinate on an inefficient market price above the upper boundary of possible buyback prices more frequently. As traders are heterogeneously informed they mistakenly infer information from trades outside the range of buyback prices more often. Third, markets with cash inflow *and* long trading horizon show significantly higher levels of overpricing, peak period prices, price run-ups, and crashes compared to both treatments with medium trading horizon. Although differences to markets without cash inflow but extended trading horizon are substantial in all measures, they are not significant. The reason is that two distinct archetypes of price paths emerge in this treatment, inflating the standard error for statistical tests. Fourth, we develop a bubble classification scheme by defining three bubble criteria. According to this scheme we observe strong bubbles and crashes in 5 out of 9 markets in the treatment with cash inflow and long trading horizon. In the other 4 markets we find relatively stable prices or only moderately

increasing prices without crashes. Hence, we show that with initially almost identical conditions different archetypical patterns of price paths emerge *within* the same treatment. We find that although subjects were selected from the same pool, average risk aversion in the bubble markets is significantly lower compared to those markets that are relatively efficient. Therefore, our setting with cash inflow and extended trading horizon appears to be a framework which can react very sensitively to marginal differences in initial parameters. Finally, we show that bubbles in markets with cash inflow and long trading horizon are driven by changes in beliefs. Remarkably, not only beliefs about future market prices but also beliefs about (constant) fundamentals show bubble and crash patterns. With this result we show that cash inflows do operate over the beliefs-channel which is a novel finding.

2 Literature

Asset market research has made significant progress in furthering our understanding of bubble phenomena during the last three decades.³ In surveys on theoretical bubble models Brunnermeier (2009) and Brunnermeier and Oehmke (2013) outline various reasons for bubbles such as rational bubbles (Blanchard and Watson, 1982), asymmetric information bubbles (Allen and Gorton, 1993), limits of arbitrage bubbles (DeLong et al., 1990; Abreu and Brunnermeier, 2003), and heterogeneous beliefs bubbles (Miller, 1977; Harrison and Kreps, 1978; Ofek and Richardson, 2003). Also, experimental asset market research has significantly contributed to a better understanding of bubbles. Many studies follow the seminal design of Smith et al. (1988) – SSW, henceforth – and investigate the effects of short selling, trading protocols, training or trader experience, emotions, common knowledge and strategic uncertainty, and alternative fundamental value processes on price efficiency.⁴ Laboratory asset market research has also improved our understanding of the role of high cash levels in financial markets. It is documented by Caginalp et al. (1998, 2001) and Haruvy and Noussair (2006) that high *initial* Cash-Asset ratios (CA-Ratio, calculated as the total amount of cash in the market over the product of shares outstanding and FV) increase prices strongly in the bubble-prone SSW-setting. Noussair and Tucker (2016) show that high initial CA-Ratios trigger overpricing even in markets with constant fundamental values that otherwise are very efficient (Kirchler et al., 2012). Moreover, all markets following the classical SSW-model with

³Half a century ago Fama (1970) postulated the seminal Efficient Market Hypothesis (EMH) and markets were believed to be very efficient. Particularly, starting with the work of Shiller (1981) it became more and more clear that markets might be quite efficient in the long run, but that periods of price inefficiencies can emerge in the short- and mid-run.

⁴See Smith et al. (1988); Van Boening et al. (1993); Dufwenberg et al. (2005); Haruvy and Noussair (2006); Haruvy et al. (2007); Lei and Vesely (2009); Huber and Kirchler (2012); Sutter et al. (2012); Kirchler et al. (2012); Breaban and Noussair (2013); Akiyama et al. (2014); Cheung et al. (2014); Akiyama et al. (2014); Andrade et al. (2015); Huber et al. (2015); Stöckl et al. (2015) for selected literature and Palan (2013) for a comprehensive survey.

deterministically declining FVs share the characteristic of an implicit cash inflow as the CA-Ratio increases exponentially over time. Because of dividend payments the cash supply in the market grows several-fold, whereas the asset value of shares outstanding decreases towards zero because of the declining fundamental value. Kirchler et al. (2012) show that keeping the CA-Ratio constant in these markets only eliminates overpricing, but mispricing still remains high.⁵ However, the declining fundamental value concept might share some unrealistic features which could make the market prone to framing effects (Oechssler, 2010; Huber and Kirchler, 2012; Kirchler et al., 2012). In these studies overpricing can develop because FVs decline and market prices stay relatively constant until the second half of trading before they crash towards zero (see the baseline treatment of Kirchler et al. (2012) as an example). Therefore, the common idea of a bubble with prices actively increasing at a strong pace is not a unique pattern in SSW-markets.⁶ Using a model with constant fundamental value, Bostian et al. (2005), Smith et al. (2014), and Holt et al. (2015) show persistent bubbles with the feature that prices increase above FVs first and crash towards the FV at the end of trading. In their design the asset pays a positive dividend and each unit of the asset is bought back at a predetermined buyback value at the end of trading. Interest is paid on cash holdings and therefore the CA-Ratio increases several-fold over time.⁷ However, the cash inflow is an endogenously evolving characteristic of this model and it is unclear how these markets develop without cash inflow. Therefore, the exact contribution of money flowing into markets of this design is unclear.

In two studies that are closely related to ours Deck et al. (2014) and Kirchler et al. (2015) investigate the inflow of new traders (i.e., the joint inflow of traders with cash). Both studies impressively show that trader inflow contributes strongly to bubbles. While Deck et al. (2014) use the classical SSW-design, Kirchler et al. (2015) develop a model with constant FVs, heterogeneous information about the buyback prices of the asset and no endogenously changing CA-Ratios in the benchmark treatment. They report that almost all of the 24 markets with trader inflow show bubble and crash patterns. Particularly the crashes at the end are an indication that backward induction about fundamentals becomes important towards maturity. We mostly build on the

⁵The authors transfer all dividend payments over time to a special account which is added to subjects' cash holdings at the end of the market. In addition, cash is deducted from traders' cash balances to achieve a constant CA-Ratio of 1 over time. In general, the endogenously increasing CA-Ratio is a unique feature of SSW markets. In these models the CA-Ratio increases exponentially, creating the strongest cash inflows in the final periods which is in stark contrast to our setting. Having strong increases in the CA-Ratio in the final periods is unlikely to cause price rallies as speculation becomes too risky close to maturity of the asset. For instance, although the CA-Ratio in Kirchler et al. (2012) increases from 1 to 19 in markets of ten periods, it stays moderate at levels of 2.33 and 3 in periods 5 and 6, respectively.

⁶In some studies using this model, there is an initial (moderate) price increase before prices crash (Smith et al., 1988; Cheung et al., 2014).

⁷With this smart model design the dividend yield (expected dividend over buyback value) equals the interest rate leading to a constant fundamental value equalling the buyback price.

design of Kirchler et al. (2015) to set up our experiment.

3 The Experiment

3.1 Market and Treatment Design

In each market subjects trade assets of a fictitious company for experimental currency (Taler) in a sequence of periods of 180 seconds each. No interest is paid on Taler holdings. The asset does not pay dividends and there are no transaction costs. At the end of the experiment each unit of the common value asset pays either 30 or 80 Taler with equal probability.⁸

As in Kirchler et al. (2015) information about the company’s fundamentals is distributed heterogeneously.⁹ In all treatments half of the traders are informed about the low buyback price and its probability, while the other half are informed about the high buyback price and its probability. Both groups only know about the existence of a second buyback price, but know nothing about its value. Following the SSW literature on multi-period experimental asset markets we use the risk-neutral fundamental value (FV) of 55 as benchmark.

As outlined in Table 1 we implement a 2x2 design with the treatment variables “Cash Inflow” and “Trading Horizon”.

Table 1: Treatments of the experiment.

		Trading Horizon	
		MEDIUM	LONG
Cash Inflow	NO	BASE8	BASE14
	YES	CASH8	CASH14

Cash Inflow indicates whether the CA-Ratio increases over time or not, Trading Horizon stands for the number of trading periods (8 or 14).

Treatment BASE8 is identical to the baseline treatment in Kirchler et al. (2015) with the shorter trading horizon of 8 periods and no cash inflow (i.e., no increase in the CA-Ratio). Each market is populated by eight traders who are initially endowed with 20 units of the asset and 3,300 Taler. Valued at the expected value of the buyback price of 55, the total cash amount in the

⁸One random draw is conducted that determines the payout for all units of the asset.

⁹See also Miller (1977), Harrison and Kreps (1978), and Ofek and Richardson (2003) for asset pricing models with heterogeneous information.

Table 2: Treatment parameterization.

Treatments	BASE8	CASH8	BASE14	CASH14
Number of periods	8	8	14	14
Number of traders	8	8	8	8
Buyback prices	30; 80	30; 80	30; 80	30; 80
Probabilities of the buyback prices	50%; 50%	50%; 50%	50%; 50%	50%; 50%
Information structure	heterogeneous	heterogeneous	heterogeneous	heterogeneous
Initial individual share holdings	20	20	20	20
Initial individual cash holdings	3,300	3,300	3,300	3,300
CA-Ratio (Periods 1/3/5/7/14)	3/3/3/3/-	3/7/11/15/-	3/3/3/3/3	3/7/11/15/15

CA-Ratio stands for the Cash-Asset ratio in the respective periods.

market ($8 \cdot 3,300 = 26,400$ Taler) is three times the value of all units of the asset in the market ($8 \cdot 20 = 160$ units $\cdot 55$ Taler = 8,800 Taler). Thus, the CA-Ratio is constant at 3 over time.

Treatment CASH8 is identical to Treatment BASE8 except that the CA-Ratio increases over time. Each trader starts with an initial endowment of 20 units of the asset and 3,300 Taler in cash. They receive exogenous cash inflows of 4,400 Taler each in periods 3, 5, and 7. No new shares are issued at any time. This is announced in the instructions and common knowledge. The inflow of 4,400 Taler is equal to the Taler value of each trader's initial endowment (20 units $\cdot 55$ Taler = 1,100 plus 3,300 Taler in cash). Therefore, the CA-Ratio increases from initially 3 to 15 in period 7.

Treatment BASE14 is identical to Treatment BASE8 except that the trading horizon is extended to 14 periods.

Treatment CASH14 is identical to Treatment CASH8 except that the trading horizon is extended to 14 periods. In this case traders know that another seven periods of three minutes will follow after the last cash injection into the market, creating more potential for engaging in speculative activities. The CA-Ratio increases from initially 3 to 15 in period 7 and stays at this level until maturity of the asset. Table 2 summarizes the treatments and the most important variables.

3.2 Belief Elicitation

As in Kirchler et al. (2015) we elicit traders' beliefs about fundamentals and about market prices. With this approach we analyze whether potential bubbles also operate on the level of beliefs.

Specifically, at the beginning of each period and after the final period T , every trader has to guess the unknown second buyback price. At the end of the experiment one of these guesses is drawn randomly. If the selected guess is within the range of ± 10 percent of the corresponding

unknown second buyback price, the trader receives EUR 2.25. For guesses within the ranges of ± 20 percent and ± 40 percent, EUR 1.50 and EUR 0.50, respectively, are paid out.

Then traders are asked to predict average period prices for each future period (Haruvy et al., 2007). $BP_{t,t+k}^i$ indicates trader i 's beliefs in period t of the average period price in $t+k$, with $k = 1, 2, \dots, T-t$. Belief elicitation about future period prices is done in the same way as for the unknown buyback price.¹⁰

3.3 Market Architecture

We apply a typical continuous double-auction trading protocol which is standard in the literature (see the Appendix for a screenshot and a detailed explanation of the trading screen). All orders are executed according to price and then time priority in an open order book framework. Market orders have priority over limit orders and are always executed instantaneously. When posting limit orders, traders specify the price and quantity they want to trade for. When posting market orders traders only specify the quantity they want to trade and the order is executed immediately at the price of the currently best limit order. Any order size, the partial execution of limit orders, and deleting already posted limit orders are possible. Shorting assets and borrowing money are not allowed.

3.4 Experimental Implementation

We conducted nine markets for each treatment. All 36 markets were run at Innsbruck EconLab at the University of Innsbruck with a total of 288 students (bachelor and master students in business administration and economics).¹¹ Each subject participated in only one market and we made sure that subjects did not participate in earlier asset market experiments of similar design. The markets were programmed and conducted with z-Tree 3.4.2. by Fischbacher (2007). Subjects were recruited using HROOT by Bock et al. (2014).

In total, each experimental session lasted between 90 and 120 minutes, including 20 minutes to study the written instructions, one trial period of five minutes, the market experiment and an additional task measuring overconfidence and risk aversion. We measure overconfidence by asking subjects to estimate their rank according to the payout in the market experiment and calculate the difference between their actual rank and their prediction. We measure subjects' risk aversion

¹⁰Again, at the end of the experiment one $BP_{t,t+k}^i$ of trader i is drawn randomly. If the selected $BP_{t,t+k}^i$ is within the range of ± 10 percent around the realized average market price of period $t+k$, the trader receives EUR 2.25. The corresponding payouts for guesses of $BP_{t,t+k}^i$ within the ranges of ± 20 percent and ± 40 percent are EUR 1.50 and EUR 0.50, respectively.

¹¹Six out of the nine markets of BASE8 and CASH8, respectively, are taken from the study of Kirchler et al. (2015). We ran three more markets each to increase sample size.

with a classical choice list procedure. In 12 lotteries subjects can decide between selecting a risky option paying out either zero or 6.0 Euros with equal probability or choosing a fixed payout which increases in steps of 0.5 Euros from 0.5 (lottery 1) to 6.0 Euros (lottery 12). In the end one lottery is selected randomly for each subject and added to the final payout (see Appendix A4.2 for details on the lottery procedure).

Subjects' payout is composed of earnings from the risk experiment and of earnings from the asset market including the belief elicitation tasks. For the market experiment, the randomly drawn buyback price was multiplied by a subject's units of the asset held at the end of the experiment and added to the end holdings in Taler. Finally, the amount in Taler was exchanged for Euro at a conversion rate of 360:1 in BASE8, 1500:1 in CASH8, 200:1 in BASE14 and 800:1 in CASH14 to account for the different experiment lengths and Taler endowments across treatments. Average total earnings were 21.54 Euro with a standard deviation of 8.91 Euro.

4 Results

4.1 Research Questions

Figure 1 outlines average period prices of individual markets separated by treatment. Table 3 provides measures for price efficiency including significance tests for treatment differences. Following Stöckl et al. (2010) we use RD (relative deviation) and RAD (relative absolute deviation) as measures for overpricing and mispricing, respectively. With RD_MAX we measure overpricing at the peak, denoting the corresponding period by t^* . RD_MAX is calculated as RD of the peak period price, $\text{RD_MAX} = \max_t \left\{ \frac{\bar{P}_t - FV_t}{FV_t} \right\} = \frac{\bar{P}_{t^*} - FV_{t^*}}{FV_{t^*}}$. Additionally, we calculate price amplitude as in Kirchler et al. (2015), measuring price run-ups before the peak price. We compare the minimum average period price at $t^* - k$ and the maximum average period price at t^* , normalized at the FV of 55, $\text{AMPLITUDE} = \frac{\bar{P}_{t^*} - FV_{t^*}}{FV_{t^*}} - \min_{0 \leq k < t^*} \left\{ \frac{\bar{P}_{t^* - k} - FV_{t^* - k}}{FV_{t^* - k}} \right\}$.¹² The measure provides the difference from the pre-peak minimum to the maximum period price as a percentage of FV. In addition, we calculate a measure of the severity of price crashes. We compute the difference between the minimum price after the peak and the peak average price at t^* , normalized at the FV of 55, $\text{CRASH} = \min_{0 \leq l \leq T - t^*} \left\{ \frac{\bar{P}_{t^* + l} - FV_{t^* + l}}{FV_{t^* + l}} \right\} - \frac{\bar{P}_{t^*} - FV_{t^*}}{FV_{t^*}}$. With this procedure CRASH is symmetric compared to AMPLITUDE as it outlines the price drop as a percentage of FV.

¹²This measure is slightly modified compared to Haruvy and Noussair (2006) and Haruvy et al. (2007). Note that this measure is very sensitive to minor price increases as it can only be larger or equal to zero by construction. Therefore it is not surprising that even in relatively flat scenarios values are different from zero.

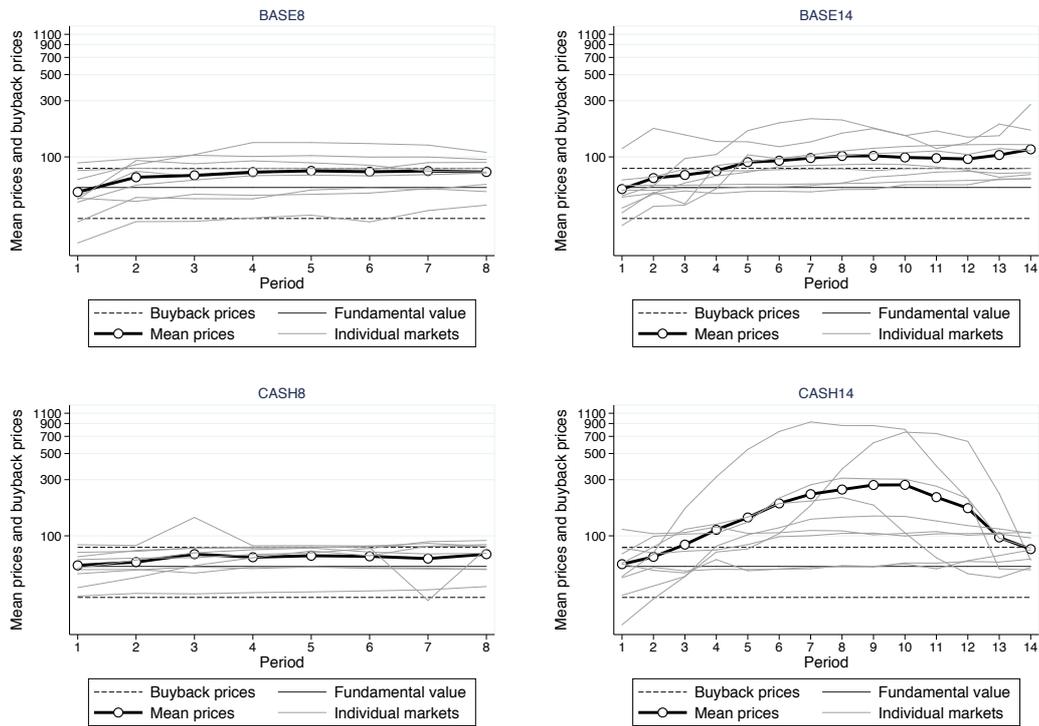


Figure 1: Average prices (bold line with circles) and volume-weighted mean prices for individual markets (grey lines) as a function of period for BASE8 (top left), CASH8 (bottom left), BASE14 (top right) and CASH14 (bottom right) in log-scale. The dashed lines show the two possible buyback prices of 30 and 80 and the solid thin line represents the risk-neutral fundamental value of 55.

Table 3: Top panel: Treatment averages of mispricing (RAD), overpricing (RD), peak price (RD_MAX), price run-ups (AMPLITUDE) and price crashes (CRASH). Bottom panel: Significance tests for treatment differences. The numbers indicate Z-values of pairwise Mann-Whitney U-tests. Sample size N of each test equals 18.

Treatment	RAD	RD	RD_MAX	AMPLITUDE	CRASH
BASE8	45.71	27.84	46.04	55.15	-10.94
CASH8	32.05	18.23	43.51	42.37	-26.72
BASE14	69.38	63.57	124.13	127.31	-24.60
CASH14	195.12	189.06	450.11	450.89	-411.96

Pairwise MW U-tests	RAD	RD	RD_MAX	AMPLITUDE	CRASH
BASE8 vs. CASH8	1.192	0.574	0.221	0.927	0.591
BASE8 vs. BASE14	0.044	0.839	1.104	1.192	0.046
BASE8 vs. CASH14	1.722*	2.163**	2.428**	2.163**	1.774*
CASH8 vs. BASE14	1.104	1.280	1.192	1.898*	0.409
CASH8 vs. CASH14	2.340**	2.517**	2.340**	2.517**	1.259
BASE14 vs. CASH14	1.192	1.369	1.369	1.015	1.592

*, ** and *** represent the 10%, 5%, and 1% significance levels of a double-sided test.

Result 1: In markets with medium trading horizon (BASE8 and CASH8) only moderate levels of price inefficiencies are observed.

Support: As outlined in Table 3 overpricing is 28 and 18 percent, respectively, in BASE8 and CASH8, and mispricing ranges from 32 to 46 percent which is moderate given the uncertainty and incomplete information subjects face.¹³ Markets do not exhibit strong price rallies and no crashes either. Amplitude seems to be substantial, but values of 42 and 55 percent (in units of FV) are translated into price increases from the minimum to the maximum of 23 and 30, respectively. Most of these price changes already occur as an adjustment from the first to the second period. Then markets remain very stable at a moderately overpriced level and average treatment prices stay within the boundaries of buyback prices of 30 and 80. We run pairwise Mann-Whitney U-tests and find no differences between the two treatments in any measure (see the bottom panel of Table 3 for details on the significance tests).

Result 2: In markets with long trading horizon and without cash inflow (BASE14) overpricing, maximum prices and price amplitudes are more pronounced than in the medium horizon treatments, but mainly insignificantly so.

Support: In Treatment BASE14 overpricing and mispricing is larger with values of 64 and 69 percent, respectively, but RD and RAD do not differ significantly from the treatments with

¹³As pointed out in section 3.4, six out of the nine markets of BASE8 and CASH8 are taken from the study of Kirchler et al. (2015). Our results seem rather robust, as we find no substantial differences between the “old” and the “new” markets (in the new markets, RD is 35% in BASE8 and 26% in CASH8, while RAD is 46% in BASE8 and 30% in CASH8). Detailed results for all markets and all measures can be found in the Appendix (Tables A1-A4).

medium trading horizon. Price increases with an average of 70 (or 127 percent) are, however, weakly significantly stronger compared to the amplitudes observed in CASH8. As we observe no significant crashes but relatively stable prices in the second half of trading this pattern resembles the “information mirages” reported in Camerer and Weigelt (1991). Prices increase for the first half of trading and then remain relatively stable until the end. It seems that traders coordinate on an inefficient market price above the upper boundary of possible buyback prices more frequently compared to medium horizon markets. As traders are heterogeneously informed they possibly infer information from trades outside the range of buyback prices more often.

Result 3: Only in markets with long trading horizon *and* cash inflow (CASH14) are overpricing, mispricing, maximum prices, price amplitudes and crashes significantly higher than in markets with medium trading horizon.

Support: RD (189 percent), RAD (195 percent), RD_MAX (450 percent), AMPLITUDE (451 percent) and CRASH (−412 percent) are highest, in absolute terms, in Treatment CASH14 and significantly different to both treatments with medium trading horizon in all but one case. Although differences to Treatment BASE14 are very substantial, we find no significant differences in any measure. The reason is that two archetypes of price paths emerge in Treatment CASH14 inflating the standard error for statistical tests in all measures. Close inspection of Figure 1 makes it clear that 5 out of 9 markets show clearly pronounced price run-ups to levels far above the upper buyback price followed by crashes towards fundamentally justified levels. In the other 4 markets we observe stable prices or moderately increasing prices without crashes.¹⁴

4.2 Bubble Identification

To highlight the degree of disagreement about bubbles in the economic community, let us restate what Eugene Fama and Robert Shiller, who famously shared the 2013 Nobel Prize in Economics, said about bubbles. In an interview when asked about bubbles Fama stated “*I don’t even know what that means. People who get credit have to get it from somewhere. Does a credit bubble mean that people save too much during that period? I don’t know what a credit bubble means. I don’t even know what a bubble means. These words have become popular. I don’t think they have any meaning.*” and “*If a bubble is defined as an irrational strong price increase that implies a*

¹⁴An interesting additional finding concerns the distribution of final wealth after trading (assets evaluated at the fundamental value of 55): with 8 traders, average relative final wealth (compared to the total wealth in the market) is 12.5%. Unequal redistribution of wealth is favored by longer periods of less efficient prices. In the CASH-treatments, dispersion of relative final wealth is naturally reduced due to the dominance of cash. We confirm this for BASE8 and CASH8 (where the standard deviation of relative final wealth is 2.77% and 1.14%, respectively). This finding reverses however when we compare BASE14 to CASH14. Relative final wealth dispersion is lower in BASE14 than in CASH14 (4.21% compared to 6.38%), due to the strong mispricing in some of the markets in CASH14.

*predictable strong decline, then there's not much evidence that such things exist."*¹⁵

Robert Shiller by contrast believes that bubbles exist and states *"I define a bubble as a social epidemic that involves extravagant expectations for the future. Today, there is certainly a social and psychological phenomenon of people observing past price increases and thinking that they might keep going."*¹⁶

In the literature bubble definitions are heterogeneous and generally relatively vague. According to the survey of Brunnermeier (2009) *"[b]ubbles refer to asset prices that exceed an asset's fundamental value because current owners believe that they can resell the asset at an even higher price in the future."* King et al. (1993) speak of a bubble when *"...traders invariably trade in high volume at prices that are considerably at variance from intrinsic value..."* Noussair et al. (2001) follow the definition of King et al. (1993) and quantify a bubble according to two criteria: 1) The median transaction price in five consecutive periods is at least 50 units of experimental currency (about 13.9 percent) greater than the fundamental value. 2) The average price is at least two standard deviations (of transaction prices) greater than the fundamental value for five consecutive periods. In the experimental study of Oechssler et al. (2011) a bubble is taken to occur if the median daily price of an asset exceeds the fundamental value by more than 60 percent for at least three consecutive periods (i.e., is above the highest expected dividend).

With these definitions it becomes obvious that bubbles are very difficult to pin down precisely. First, what are the variables to measure a bubble by? Second, what are the threshold values of these variables to separate bubble from non-bubble markets? In our general definition a possible bubble episode is characterized by the time interval between the periods with the lowest market prices before and after the price peak (relative to the fundamental value). With this definition a bubble requires a subsequent crash to separate it from other forms of mispricing such as information mirages (Camerer and Weigelt, 1991) without crashes. Therefore all markets without a crash are ruled out by definition. However, rational bubbles with infinite horizon are defined differently, given the absence of a crash. For experimental markets this distinction is unimportant because of the finite maturity.

We propose and develop a bubble classification scheme following three criteria (C1, C2, and C3). With this approach we are able to separate bubble markets from markets without a bubble (e.g., efficient markets, inefficient markets with information mirages). Specifically, a bubble shows C1 a peak average period price (RD_MAX) that has to be "significant". A bubble is furthermore characterized by C2 a "significant" price run-up (AMPLITUDE) followed by C3 a "significant"

¹⁵<http://www.newyorker.com/news/john-cassidy/interview-with-eugene-fama>

¹⁶<http://uk.businessinsider.com/robert-shiller-stock-market-bubble-2015-5?r=US&IR=T>

price drop (CRASH). In what follows, we define the term “significant”.

For criteria C1 to C3 we calculate threshold values that need to be exceeded for a deviation to be deemed significant (95%-level). The *baseline treatment* in absence of any treatment variation serves as benchmark, based on the rationale that the baseline represents the expected price characteristics of the asset without treatment intervention. We consider price developments to constitute a bubble if the deviations in *all three* measures, i.e., C1 the maximum period price (RD_MAX), C2 the price run-up (AMPLITUDE), and C3 the CRASH are above the 95 percent quantile (below the 5 percent quantile for C3) of the corresponding measure in the baseline distribution. If only one of the measures fails to exceed this defined range, we do not classify the market as exhibiting a bubble.

C1: Price bubbles are characterized by an extraordinarily high peak average period price. A market i fulfills criterion C1 iff

$$\text{RD_MAX}_i > \text{MAX}\{0; \overline{\text{RD_MAX}}^{\text{BASELINE}} + t(df)_{0.95} \cdot \sigma(\text{RD_MAX}^{\text{BASELINE}})\}, \quad (1)$$

with $\overline{\text{RD_MAX}}^{\text{BASELINE}}$ indicating the mean of the maximum period peak prices of the baseline markets (i.e., in our case 9 markets of Treatment BASE8). $t(df)_{0.95}$ stands for the 95 percent quantile of a student t-distribution with $N - 1$ degrees of freedom (df) and N is the number of markets in the baseline (we hence have $t(8)_{0.95} = 1.86$). $\sigma(\text{RD_MAX}^{\text{BASELINE}})$ stands for the standard deviation of RD_MAX in the N baseline markets. If RD_MAX_i is higher than the 95 percent quantile, its peak period price is considered to be significantly larger than in the baseline. Importantly, we impose the additional condition that RD_MAX_i must exceed zero to rule out potential price paths that never exceed the FV. With this definition we build on previous work by King et al. (1993), Noussair et al. (2001) and Brunnermeier (2009) that prices during a bubble exceed fundamentals.¹⁷

C2: Price bubbles are characterized by exhibiting extraordinary price rallies towards the peak

¹⁷We focus on RD_MAX instead of the general overpricing RD because the latter could be a bad proxy for a bubble according to our bubble definition. Markets with bubble-like price patterns can exhibit low or even negative levels of RD, particularly if crashes undershoot the fundamental value in a similar way as the price run-up overshoots fundamentals (see the literature on the chartist/fundamentals approach in heterogeneous agent models that are characterized by this overshooting pattern in both directions (Lux and Marchesi, 1999, 2000; Hommes, 2006)).

price. A market i fulfills criterion C2 iff

$$\text{AMPLITUDE}_i > \overline{\text{AMPLITUDE}}^{\text{BASELINE}} + t(df)_{0.95} \cdot \sigma(\text{AMPLITUDE}^{\text{BASELINE}}), \quad (2)$$

with $\overline{\text{AMPLITUDE}}^{\text{BASELINE}}$ indicating the mean AMPLITUDE of the baseline markets. $\sigma(\text{AMPLITUDE}^{\text{BASELINE}})$ stands for the standard deviation of AMPLITUDE in the N baseline markets. If AMPLITUDE_i is above the 95 percent quantile, its price run-up is considered to be significantly larger than in a baseline without treatment intervention.

C3: Price bubbles are characterized by exhibiting extraordinary crashes. A market i fulfills criterion C3 iff

$$\text{CRASH}_i < \overline{\text{CRASH}}^{\text{BASELINE}} - t(df)_{0.95} \cdot \sigma(\text{CRASH}^{\text{BASELINE}}), \quad (3)$$

with $\overline{\text{CRASH}}^{\text{BASELINE}}$ indicating the mean CRASH of the baseline markets and $\sigma(\text{CRASH}^{\text{BASELINE}})$ defining the standard deviation of CRASH among the N markets in the baseline. If CRASH_i is below the 5 percent quantile, its price crash is considered to be significantly stronger than in the baseline.

Result 4: Following the bubble classification, 5 out of 9 markets are identified as bubble-markets in Treatment CASH14. Out of the remaining 27 markets in the other treatments only one market exhibits a bubble (in Treatment BASE14).

Support: Figure 2 depicts the individual markets of the four treatments, separated into bubble markets (bold black lines) and non-bubble markets (grey lines). Following our classification we arrive at 6 bubbles in total. One bubble emerges in Treatment BASE14. In this market the price starts at 57, peaks at 211 (RD_MAX of 284 percent) and crashes towards 118 in period 11. In Treatment CASH14, however, 5 out of 9 markets exhibit bubbles. Applying a chi-square test, we find that the fraction of markets that exhibit bubbles is significantly higher in Treatment CASH14 than in Treatment BASE14 (p-value of 0.046).¹⁸ Table 4 provides treatment means of bubble measures for the bubble and non-bubble markets of *tcashfourteen*, respectively. Among these markets AMPLITUDE ranges from 211 to 1558 percent of the FV and prices peak in a range of 147 to 928 Taler. Crashes are strong in magnitude with values of CRASH between -78 and -1594

¹⁸The corresponding Fisher-Yates tests for small samples yields a p-value of 0.131.

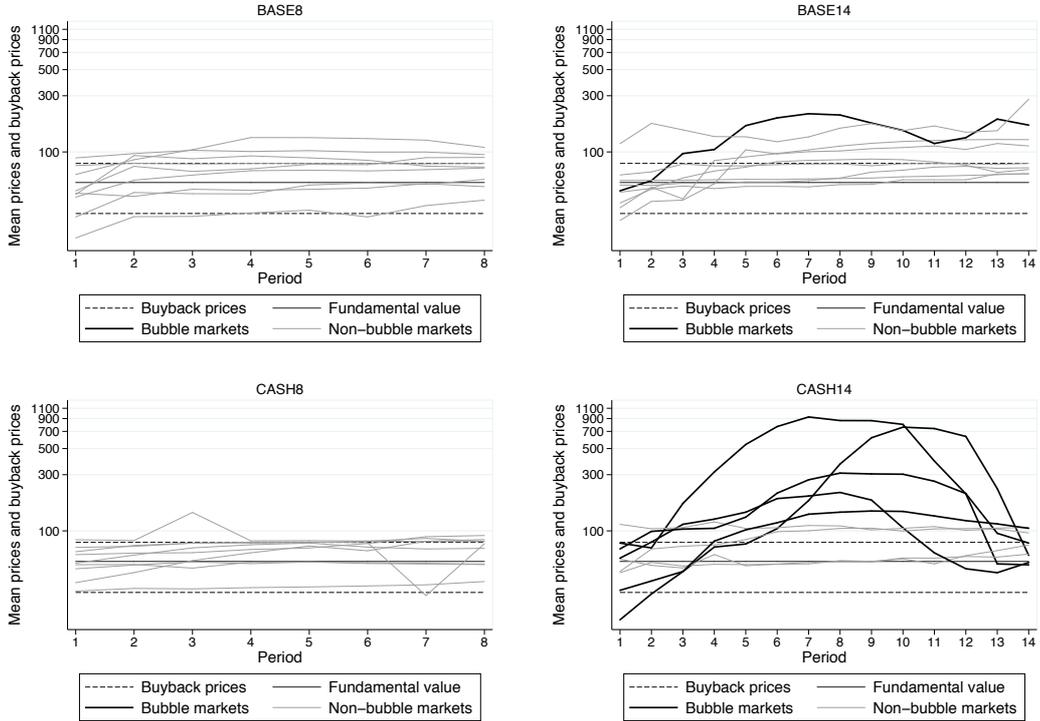


Figure 2: Volume-weighted mean prices for individual markets as a function of period for BASE8 (top left), CASH8 (bottom left), BASE14 (top right) and CASH14 (bottom right) in log-scale. Bubble markets are indicated with bold black lines. The dashed lines show the two possible buyback prices of 30 and 80 and the solid thin line represents the risk-neutral fundamental value of 55.

percent. For further details on all bubble measures in each individual market and for individual markets' bubble classification, we refer to Appendix A1.¹⁹

The important finding of Treatment CASH14 is that with initially almost identical conditions different archetypical patterns of price paths emerge *within* the same treatment. Although all subjects are selected from the same subject pool we investigate potential subject differences between the bubble and non-bubble markets. Table 5 outlines the differences for gender, overconfidence

¹⁹We ran a set of robustness checks to corroborate the consistency of this approach. First, we also worked out a non-parametric version of our bubble-classification scheme based on a one-sample Wilcoxon signed-rank test to compare the median of each bubble-measure (RD_MAX, AMPLITUDE, CRASH) in the baseline distribution with the corresponding measure in a specific market. Corresponding to the 95%-quantiles in the parametric approach we now use a significance level of 5% in a one-sided test in the non-parametric approach. All markets that are identified by the parametric approach are also identified by the non-parametric approach described above. Further, the non-parametric approach only identifies two more markets as bubbles (market 7 in Treatment BASE8 and market 3 in Treatment CASH8). Second, we lowered the threshold in C1-C3 in the parametric approach to the 90%- and the 80%-quantile instead of the 95%-quantile. We observe exactly the same outcome as in our first robustness check outlined above. Third, we analysed the outcome of our classification scheme if we applied only two of the three criteria at the 95%-quantile. Relaxing C1 does not change the set of markets identified as bubbles, relaxing C2 leads to an additional identification of market 3 in Treatment CASH8 and relaxing C3 leads to an additional identification of market 6 in Treatment BASE14. We believe these results to be very consistent and to support the robustness of the underlying idea.

Table 4: Averages of mispricing (RAD), overpricing (RD), peak price (RD_MAX), price run-ups (AMPLITUDE) and price crashes (CRASH) for all 9 markets of Treatment CASH14. Lines 2 and 3 indicate the averages for the 5 bubble markets and the 4 non-bubble markets, respectively.

Treatment	RAD	RD	RD_MAX	AMPLITUDE	CRASH
CASH14, all markets	195.12	189.06	450.11	450.89	-411.96
CASH14, bubble markets	315.29	307.51	757.30	766.66	-733.12
CASH14, non-bubble markets	44.91	41.00	66.12	56.17	-10.50

*, ** and *** represent the 10%, 5%, and 1% significance levels of a double-sided test.

(realized rank – predicted rank), semester and risk attitude.²⁰ We find no significant differences between bubble and non-bubble markets except for risk attitudes. The subjects in the bubble markets are significantly less risk-averse as they switch 0.84 lotteries later to the safe option than their counterparts in the non-bubble markets. We conclude that the combination of extended trading horizon and the inflow of sufficient cash over time creates a fragile environment which likely creates bubbles as soon as certain characteristics, such as lowered risk aversion among subjects, are fulfilled.

Table 5: Averages of individual characteristics and t-tests between bubble and non-bubble markets in Treatment CASH14.

Markets	Fraction		Semester	Risk
	Female	Overconfidence		Attitude
CASH14, bubble markets	0.48	0.05	4.88	5.97
CASH14, non-bubble markets	0.47	0.41	6.06	5.13
Difference	0.01	-0.36	-1.18	0.84**

N equals 72 except for Risk Attitude, where five subjects with inconsistent decisions in the risk-aversion task (multiple switching points) have been removed. *, ** and *** represent the 10%, 5%, and 1% significance levels of a double-sided t-test.

We are aware that with this methodology bubbles strongly depend on the selection of the baseline treatment.²¹ If this treatment is already very inefficient then our classification may be insufficient. Therefore, this classification is most suited for studies with relatively efficient baselines and with treatment interventions that are expected to increase price inefficiencies. At the same time our bubble classification, particularly the fact that all three criteria have to be fulfilled simultaneously, is very strict. The probability for a type 1-error in our classification

²⁰For the latter we calculate the switching point at which subjects switch from the risky option (either 0 or 6 Euros with equal probabilities) to the safe payment across the 12 lotteries (see details on the risk elicitation task in the Appendix). The higher the number, the less risk-averse a subject is.

²¹In another robustness check, we also applied the proposed classification scheme using Treatment BASE14 as baseline. In this case 3 out of 9 markets in Treatment CASH14 were still identified as bubble markets.

scheme lies between 0.05 and 0.0001 (0.05^3). In our case we are confident that this “objective” bubble classification has detected the markets exhibiting the most bubble-like price paths. Those that are not classified as bubbles show clearly different patterns. Some markets show overpricing but no crash, especially in Treatment BASE14. Some other markets show prices that are either very stable or show only moderate price increases at levels in between the two buyback prices (see markets in both treatments with medium trading horizon and also markets in CASH14).

4.3 Beliefs and Bubbles

Elicited beliefs about prices allow us to investigate whether traders correctly anticipate the observed price patterns. In addition, we can investigate whether cash inflow and the related bubble behavior of markets is correlated with beliefs about fundamentals (i.e., the unknown buyback price).

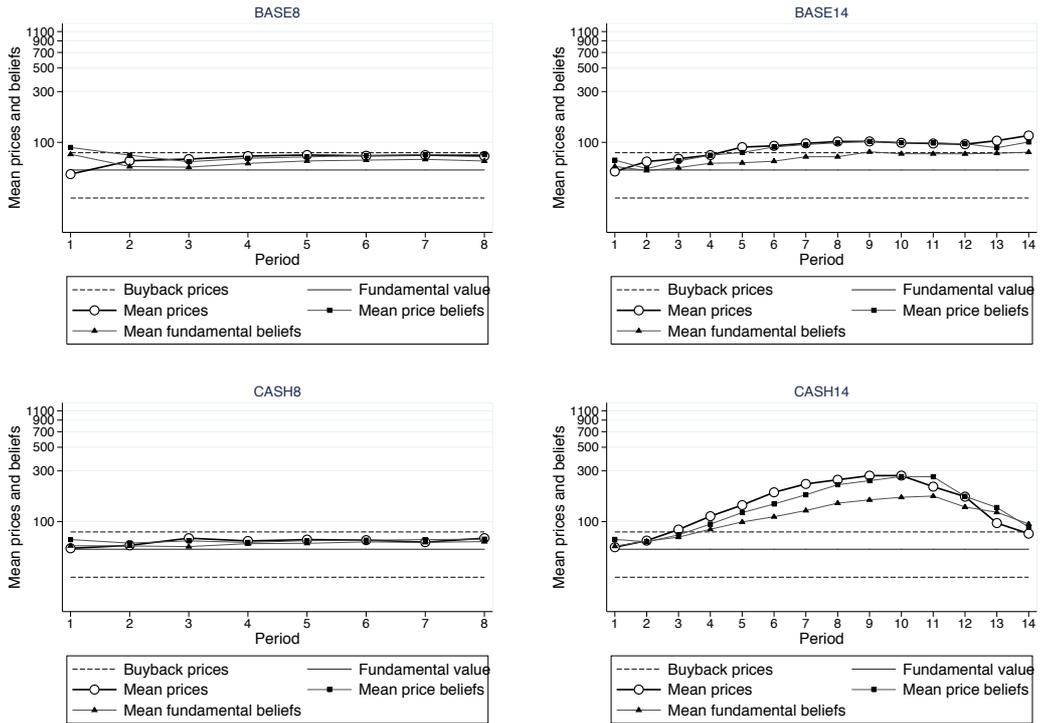


Figure 3: Average beliefs about market prices (solid line with squares) for period t , elicited in t , average beliefs about buyback prices (solid line with triangles) as a function of period for BASE8 (top left), CASH8 (bottom left), BASE14 (top right) and CASH14 (bottom right) in log-scale. The average treatment price is depicted as black solid line with circles. The dashed lines show the two possible buyback prices of 30 and 80 and the solid thin line represents the risk-neutral fundamental value of 55.

Figure 3 and Table 6 show average beliefs about market prices ($\overline{\text{BP}}$) for period t , elicited in t , average beliefs about the fundamental value ($\overline{\text{BFV}}$), elicited in t , and mean treatment prices over time. In line with our variables for price efficiency from Table 3 we calculate measures for $\text{RAD}^{\overline{\text{BP}}}$, $\text{RD}^{\overline{\text{BP}}}$, $\text{RD_MAX}^{\overline{\text{BP}}}$, $\text{AMPLITUDE}^{\overline{\text{BP}}}$, and $\text{CRASH}^{\overline{\text{BP}}}$ in Table 6 and test for treatment differences. In the bottom panels of Table 6 we apply the same procedure for beliefs about fundamentals ($\overline{\text{BFV}}$), i.e., the average of the known buyback price and the guess for the unknown buyback price. See Appendix A2 for details on the formulae.

Result 5: Average beliefs about prices ($\overline{\text{BP}}$) show analogous treatment differences compared to price developments. Again, only markets of Treatment CASH14 exhibit pronounced bubble and crash patterns in price beliefs. Moreover, we detect strong speculative motives among the most optimistic traders in the bubble markets of Treatment CASH14.

Support: We observe no statistical differences between BASE8 and CASH8 in any measure. Beliefs about prices are slightly but insignificantly higher in BASE14 and most pronounced for $\text{AMPLITUDE}^{\overline{\text{BP}}}$. However, beliefs are very different in CASH14. With RD_MAX of 430 percent, $\text{AMPLITUDE}^{\overline{\text{BP}}}$ of 436 percent and $\text{CRASH}^{\overline{\text{BP}}}$ of -389 percent average price beliefs $\overline{\text{BP}}$ follow a “bubble-like” pattern as well. Here, the magnitude of most of the variables is significantly higher than in both treatments with medium horizon, especially for the variable $\text{AMPLITUDE}^{\overline{\text{BP}}}$. This pattern is particularly pronounced for the five bubble markets in Treatment CASH14. Here, the values for $\text{RD_MAX}^{\overline{\text{BP}}}$, $\text{AMPLITUDE}^{\overline{\text{BP}}}$, and $\text{CRASH}^{\overline{\text{BP}}}$ are 725, 733, and -687 percent, respectively. Instead, the values for the four non-bubble markets are very similar to those of treatments BASE8 and CASH8. Thus, on average subjects seem to make quite naive predictions, as beliefs for the following periods’ prices are regularly similar to the current period’s average price. There is of course strong dispersion in beliefs, as optimists show markedly higher values. Following the approach of Kirchler et al. (2015) we calculate optimists’ beliefs as the 85-percentile in each measure (i.e., this is the belief of the subject with the second-highest belief). We find very similar qualitative patterns in significance levels across treatments in all variables. See Table A7 in the Appendix for optimists’ belief data and significance tests.

Table 6: Top two panels: Beliefs about mean market prices for period t , elicited in t ($\overline{\text{BP}}$). Treatment averages for mispricing ($\text{RAD}^{\overline{\text{BP}}}$), overpricing ($\text{RD}^{\overline{\text{BP}}}$), peak prices ($\text{RD_MAX}^{\overline{\text{BP}}}$), price run-ups ($\text{AMPLITUDE}^{\overline{\text{BP}}}$) and price crashes ($\text{CRASH}^{\overline{\text{BP}}}$) and significance tests for treatment differences. Bottom two panels: Beliefs about fundamentals ($\overline{\text{BFV}}$). Treatment averages for mispricing ($\text{RAD}^{\overline{\text{BFV}}}$), overpricing ($\text{RD}^{\overline{\text{BFV}}}$), peak prices ($\text{RD_MAX}^{\overline{\text{BFV}}}$), price run-ups ($\text{AMPLITUDE}^{\overline{\text{BFV}}}$) and price crashes ($\text{CRASH}^{\overline{\text{BFV}}}$) and significance tests for treatment differences. The numbers of the statistical tests indicate Z-values of pairwise Mann-Whitney U-tests. Sample size N of each test equals 18.

Beliefs Prices – $\overline{\text{BP}}$	$\text{RAD}^{\overline{\text{BP}}}$	$\text{RD}^{\overline{\text{BP}}}$	$\text{RD_MAX}^{\overline{\text{BP}}}$	$\text{AMPLITUDE}^{\overline{\text{BP}}}$	$\text{CRASH}^{\overline{\text{BP}}}$
BASE8	48.73	37.07	83.86	23.71	-56.56
CASH8	32.41	20.34	60.15	38.28	-39.16
BASE14	62.45	58.33	108.15	106.92	-41.31
CASH14	182.18	178.06	429.65	436.46	-389.15
CASH14, bubble markets	296.23	290.87	724.73	733.36	-686.77
CASH14, non-bubble markets	39.61	37.05	60.80	65.34	-17.13
Pairwise MW U-tests	$\text{RAD}^{\overline{\text{BP}}}$	$\text{RD}^{\overline{\text{BP}}}$	$\text{RD_MAX}^{\overline{\text{BP}}}$	$\text{AMPLITUDE}^{\overline{\text{BP}}}$	$\text{CRASH}^{\overline{\text{BP}}}$
BASE8 vs. CASH8	1.192	0.839	1.193	0.864	0.311
BASE8 vs. BASE14	0.132	0.662	0.397	2.454**	0.758
BASE8 vs. CASH14	1.634	1.987**	1.457	2.974***	1.198
CASH8 vs. BASE14	0.751	1.192	1.104	1.598	0.402
CASH8 vs. CASH14	2.075**	2.252**	2.076**	2.699***	1.465
BASE14 vs. CASH14	1.104	1.280	1.192	1.369	1.740*
Beliefs Fundamentals – $\overline{\text{BFV}}$	$\text{RAD}^{\overline{\text{BFV}}}$	$\text{RD}^{\overline{\text{BFV}}}$	$\text{RD_MAX}^{\overline{\text{BFV}}}$	$\text{AMPLITUDE}^{\overline{\text{BFV}}}$	$\text{CRASH}^{\overline{\text{BFV}}}$
BASE8	27.74	20.35	62.95	28.33	-52.40
CASH8	23.64	12.32	27.85	25.13	-12.28
BASE14	32.80	28.38	62.42	67.12	-23.31
CASH14	113.89	111.05	266.40	264.61	-198.71
CASH14, bubble markets	178.71	177.79	442.95	438.64	-344.95
CASH14, non-bubble markets	32.86	27.62	45.71	47.07	-15.91
Pairwise MW U-tests	$\text{RAD}^{\overline{\text{BFV}}}$	$\text{RD}^{\overline{\text{BFV}}}$	$\text{RD_MAX}^{\overline{\text{BFV}}}$	$\text{AMPLITUDE}^{\overline{\text{BFV}}}$	$\text{CRASH}^{\overline{\text{BFV}}}$
BASE8 vs. CASH8	0.132	0.397	1.280	0.315	2.219**
BASE8 vs. BASE14	0.044	0.751	0.132	1.294	1.548
BASE8 vs. CASH14	1.987**	2.163**	1.634	2.365**	0.972
CASH8 vs. BASE14	0.309	1.015	0.927	1.460	0.402
CASH8 vs. CASH14	1.987**	2.252**	2.340**	2.433**	2.219**
BASE14 vs. CASH14	1.898*	1.898*	1.457	1.414	2.079**

*, ** and *** represent the 10%, 5%, and 1% significance levels of a double-sided test.

Similar to Kirchler et al. (2015), we also run panel-regressions to analyze belief dynamics. We calculate the differences between subjects' future price beliefs and past period prices ($\overline{P}_{m,t-1}$) according to the following equations:

$$\overline{BeP}_{m,t,t+k} = \overline{BP}_{m,t,t+k} - \overline{P}_{m,t-1}; k \in \{0,1,2,3\}, \quad (4)$$

$$BeP_{m,t,t+k}^{\text{OPT}} = \text{OPT}(\text{BP}_{m,t,t+k}) - \overline{P}_{m,t-1}. \quad (5)$$

$\overline{BP}_{m,t,t+k}$ stands for the average belief about future market prices for period $t+k$ among all subjects, elicited in period t , with $k \in \{0, 1, 2, 3\}$. $\text{OPT}(\text{BP}_{m,t,t+k})$ represents the corresponding beliefs of the optimists.

With the market-fixed-effects (cross section, CS) panel regression of Equation (6) we test each treatment separately for significance. $y1_{m,t,t+k}$ is a generic placeholder for the differences between beliefs and the previous period's price, \overline{BeP} and BeP^{OPT} . A positive value of the intercept indicates that beliefs about future prices are higher than last period's average trading price. To detect potential speculative motives, the data used for the regression comprises prices and beliefs up to each market's individual price peak in $t = t^*$.

$$y1_{m,t,t+k} = \alpha + \epsilon_{m,t}; k \in \{0, 1, 2, 3\}. \quad (6)$$

While average beliefs are slightly higher than last period's prices in all of the treatments, we only detect strong speculative motives in the bubble markets of treatment CASH14, especially in the beliefs of the most optimistic traders (see Table 7 for details). In these markets, optimists' price forecasts not only exceed last period's prices, but also exhibit a pronounced upward trend for future periods: on average, optimists expect prices to rise by 47 Taler in the upcoming period and by even 96 Taler in $t+3$. This finding is also corroborated by Figure 4 which displays the mid-term forecasts for optimists over time. In Period 3, right after the first cash inflow, optimists' price expectations in the bubble markets (left panel) start to rise. From Period 4 onwards, the forecasts reveal that the optimists expect strong price rallies for the upcoming periods.

Table 7: Market (CS) fixed-effects panel regression according to Equation (6). \overline{BeP} and BeP^{OPT} detect speculative motives by comparing beliefs (market average and 85-percentile, respectively) about future market prices up to $t + 3$, elicited in period t , with the average market price of the last period. Higher values, particularly increasing with $t + k$, indicate more speculative motives. Data include prices and beliefs from $t = 1$ to $t = t^*$ (period with the peak price in each market). .

Treatment	$BeP_{m,t,t+k}$				$BeP_{m,t,t+k}^{\text{OPT}}$			
	t,t	$t,t+1$	$t,t+2$	$t,t+3$	t,t	$t,t+1$	$t,t+2$	$t,t+3$
BASE8	7.20**	6.70***	7.60**	6.92***	13.17***	13.16***	18.08***	19.13***
CASH8	3.16***	4.69***	2.74***	2.44**	5.34***	7.33***	7.62***	8.25***
BASE14	1.06	2.59**	1.80*	2.78**	8.86***	11.87***	11.17***	14.07***
CASH14, bubble markets	10.87**	25.64***	30.78***	35.85***	47.13***	65.16***	82.91***	96.02***
CASH14, non-bubble markets	0.42	0.58	0.61	1.01	5.25***	7.58***	8.67***	10.19***
$N(\text{BASE8})$	41	37	32	27	41	37	32	27
$N(\text{CASH8})$	43	40	36	32	43	40	36	32
$N(\text{BASE14})$	100	97	91	84	100	97	91	84
$N(\text{CASH14, bubble markets})$	37	37	37	37	37	37	37	37
$N(\text{CASH14, non-bubble markets})$	42	39	36	33	42	39	36	33
Fixed effects	CS	CS	CS	CS	CS	CS	CS	CS

*, ** and *** represent the 10%, 5%, and 1% significance levels of a double-sided t-test.

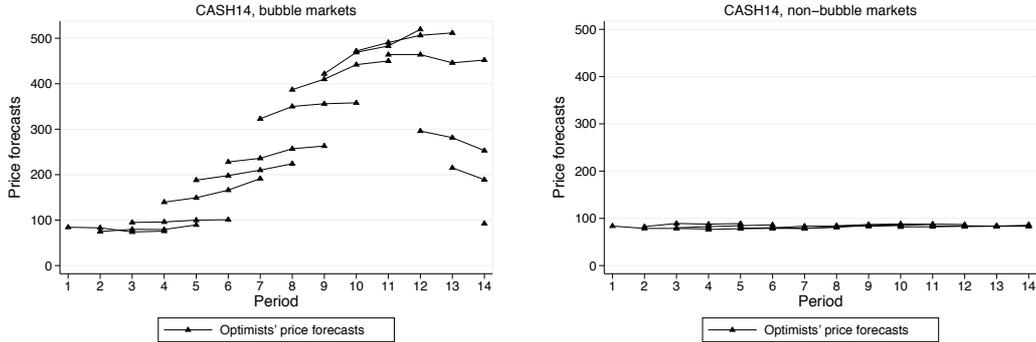


Figure 4: Optimists' beliefs about future market prices (up to period $t + 3$), elicited in period t , for treatment CASH14. The left panel shows the forecasts in markets identified as bubbles, the right panel the forecasts in markets not identified as bubbles.

Result 6: Average beliefs about fundamentals ($\overline{\text{BFV}}$) are only adapted markedly in Treatment CASH14. Here, beliefs increase initially and crash towards fundamentally justified values in the end.

Support: Importantly, the cash inflow in CASH14 does not only operate on the level of price beliefs, but subjects also adapt their beliefs about fundamentals. Here, average beliefs increase to an average maximum value of 146 ($\text{RD_MAX}^{\overline{\text{BFV}}}$ of 266 percent) and crash towards fundamentally justified values at maturity. On average fundamentals are estimated at 116 Taler instead of the true 55 Taler ($\text{RD}^{\overline{\text{BFV}}}$ of 111 percent). All five variables of Treatment CASH14 are more strongly pronounced than in the other three treatments with most differences being significant. These findings are remarkable as fundamentals do not change over time. Like for the price beliefs this pattern is particularly pronounced for the five bubble markets in Treatment CASH14. Here, the values for $\text{RD_MAX}^{\overline{\text{BFV}}}$, $\text{AMPLITUDE}^{\overline{\text{BFV}}}$, and $\text{CRASH}^{\overline{\text{BFV}}}$ are 443, 439, and -345 percent, respectively. In contrast, the values of the bubble measures in the four non-bubble markets are very similar to those of treatments BASE8 and CASH8. We also calculate optimists' beliefs about fundamentals as the 85-percentile in each measure. Again, we report very similar qualitative patterns in significance levels across treatments in all variables (see Table A7 in the Appendix for optimists' belief data and significance tests).

5 Conclusion and Discussion

In this paper we investigated the impact of cash inflow and variations in trading horizon on price efficiency. We observed that i) markets with medium trading horizon did not show substantial

overpricing and price rallies no matter whether there was cash inflow or not. We also showed that ii) markets with long trading horizon but without cash inflow did not exhibit significantly higher levels of overpricing and price amplitude compared to markets with medium maturity. Importantly, we found that iii) markets with the joint effect of cash inflow *and* long trading horizon produced significantly higher levels of overpricing, maximum market prices, price amplitudes, and crashes compared to both treatments with medium trading horizon. In this treatment we found two archetypes of price paths, i.e, one type that is relatively efficient without much price variability and one with strong price run-ups followed by severe crashes. iv) We developed a bubble classification scheme relying on three criteria, separating bubble from non-bubble markets based on statistical differences from the baseline treatment. Applying this scheme we observed bubbles and crashes in 5 out of 9 markets in the treatment with cash inflow and long trading horizon and only one bubble in all 27 markets of the other treatments. Finally, v) we reported that bubbles in markets with cash inflow and long trading horizon are accompanied by changes in beliefs. We showed that as soon as cash is injected into the market beliefs about prices and, importantly, beliefs about fundamentals rise. With this result we show that bubbles also influence beliefs about fundamentals.

With this study we contribute to the literature in the following dimensions: First, we show that the joint effect of cash inflow and long trading horizon *can* result in bubbles. We argue that with longer trading horizon backward induction is probably less prominent initially, which provides traders with more time for speculation. However, this must be accompanied by cash inflow to trigger bubbles and crashes. This finding is novel and adds to the literature on the impact of high *initial* CA-Ratios (Caginalp et al., 1998; Haruvy and Noussair, 2006) in markets. We also add to the literature on trader inflow (Xiong and Yu, 2011; Deck et al., 2014; Kirchler et al., 2015) and show that cash inflow might have similar, albeit weaker – in comparison to Kirchler et al. (2015) – effects.

Second, we set up a bubble classification scheme and show that almost identical initial conditions can result in different archetypical patterns of price paths *within* the same treatment. Either markets stay relatively efficient or they create bubble-and-crash-patterns. We find that although subjects were selected from the same pool, average risk aversion in the bubble markets is significantly lower compared to those markets that are relatively efficient. We consider it important to show that within one particular treatment different archetypical price patterns emerge, pointing at the sensitivity of the treatment variation and at the limits of predictability and control we can hope to achieve also in real markets.

Third, we show that bubbles in markets with cash inflow and long trading horizon are accompanied by changes in beliefs. We did not only find that price beliefs change in bubble markets

as a result of speculation, but we also showed that the cash inflow led subjects to become more optimistic in their beliefs about fundamentals. This result is remarkable as fundamentals stay constant over time which was common knowledge among subjects.

We believe that our findings provide novel and important insights for researchers in experimental asset market research. In particular, the setting with cash inflow, extended trading horizon and heterogeneous information appears to be an interesting and fragile environment framework which can react very sensitively to marginal differences in initial parameters (e.g., risk aversion of subjects, cognitive abilities of subjects). This model allows researchers to investigate bubble and crash phenomena and relatively efficient market prices *within* the same framework. As in the recent studies of Holt et al. (2015) and Kirchler et al. (2015), all bubbles are characterized by a price run-up (starting at relatively efficient prices) and a subsequent crash (ending at relatively efficient prices). We consider this an improvement to studies that show relatively stable prices which crash late as is often observed in markets with declining fundamentals.

References

- Abreu, Dilip, Markus K. Brunnermeier. 2003. Bubbles and crashes. *Econometrica* **71**(1) 173–204.
- Akiyama, Eizo, Nobuyuki Hanaki, Ryuichiro Ishikawa. 2014. How do experienced traders respond to inflows of inexperienced traders? an experimental analysis. *Journal of Economic Dynamics and Control* **45** 1–18.
- Allen, Franklin, Gary Gorton. 1993. Churning bubbles. *Review of Economic Studies* **60**(4) 813–836.
- Andrade, Eduardo B., Terrance Odean, Shengle Lin. 2015. Bubbling with excitement: An experiment. *Review of Finance* **forthcoming**.
- Blanchard, Olivier J., Mark W. Watson. 1982. Bubbles, rational expectations and financial markets. Howard M. Wachtel, ed., *Crisis in the Economic and Financial Structure*. Lexington Books, Lexington et al., 295–315.
- Bock, Olaf, Ingmar Baetge, Andreas Nicklisch. 2014. hroot: Hamburg registration and organization online tool. *European Economic Review* **71** 117–120. doi:10.1016/j.euroecorev.2014.07.003.
- Bostian, AJ, Jacob Goeree, Charles A. Holt. 2005. Price bubbles in asset market experiments with a flat fundamental value. Working paper prepared for the Experimental Finance Conference.
- Breaban, Adriana, Charles N. Noussair. 2013. Emotional state and market behavior. Working paper.
- Brunnermeier, Markus. 2009. Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives* **23** 77–100.
- Brunnermeier, Markus, Martin Oehmke. 2013. Bubbles, financial crises, and systemic risk. George Constantinides, Milton Harris, Rene Stulz, eds., *Handbook of the Economics of Finance*, vol. 2B. North-Holland, 1221–1288.
- Buch, Claudia M., Sandra Eickmeier, Esteban Prieto. 2014. In search for yield? survey-based evidence on bank risk taking. *Journal of Economic Dynamics and Control* **43** 12–30.
- Burks, Stephen V., Jeffrey P. Carpenter, Lorenz Goette, Aldo Rustichini. 2009. Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Science* **106**(19) 7745–7750.

- Caginalp, Gunduz, David Porter, Vernon Smith. 1998. Initial cash/asset ratio and asset prices: an experimental study. *Proceedings of the National Academy of Sciences* **95** 756–761.
- Caginalp, Gunduz, David Porter, Vernon Smith. 2001. Financial bubbles: Excess cash, momentum and incomplete information. *The Journal of Psychology and Financial Markets* **2**(2) 80–99.
- Camerer, Colin, K. Weigelt. 1991. Information mirages in experimental asset markets. *The Journal of Business* **64** 463–493.
- Cheung, Stephen L., Morten Hedegaard, Stefan Palan. 2014. To see is to believe - common expectations in experimental asset markets. *European Economic Review* **66** 84–96.
- Deck, Cary, David Porter, Vernon L. Smith. 2014. Double bubbles in asset markets with multiple generations. *Journal of Behavioral Finance* **15**(2) 79–88.
- DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, Robert J. Waldmann. 1990. Noise trader risk in financial markets. *Journal of Political Economy* **98**(4) 703–738.
- Dufwenberg, Martin, Tobias Lindqvist, Evan Moore. 2005. Bubbles and experience: An experiment. *The American Economic Review* **95**(5) 1731–1737.
- Fama, Eugene F. 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance* **45** 383–417.
- Fischbacher, Urs. 2007. z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics* **10**(2) 171–178.
- Galbraith, John Kenneth. 1994. *A short history of financial euphoria*. Penguin Business, London.
- Harrison, Michael, David Kreps. 1978. Speculative investor behavior in a stock market with heterogeneous expectations. *The Quarterly Journal of Economics* **92**(2) 323–336.
- Haruvy, Ernan, Yaron Lahav, Charles Noussair. 2007. Traders' expectations in asset markets: experimental evidence. *The American Economic Review* **97**(5) 1901–1920.
- Haruvy, Ernan, Charles N. Noussair. 2006. The effect of short selling on bubbles and crashes in experimental spot asset markets. *The Journal of Finance* **61**(3) 1119–1157.
- Hirota, Shinichi, Shyam Sunder. 2007. Price bubbles sans dividend anchors: Evidence from laboratory stock markets. *Journal of Economic Dynamics & Control* **31**(6) 1875–1909.
- Holt, Charles A., Megan Porzio, Michelle Yingze Song. 2015. Price bubbles and expectations in experimental asset markets: gender and risk aversion. *Working Paper* .

- Hommes, Charles. 2006. Heterogeneous agent models in economics and finance. Leigh Tesfatsion, Kenneth L. Judd, eds., *Handbook of Computational Economics, Edition 1, Volume 2*. 1109–1186.
- Huber, Jürgen, Michael Kirchler. 2012. The impact of instructions and procedure on reducing confusion and bubbles in experimental asset market. *Experimental Economics* **15** 89–105.
- Huber, Jürgen, Michael Kirchler, Thomas Stöckl. 2015. The influence of investment experience on market prices. laboratory evidence. *Experimental Economics* **forthcoming**.
- Kindleberger, Charles Poor, Robert Z. Aliber. 2011. *Manias, Panics, and Crashes: A History of Financial Crises*. 6th ed. Palgrave Macmillan.
- King, Ronald, Vernon Smith, Arlington Williams, Mark Van Boening. 1993. The robustness of bubbles and crashes in experimental stock markets. Richard Day, Ping Chen, eds., *Nonlinear Dynamics and Evolutionary Economics*. Oxford University Press, New York et al., 183–200.
- Kirchler, Michael, Caroline Bonn, Jürgen Huber, Michael Razen. 2015. The “inflow-effect” - trader inflow and price efficiency. *European Economic Review* **77** 1–19.
- Kirchler, Michael, Jürgen Huber, Thomas Stöckl. 2012. That she bursts - reducing confusion reduces bubbles. *The American Economic Review* **102**(2) 865–883.
- Lei, Vivian, Filip Vesely. 2009. Market efficiency: Evidence from a no-bubble asset market experiment. *Pacific Economic Review* **14**(2) 246–258.
- Lux, Thomas, Michele Marchesi. 1999. Scaling and criticality in a stochastic multi-agent model of a financial market. *Letters to Nature* **397** 498–500.
- Lux, Thomas, Michele Marchesi. 2000. Volatility clustering in financial markets, a microsimulation of interacting agents. *International Journal of Theoretical and Applied Finance* **3** 675–702.
- McKelvey, Richard D., Thomas R. Palfrey. 1992. An experimental study of the centipede game. *Econometrica* **60**(4) 803–836.
- Mian, Atif, Amir Sufi. 2014. *House of debt*. University of Chicago Press.
- Miller, Edward M. 1977. Risk, uncertainty, and divergence of opinion. *The Journal of Finance* **32**(4) 1151–1168.
- Noussair, Charles N., Stephane Robin, Bernard Ruffieux. 2001. Price bubbles in laboratory asset markets with constant fundamental values. *Experimental Economics* **4** 87–105.

- Noussair, Charles N., Steven Tucker. 2016. Cash inflows and bubbles in asset markets with constant fundamental values. *Economic Inquiry* **54**(3) 1596–1606.
- Oechssler, Jörg. 2010. Searching beyond the lamppost: Let's focus on economically relevant questions. *Journal of Economic Behavior and Organization* **73** 65–67.
- Oechssler, Jörg, Carsten Schmidt, Wendelin Schnedler. 2011. On the ingredients for bubble formation: informed traders and communication. *Journal of Economic Dynamics and Control* **35**(11) 1831–1851.
- Ofek, Eli, Matthew Richardson. 2003. Dotcom mania: The rise and fall of internet stock prices. *Journal of Finance* **58** 1113 – 1138.
- Palan, Stefan. 2013. A review of bubbles and crashes in experimental asset markets. *Journal of Economic Surveys* **27**(3) 570–588.
- Plott, Charles, Shyam Sunder. 1982. Efficiency of experimental security markets with insider information: An application of rational-expectations models. *Journal of Political Economy* **90** 663–698.
- Plott, Charles R., Shyam Sunder. 1988. Rational expectations and the aggregation of diverse information in laboratory security markets. *Econometrica* **56**(5) 1085–1118.
- Schularick, Moritz, Alan M. Taylor. 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises. *American Economic Review* **102**(2) 1029–1061.
- Shiller, Robert J. 1981. Do stock prices move too much to be justified by subsequent changes in dividends? *The American Economic Review* **71**(3) 421–436.
- Smith, Alec, Terry Lohrenz, Justin King, Read Montague, Colin Camerer. 2014. Irrational exuberance and neural crash warning signals during endogenous experimental market bubbles. *Proceedings of the National Academy of Sciences* **111**(29) 10503–10508.
- Smith, Vernon L., Gerry L. Suchanek, Arlington W. Williams. 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica* **56**(5) 1119–1151.
- Stöckl, Thomas. 2014. Price efficiency and trading behavior in limit order markets with competing insiders. *Experimental Economics* **17** 314–334. doi:10.1007/s10683-013-9369-5.
- Stöckl, Thomas, Juergen Huber, Michael Kirchler. 2015. Multi-period experimental asset markets with distinct fundamental value regimes. *Experimental Economics* **18** 314–334. doi: 10.1007/s10683-014-9404-1.

- Stöckl, Thomas, Jürgen Huber, Michael Kirchler. 2010. Bubble measures in experimental asset markets. *Experimental Economics* **13** 284–298.
- Sutter, Matthias, Jürgen Huber, Michael Kirchler. 2012. Bubbles and information: An experiment. *Management Science* **58** 384–393.
- Tirole, Jean. 1982. On the possibility of speculation under rational expectation. *Econometrica* **50**(5) 1163–1181.
- Van Boening, Mark, Arlington W. Williams, Shawn LaMaster. 1993. Price bubbles and crashes in experimental call markets. *Economics Letters* **41**(2) 179–185.
- Xiong, Wei, Jialin Yu. 2011. The chinese warrants bubble. *The American Economic Review* **101**(6) 2723–2753.

Appendix

A1 Bubble Measures for Individual Markets

Table A1: Bubble measures for all markets in Treatment BASE8.

Market	RAD	RD	RD_MAX	AMPLITUDE	CRASH
<i>Threshold for bubble classification</i>	–	–	141.96	124.65	–41.07
M1	39.66	35.86	63.16	78.36	0.00
M2	78.85	78.85	87.75	26.00	–15.09
M3	15.24	–13.65	6.35	55.37	0.00
M4	44.19	44.19	45.62	6.33	–1.88
M5	45.58	–45.58	–29.18	37.04	0.00
M6	50.89	45.66	69.50	90.41	–34.22
M7	101.08	101.08	140.69	123.68	–41.76*
M8	12.76	–12.76	–2.26	21.53	–5.52
M9	23.13	16.91	32.73	57.61	0.00

Threshold values for bubble measures qualifying a bubble according to our criteria outlined in Section 4.2 are displayed in the first row. Values marked with * exceed the corresponding threshold. Markets in **bold** and marked with ** are classified as bubble markets.

Table A2: Bubble measures for all markets in Treatment CASH8.

Market	RAD	RD	RD_MAX	AMPLITUDE	CRASH
<i>Threshold for bubble classification</i>	–	–	141.96	124.65	–41.07
M1	4.81	–4.81	–1.09	11.14	–4.96
M2	42.87	42.87	56.79	35.92	–8.32
M3	63.59	63.59	160.60*	109.96	–112.78*
M4	41.90	29.72	46.10	14.46	–94.81*
M5	39.16	–39.16	–32.52	11.53	0.00
M6	5.01	–5.01	–0.94	12.50	–3.97
M7	27.22	26.40	43.26	46.53	–15.66
M8	34.65	34.65	66.06	51.91	0.00
M9	29.24	15.84	53.37	87.36	0.00

Threshold values for bubble measures qualifying a bubble according to our criteria outlined in Section 4.2 are displayed in the first row. Values marked with * exceed the corresponding threshold. Markets in **bold** and marked with ** are classified as bubble markets.

Table A3: Bubble measures for all markets in Treatment BASE14.

Market	RAD	RD	RD_MAX	AMPLITUDE	CRASH
<i>Threshold for bubble classification</i>	–	–	141.96	124.65	–41.07
M1	10.64	–6.37	18.18	51.26	0.00
M2	75.25	58.84	114.36	166.74*	–9.87
M3	87.34	76.57	131.90	170.96*	–0.69
M4**	164.69	162.55	283.80*	298.82*	–169.37*
M5	39.19	39.19	45.44	29.57	0.00
M6	185.94	185.94	409.09*	295.38*	0.00
M7	36.63	32.63	58.18	75.44	–36.18
M8	9.33	9.33	18.98	14.93	0.00
M9	15.44	13.50	37.20	42.67	–5.30

Threshold values for bubble measures qualifying a bubble according to our criteria outlined in Section 4.2 are displayed in the first row. Values marked with * exceed the corresponding threshold. Markets in **bold** and marked with ** are classified as bubble markets.

Table A4: Bubble measures for all markets in Treatment CASH14.

Market	RAD	RD	RD_MAX	AMPLITUDE	CRASH
<i>Threshold for bubble classification</i>	–	–	141.96	124.65	–41.07
M1**	430.76	411.73	1282.39*	1350.47*	–1269.60*
M2**	695.14	693.55	1587.77*	1557.59*	–1594.17*
M3	7.33	2.27	15.39	27.36	0.00
M4	9.74	1.72	37.91	57.69	0.00
M5**	115.35	110.33	285.52*	278.90*	–305.28*
M6	93.90	93.90	116.62	27.20	–42.01*
M7**	231.41	231.41	462.75*	435.07*	–419.56*
M8	68.67	66.11	94.55	112.43	0.00
M9**	103.77	90.51	168.08*	211.26*	–76.97*

Threshold values for bubble measures qualifying a bubble according to our criteria outlined in Section 4.2 are displayed in the first row. Values marked with * exceed the corresponding threshold. Markets in **bold** and marked with ** are classified as bubble markets.

A2 Formulae for Belief Calculation

Table A5: Formulae for price beliefs.

Average mispricing of beliefs	$\text{RAD}^{\overline{\text{BP}}} = \sum_{t=1}^T \frac{ \overline{\text{BP}}_t - FV_t }{T}$
Average overpricing of beliefs	$\text{RD}^{\overline{\text{BP}}} = \sum_{t=1}^T \frac{\overline{\text{BP}}_t - FV_t}{T}$
Peak price beliefs	$\text{RD_MAX}^{\overline{\text{BP}}} = \max_t \left\{ \frac{\overline{\text{BP}}_t - FV_t}{FV_t} \right\} = \frac{\overline{\text{BP}}_{t^*} - FV_{t^*}}{FV_{t^*}}$
Price belief run-ups	$\text{AMPLITUDE}^{\overline{\text{BP}}} = \frac{\overline{\text{BP}}_{t^*} - FV_{t^*}}{FV_{t^*}} - \min_{0 \leq k < t^*} \left\{ \frac{\overline{\text{BP}}_{t^* - k} - FV_{t^* - k}}{FV_{t^* - k}} \right\}$
Price belief crashes	$\text{CRASH}^{\overline{\text{BP}}} = \min_{0 \leq l \leq T - t^*} \left\{ \frac{\overline{\text{BP}}_{t^* + l} - FV_{t^* + l}}{FV_{t^* + l}} \right\} - \frac{\overline{\text{BP}}_{t^*} - FV_{t^*}}{FV_{t^*}}$

$\overline{\text{BP}}_t$ is the average price forecast across subjects for period t , elicited in period t , FV_t is the fundamental value in period t . t^* denotes the period with the highest average price forecast.

Table A6: Formulae for fundamental value beliefs.

Average mispricing	$\text{RAD}^{\overline{\text{BFV}}} = \sum_{t=1}^T \frac{ \overline{\text{BFV}}_t - FV_t }{T}$
Average overpricing	$\text{RD}^{\overline{\text{BFV}}} = \sum_{t=1}^T \frac{\overline{\text{BFV}}_t - FV_t}{T}$
Peak fundamental beliefs	$\text{RD_MAX}^{\overline{\text{BFV}}} = \max_t \left\{ \frac{\overline{\text{BFV}}_t - FV_t}{FV_t} \right\} = \frac{\overline{\text{BFV}}_{t^*} - FV_{t^*}}{FV_{t^*}}$
Fundamental beliefs run-ups	$\text{AMPLITUDE}^{\overline{\text{BFV}}} = \frac{\overline{\text{BFV}}_{t^*} - FV_{t^*}}{FV_{t^*}} - \min_{0 \leq k < t^*} \left\{ \frac{\overline{\text{BFV}}_{t^* - k} - FV_{t^* - k}}{FV_{t^* - k}} \right\}$
Fundamental beliefs crashes	$\text{CRASH}^{\overline{\text{BFV}}} = \min_{0 \leq l \leq T - t^*} \left\{ \frac{\overline{\text{BFV}}_{t^* + l} - FV_{t^* + l}}{FV_{t^* + l}} \right\} - \frac{\overline{\text{BFV}}_{t^*} - FV_{t^*}}{FV_{t^*}}$

$\overline{\text{BFV}}_t$ is the average belief about fundamentals across subjects in period t , FV_t is the fundamental value in period t . t^* denotes the period with the highest average belief about fundamentals.

A3 Additional Figures and Tables

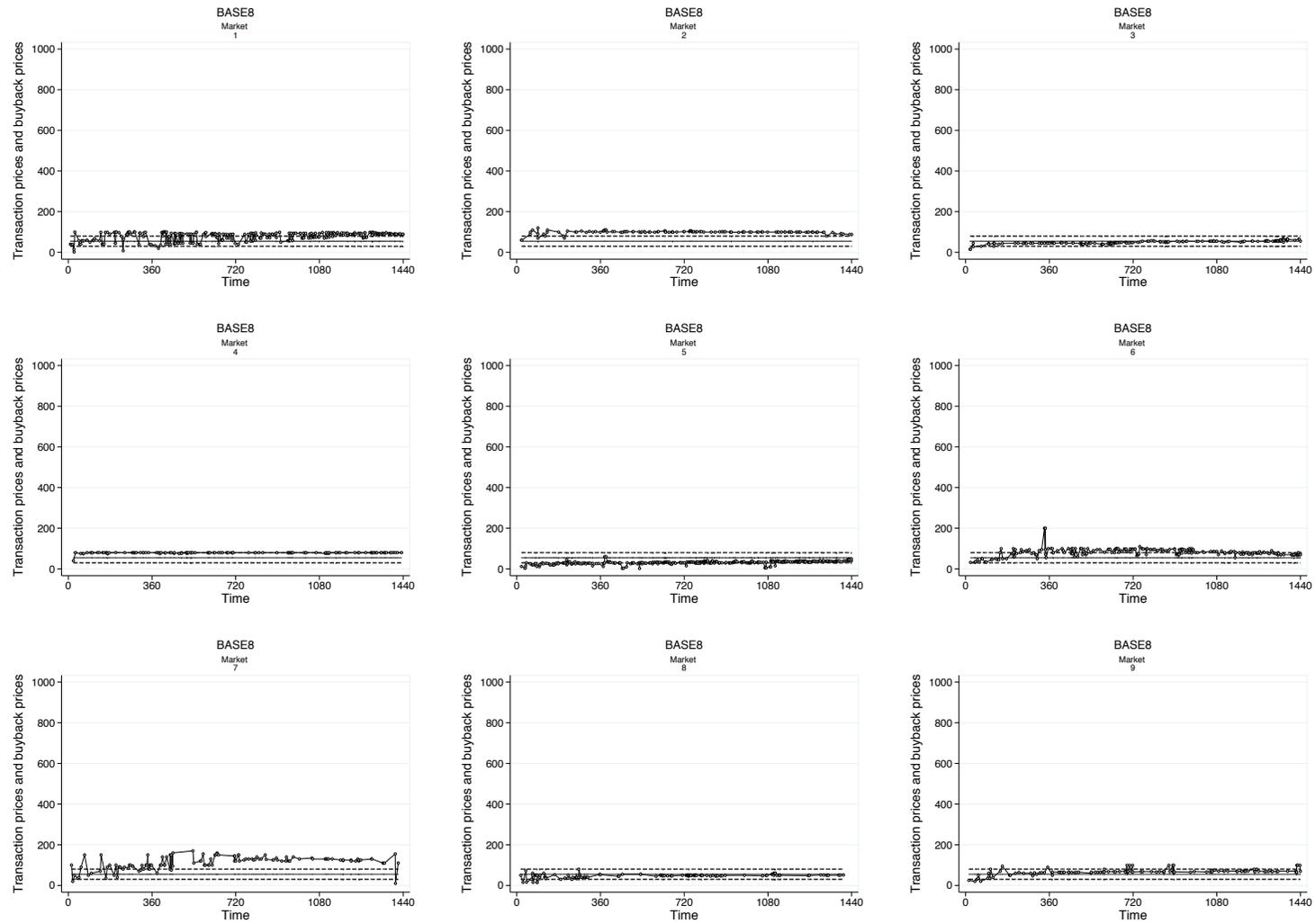


Figure A1: Individual transaction prices for each market of Treatment BASE8. The dashed lines show the two possible buyback prices of 30 and 80 and the solid line represents the risk-neutral fundamental of 55.

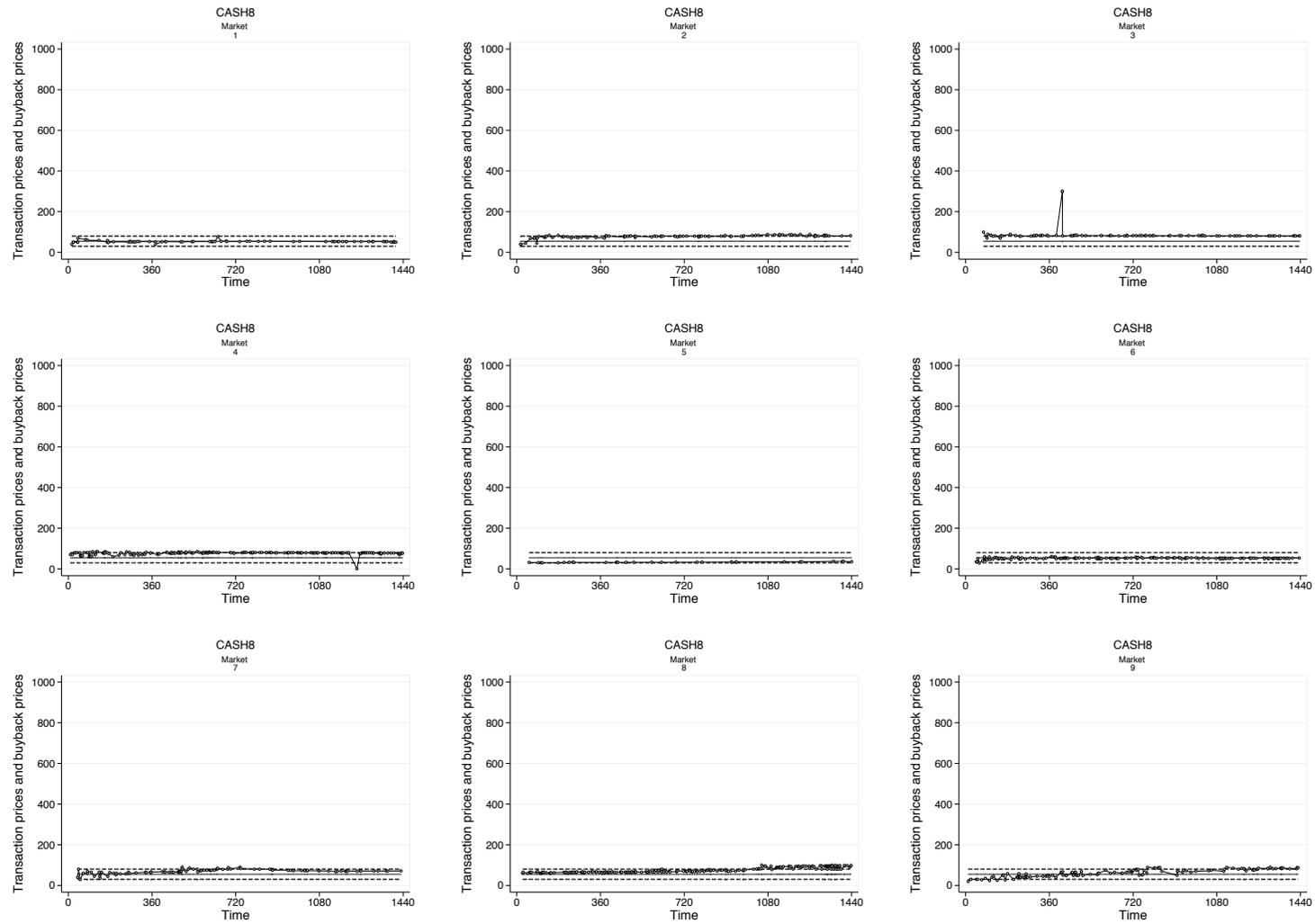


Figure A2: Individual transaction prices for each market of Treatment CASH8. The dashed lines show the two possible buyback prices of 30 and 80 and the solid line represents the risk-neutral fundamental value of 55.

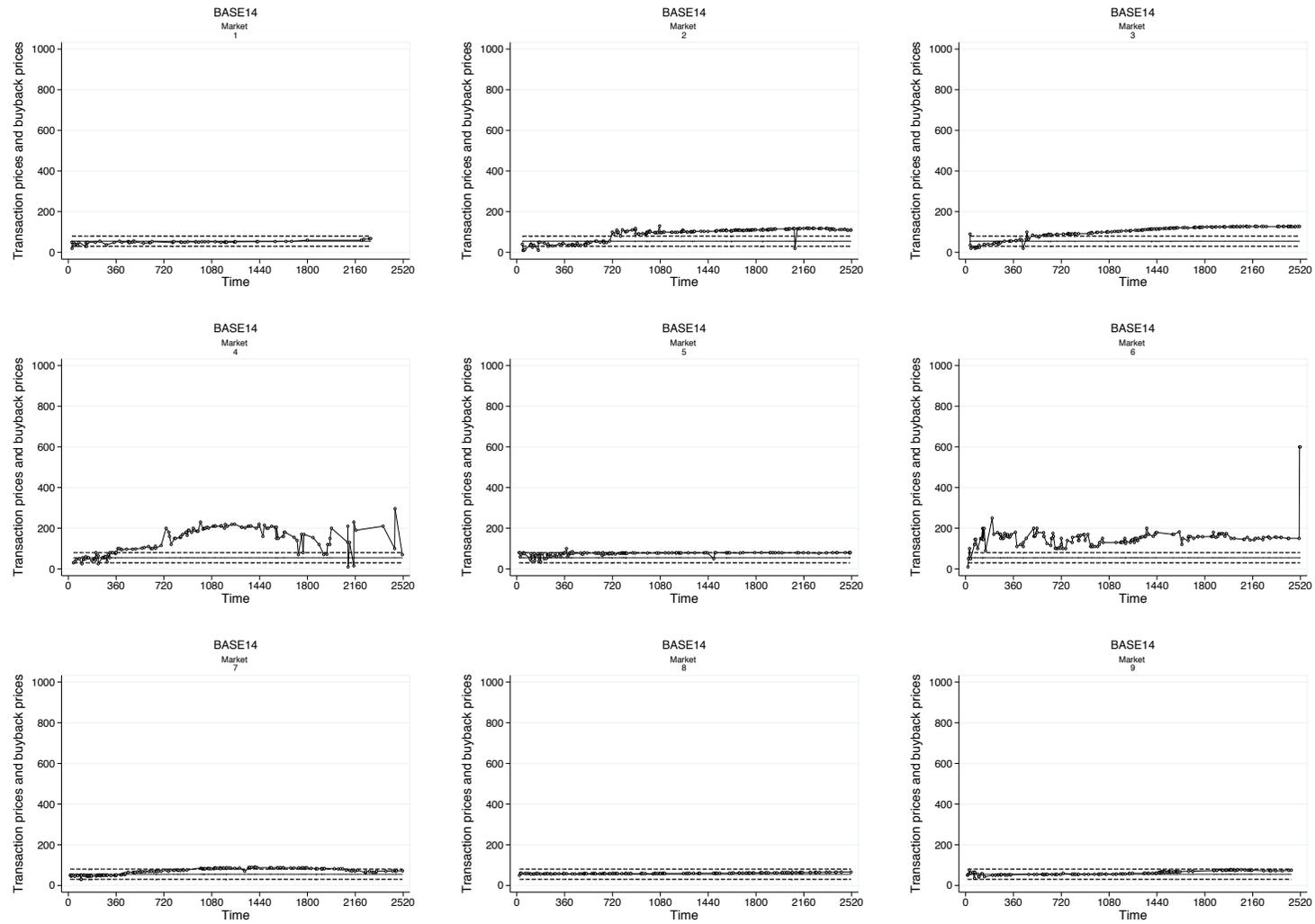


Figure A3: Individual transaction prices for each market of Treatment BASE14. The dashed lines show the two possible buyback prices of 30 and 80 and the solid line represents the risk-neutral fundamental value of 55.

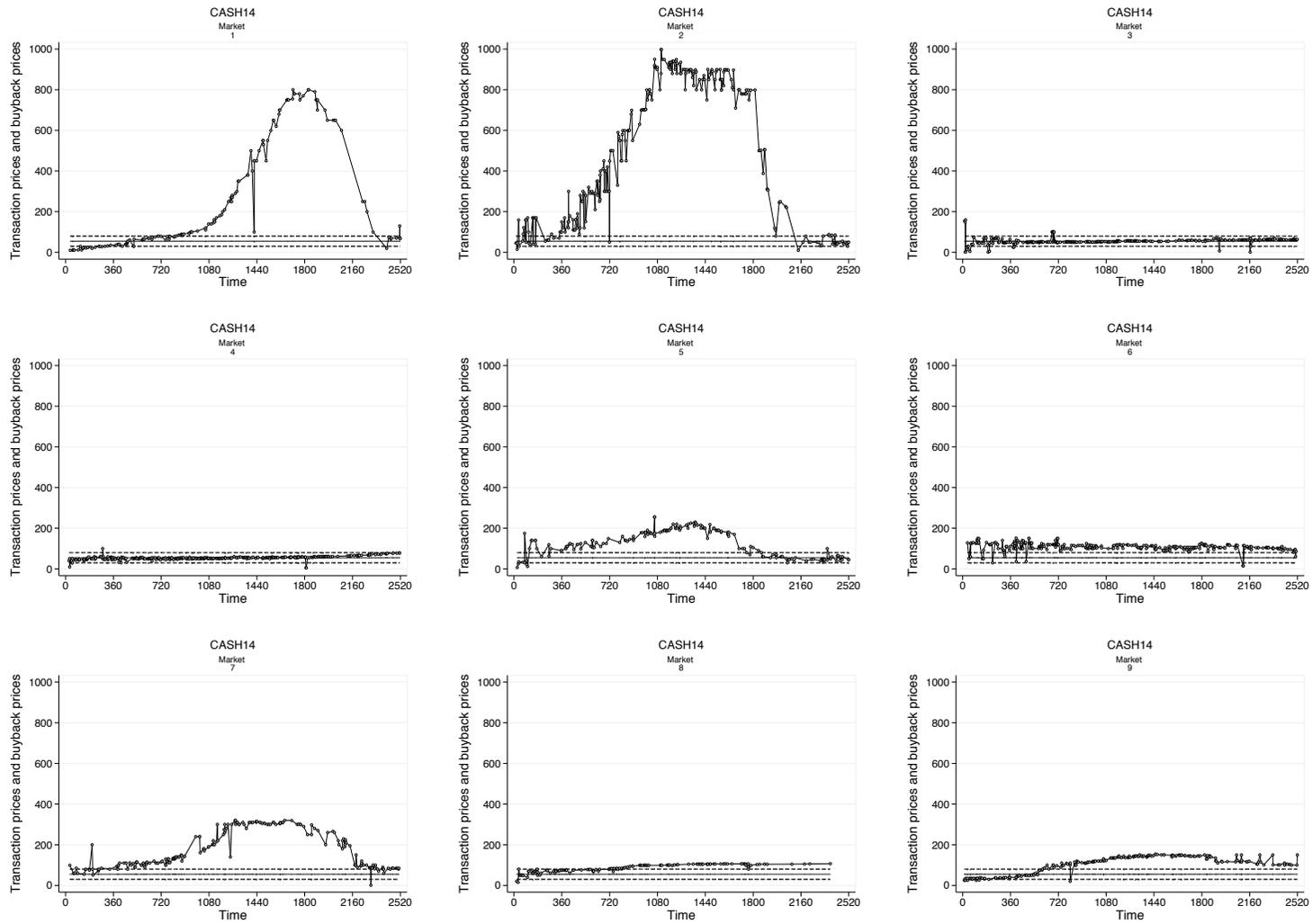


Figure A4: Individual transaction prices for each market of Treatment CASH14. The dashed lines show the two possible buyback prices of 30 and 80 and the solid line represents the risk-neutral fundamental value of 55.

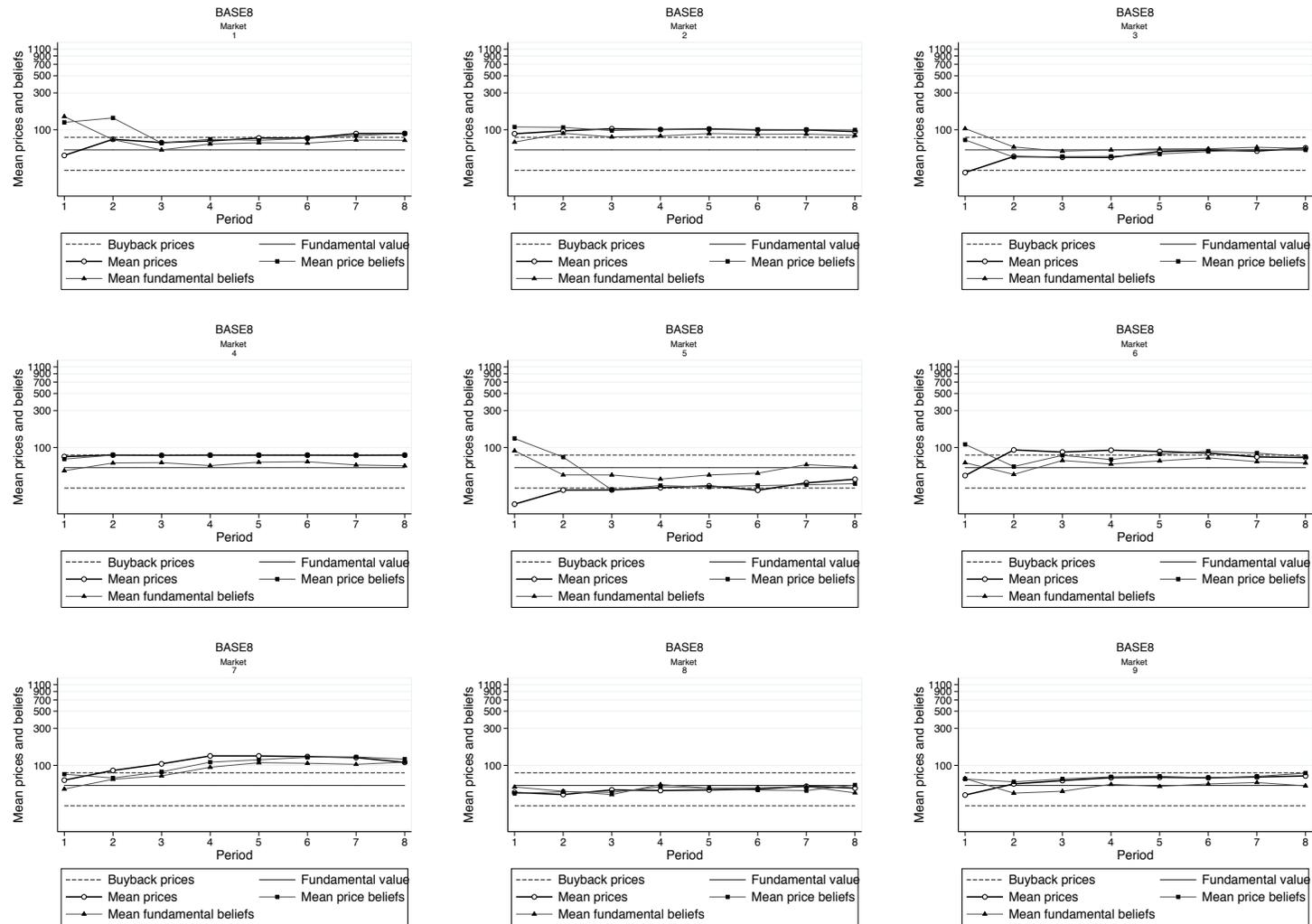


Figure A5: Mean treatment prices (bold line with circles), average beliefs about fundamentals (solid line with triangles), and average beliefs about prices for t , elicited in t (solid line with squares) of Treatment BASE8. The dashed lines show the two possible buyback prices of 30 and 80 and the solid thin line represents the risk-neutral fundamental value of 55.

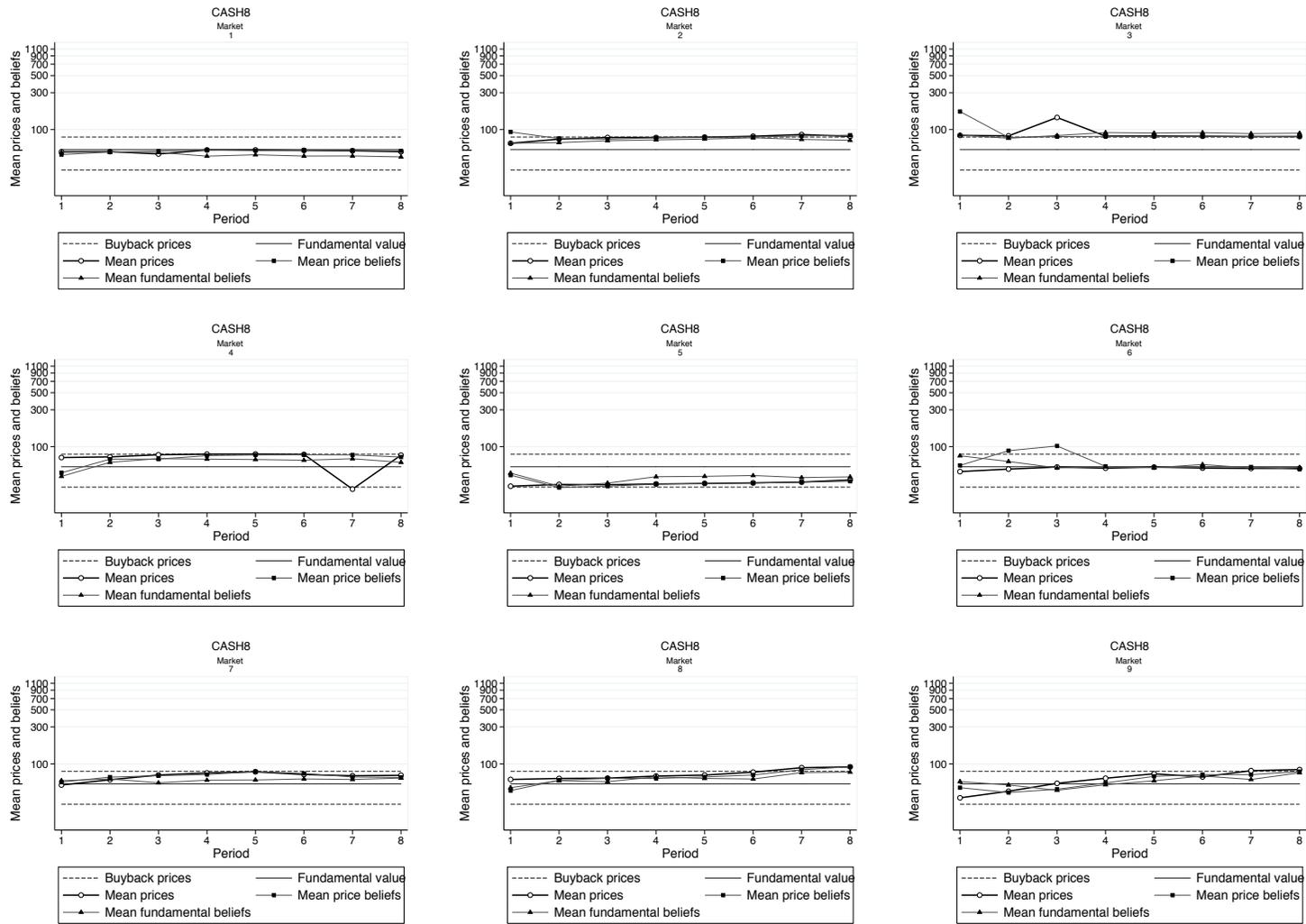


Figure A6: Mean treatment prices (bold line with circles), average beliefs about fundamentals (solid line with triangles), and average beliefs about prices for t , elicited in t (solid line with squares) of Treatment CASH8. The dashed lines show the two possible buyback prices of 30 and 80 and the solid thin line represents the risk-neutral fundamental value of 55.

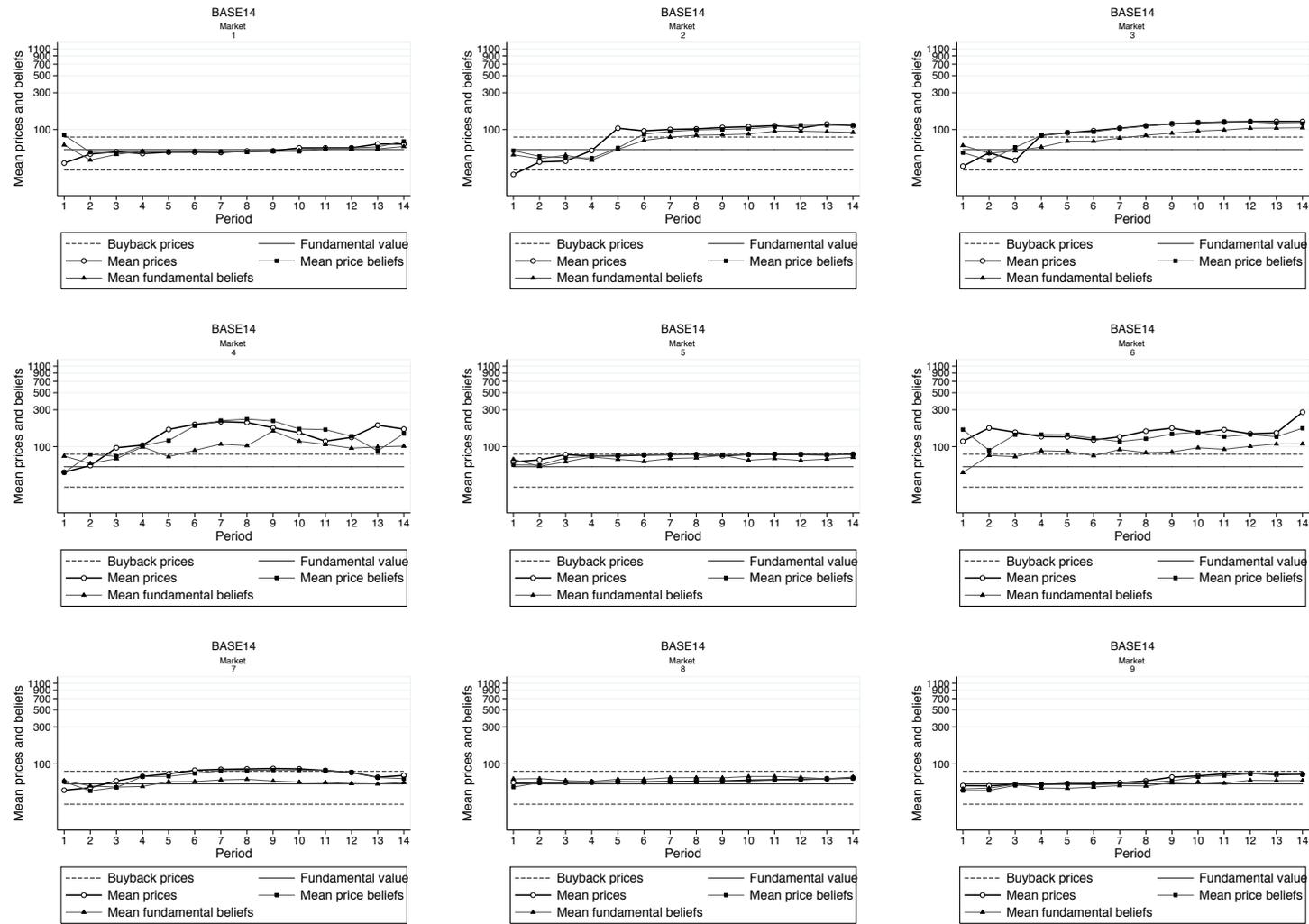


Figure A7: Mean treatment prices (bold line with circles), average beliefs about fundamentals (solid line with triangles), and average beliefs about prices for t , elicited in t (solid line with squares) of Treatment BASE14. The dashed lines show the two possible buyback prices of 30 and 80 and the solid thin line represents the risk-neutral fundamental value of 55.

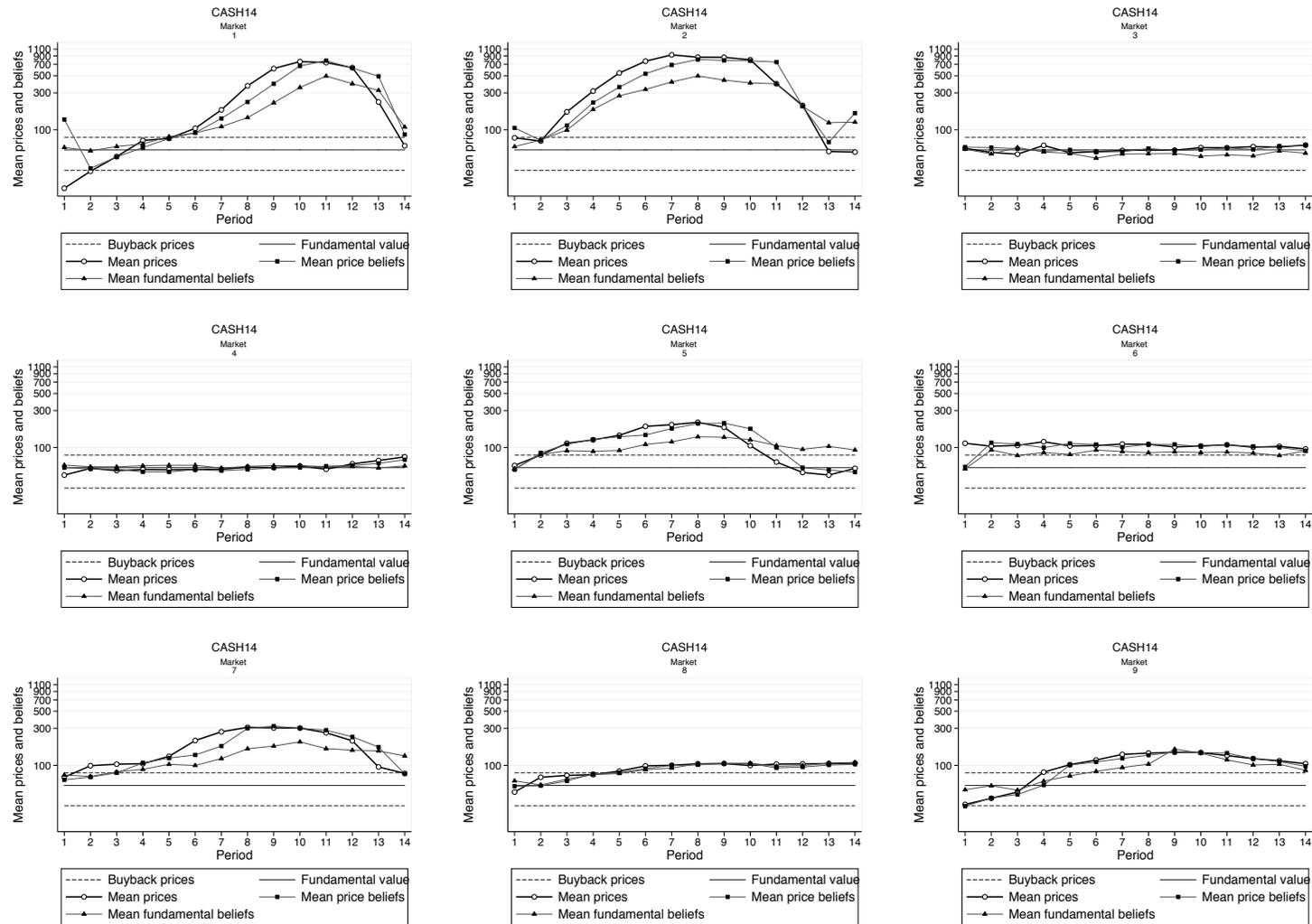


Figure A8: Mean treatment prices (bold line with circles), average beliefs about fundamentals (solid line with triangles), and average beliefs about prices for t , elicited in t (solid line with squares) of Treatment CASH14. The dashed lines show the two possible buyback prices of 30 and 80 and the solid thin line represents the risk-neutral fundamental value of 55.

Table A7: Top two panels: Optimists' beliefs about mean market prices for period t , elicited in t (BP). Treatment averages for mispricing ($\text{RAD}^{\text{OPT}(\text{BP})}$), overpricing ($\text{RD}^{\text{OPT}(\text{BP})}$), peak prices ($\text{RD_MAX}^{\text{OPT}(\text{BP})}$), price run-ups ($\text{AMPLITUDE}^{\text{OPT}(\text{BP})}$) and price crashes ($\text{CRASH}^{\text{OPT}(\text{BP})}$) and significance tests for treatment differences. Bottom two panels: Optimists' beliefs about fundamentals (BFV). Treatment averages for mispricing ($\text{RAD}^{\text{OPT}(\text{BFV})}$), overpricing ($\text{RD}^{\text{OPT}(\text{BFV})}$), peak prices ($\text{RD_MAX}^{\text{OPT}(\text{BFV})}$), price run-ups ($\text{AMPLITUDE}^{\text{OPT}(\text{BFV})}$) and price crashes ($\text{CRASH}^{\text{OPT}(\text{BFV})}$) and significance tests for treatment differences. The numbers of the statistical tests indicate Z-values of pairwise Mann-Whitney U-tests. Sample size N of each test equals 18.

Beliefs Prices – BP	$\text{RAD}^{\text{OPT}(\text{BP})}$	$\text{RD}^{\text{OPT}(\text{BP})}$	$\text{RD_MAX}^{\text{OPT}(\text{BP})}$	$\text{AMPLITUDE}^{\text{OPT}(\text{BP})}$	$\text{CRASH}^{\text{OPT}(\text{BP})}$
BASE8	64.56	55.62	161.82	27.07	-126.26
CASH8	34.36	26.31	53.13	19.19	-25.11
BASE14	78.42	76.72	141.62	80.00	-71.31
CASH14	220.11	217.37	497.98	461.62	-443.23
CASH14, bubble markets	356.21	352.16	825.45	801.82	-757.09
CASH14, non-bubble markets	49.99	48.88	88.64	36.36	-50.91
Pairwise MW U-tests	$\text{RAD}^{\text{OPT}(\text{BP})}$	$\text{RD}^{\text{OPT}(\text{BP})}$	$\text{RD_MAX}^{\text{OPT}(\text{BP})}$	$\text{AMPLITUDE}^{\text{OPT}(\text{BP})}$	$\text{CRASH}^{\text{OPT}(\text{BP})}$
BASE8 vs. CASH8	1.898*	1.634	2.479**	0.436	2.476**
BASE8 vs. BASE14	0.132	0.221	0.177	1.462	0.928
BASE8 vs. CASH14	1.545	1.810*	1.193	2.450**	1.193
CASH8 vs. BASE14	1.369	1.634	2.078**	1.365	0.932
CASH8 vs. CASH14	2.340**	2.517**	2.888***	2.298**	2.960***
BASE14 vs. CASH14	1.369	1.192	1.238	1.384	1.945*
Beliefs Fundamentals – BFV	$\text{RAD}^{\text{OPT}(\text{BFV})}$	$\text{RD}^{\text{OPT}(\text{BFV})}$	$\text{RD_MAX}^{\text{OPT}(\text{BFV})}$	$\text{AMPLITUDE}^{\text{OPT}(\text{BFV})}$	$\text{CRASH}^{\text{OPT}(\text{BFV})}$
BASE8	58.24	57.48	102.02	37.37	-59.60
CASH8	42.07	39.55	59.80	35.96	-18.59
BASE14	68.99	68.33	116.36	71.52	-44.04
CASH14	204.17	203.91	469.29	424.65	-365.66
CASH14, bubble markets	321.40	321.14	772.73	726.91	-621.82
CASH14, non-bubble markets	57.63	57.37	90.00	46.82	-45.45
Pairwise MW U-tests	$\text{RAD}^{\text{OPT}(\text{BFV})}$	$\text{RD}^{\text{OPT}(\text{BFV})}$	$\text{RD_MAX}^{\text{OPT}(\text{BFV})}$	$\text{AMPLITUDE}^{\text{OPT}(\text{BFV})}$	$\text{CRASH}^{\text{OPT}(\text{BFV})}$
BASE8 vs. CASH8	0.972	1.104	1.284	0.491	1.629
BASE8 vs. BASE14	0.397	0.397	0.754	0.810	0.845
BASE8 vs. CASH14	1.722*	1.634	1.946*	2.219**	1.729*
CASH8 vs. BASE14	1.458	1.545	1.994**	0.625	0.361
CASH8 vs. CASH14	2.253**	2.252**	2.612***	2.302**	2.840***
BASE14 vs. CASH14	1.545	1.545	1.680*	1.598	1.949*

Following the approach of Kirchler et al. (2015) we calculate optimists' beliefs as the 85-percentile in each measure (i.e., this is the belief of the subject with the second-highest belief). *, ** and *** represent the 10%, 5%, and 1% significance levels of a double-sided test.

A4 Instructions of the Experiment

A4.1 Experimental Instructions of the Market Experiments²²

Dear Participant! We welcome you to this experimental session and kindly ask you to refrain from talking to each other for the duration of the experiment. If you have any questions concerning the experimental procedure or the instructions, please raise your hand and the supervisor will answer your questions privately.

Background of the experiment This experiment is concerned with replicating an asset market where 8 traders can trade an asset of a fictitious company over 14 periods, whereas each period lasts for 3 minutes (180 sec.).

Information on the market architecture and your tasks as a trader

Trading

Participating in the market as an active trader you can sell and buy assets. Trade is accomplished in form of a double auction, i.e., each trader can appear as buyer and seller at the same time. You can submit any quote the asset with prices ranging from 0 to a maximum of 999 Taler (with at most two decimal places). For every quote you make, you have to enter the number of assets you intend to trade as well. Market price is only determined by supply and demand of the active traders in the market.

If you buy assets, your Taler holdings will be decreased by the respective expenditures (price * quantity) and the number of assets will be increased by the quantity of newly bought assets. Inversely, if you sell assets, your Taler holdings will be increased by the respective revenues (price * quantity) and the number of assets will be decreased by the quantity of newly sold assets. Each trader gets a certain amount of Taler as part of their initial endowment, which will be announced to them before market entry, and 20 units of the asset. Note that your asset and Taler holdings carry over from one period to the next and that your Taler and asset holdings cannot drop below zero.

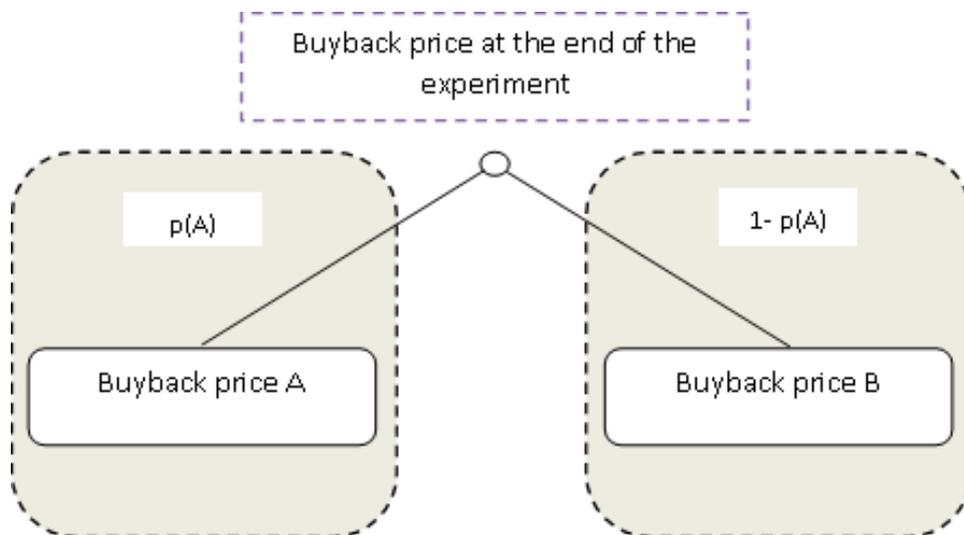
At the end of period 2, period 4 and period 6 you will receive earnings from other sources of income, which will be added to your current Taler holdings (see table below for details).

²²Instructions are for BASE14, text changes in CASH14 are *italic*. Instructions and graphs for BASE8 and CASH8 are analogous and can be obtained upon request.

<i>End of Period</i>	1	2	3	4	5	6	7-14
<i>Additional earnings</i>	0	4400	0	4400	0	4400	0

Information about the asset's buyback price

At the end of the experiment the units of asset you own are bought back by the experimenter at one of two possible buyback prices (A or B with probabilities $p(A)$ and $1-p(A)$) per unit of the asset. The actual buyback price is determined randomly. Every trader gets information on one of the two possible buyback prices: Before entering the market 4 of 8 traders receive information on the probability of occurrence and the value of buyback price A, whereas the other half of the traders receives information on the probability of occurrence and the value of buyback price B.



Predictions

Additionally to your trading activity you will be asked to predict the development of mean market prices over all remaining periods and to give an estimation of the second, unknown buyback price, in each period.

Your earnings from predicting the market price and estimating the second buyback price depend on the accuracy of your prediction and your estimation and are calculated separately as follows:

Accuracy of your prediction/estimate	Earnings
within +/-10% of the correct value	2.25 EUR
within +/-20% of the correct value	1.50 EUR
within +/-40% of the correct value	0.50 EUR

At the end of the experiment one of your market price predictions and one of your buyback price estimates will be chosen randomly. Only these two guesses will be relevant for your payoff from this task.

Example: Your estimate of the buyback price in period 2 and your prediction of the mean market price in period 3 for period 5 were chosen randomly. If for instance your prediction for the market price deviates by 18% from the actual mean market price in this period and your estimate of the second buyback price is 9% higher than the actual second buyback price, you will earn 3.75 EUR in total, consisting of 1.5 EUR from predicting the market price and 2.25 EUR from guessing the second buyback price.

Calculation of your payment

Your payout as a trader (in EUR) is calculated as follows:

The number of units of the asset you hold is multiplied with the randomly drawn buyback price and then added to your Taler holdings.

$$\text{Wealth in Taler} = \text{asset holdings} * \text{buyback price} + \text{Taler}$$

Your earnings from trade will then be converted to EUR using a certain conversion rate (Taler per EUR) you will be informed about before market entry.

Additionally you receive earnings from predicting prices and guessing the second buyback price.

$$\text{Wealth in EUR} = \text{wealth in Taler}/\text{conversion rate} + \text{earnings from predicting prices and guessing the second buyback price}$$

On the following two pages you receive information on the trading screen and the history screen.

Current period

Time remaining

Period: 1 out of 1 Remaining time (sec): 165

Overview of current asset and Taler holdings as well as wealth in Taler (total wealth = Taler holdings + asset holdings * current market price)

<p>Your holdings</p> <p>Shares 20</p> <p>Taler 3300</p> <p>Total wealth in Taler</p>	<p>No trade yet</p>
---	---------------------

Current market price of the asset

Time in sec. 0 20 40 60 80 100 120 140 160 180

Price chart of the current period

<p>OFFER TO BUY: You have to enter the offered price and quantity. Trade does not take place until another participant accepts the offer.</p>	<p>OFFER TO SELL: Analogously to OFFER TO BUY (see above).</p>
<p>Orderbook - list of all offers to buy of all traders - your own offers to buy are written in blue. The offer with the blue background is the best, i.e., it is the one with the highest price for the seller.</p>	<p>Orderbook - list of all offers to sell of all traders - your own offers to sell are written in blue. The offer with the blue background is the best, i.e., it is the one with the lowest price for the buyer.</p>

<p>SELL: You sell the entered quantity, given the price with the blue background. If you enter a higher quantity than offered in the blue box, you sell the offered quantity at most.</p>	<p>BUY: You buy the entered quantity, given the price with the blue background. If you enter a higher quantity than offered in the blue box, you buy the offered quantity at most.</p>
<p>DEL Offer to buy / DEL Offer to sell: By marking own offers and pressing the DEL buttons you can delete own offers from the orderbook. Note that independently from the quantity entered the whole offer will be deleted.</p>	

Period
1 out of 1
Remaining time (sec): 2

Period	Share holdings	Taker	Closing price	Total wealth valued at the closing price
1	20	3300		

Stock and asset holdings at the end of each period

Closing prices and total wealth at the end of each period (calculation: see explanation in the trading screen)

Average market prices

A4.2 Experimental Instructions for the Risk Elicitation Task²³

Please choose between alternative A and alternative B in the following 12 lotteries. At the end, one of the lotteries will be drawn randomly and paid out to you.

- A: 0.5 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 1 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 1.5 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 2 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 2.5 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 3 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 3.5 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 4 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

²³Identical for all treatments.

- A: 4.5 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 5 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 5.5 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

- A: 6 EUR with probability $p = 100\%$.
- B: 0 EUR with probability $p = 50\%$ or 6 EUR with probability $p = 50\%$.

University of Innsbruck - Working Papers in Economics and Statistics
Recent Papers can be accessed on the following webpage:

<http://eeecon.uibk.ac.at/wopec/>

- 2016-06 **Michael Razen, Jürgen Huber, Michael Kirchler:** Cash inflow and trading horizon in asset markets
- 2016-05 **Ting Wang, Carolin Strobl, Achim Zeileis, Edgar C. Merkle:** Score-based tests of differential item functioning in the two-parameter model
- 2016-04 **Jakob W. Messner, Georg J. Mayr, Achim Zeileis:** Non-homogeneous boosting for predictor selection in ensemble post-processing
- 2016-03 **Dietmar Fehr, Matthias Sutter:** Gossip and the efficiency of interactions
- 2016-02 **Michael Kirchler, Florian Lindner, Utz Weitzel:** Rankings and risk-taking in the finance industry
- 2016-01 **Sibylle Puntischer, Janette Walde, Gottfried Tappeiner:** Do methodical traps lead to wrong development strategies for welfare? A multilevel approach considering heterogeneity across industrialized and developing countries
- 2015-16 **Niall Flynn, Christopher Kah, Rudolf Kerschbamer:** Vickrey Auction vs BDM: Difference in bidding behaviour and the impact of other-regarding motives
- 2015-15 **Christopher Kah, Markus Walzl:** Stochastic stability in a learning dynamic with best response to noisy play
- 2015-14 **Matthias Siller, Christoph Hauser, Janette Walde, Gottfried Tappeiner:** Measuring regional innovation in one dimension: More lost than gained?
- 2015-13 **Christoph Hauser, Gottfried Tappeiner, Janette Walde:** The roots of regional trust
- 2015-12 **Christoph Hauser:** Effects of employee social capital on wage satisfaction, job satisfaction and organizational commitment
- 2015-11 **Thomas Stöckl:** Dishonest or professional behavior? Can we tell? A comment on: Cohn et al. 2014, Nature 516, 86-89, "Business culture and dishonesty in the banking industry"
- 2015-10 **Marjolein Fokkema, Niels Smits, Achim Zeileis, Torsten Hothorn, Henk Kelderman:** Detecting treatment-subgroup interactions in clustered data with generalized linear mixed-effects model trees

- 2015-09 **Martin Halla, Gerald Pruckner, Thomas Schober:** The cost-effectiveness of developmental screenings: Evidence from a nationwide programme
- 2015-08 **Lorenz B. Fischer, Michael Pfaffermayr:** The more the merrier? Migration and convergence among European regions
- 2015-07 **Silvia Angerer, Daniela Glätzle-Rützler, Philipp Lergetporer, Matthias Sutter:** Cooperation and discrimination within and across language borders: Evidence from children in a bilingual city
- 2015-07 **Silvia Angerer, Daniela Glätzle-Rützler, Philipp Lergetporer, Matthias Sutter:** Cooperation and discrimination within and across language borders: Evidence from children in a bilingual city *forthcoming in European Economic Review*
- 2015-06 **Martin Geiger, Wolfgang Luhan, Johann Scharler:** When do Fiscal Consolidations Lead to Consumption Booms? Lessons from a Laboratory Experiment
- 2015-05 **Alice Sanwald, Engelbert Theurl:** Out-of-pocket payments in the Austrian healthcare system - a distributional analysis
- 2015-04 **Rudolf Kerschbamer, Matthias Sutter, Uwe Dulleck:** How social preferences shape incentives in (experimental) markets for credence goods *forthcoming in Economic Journal*
- 2015-03 **Kenneth Harttgen, Stefan Lang, Judith Santer:** Multilevel modelling of child mortality in Africa
- 2015-02 **Helene Roth, Stefan Lang, Helga Wagner:** Random intercept selection in structured additive regression models
- 2015-01 **Alice Sanwald, Engelbert Theurl:** Out-of-pocket expenditures for pharmaceuticals: Lessons from the Austrian household budget survey

University of Innsbruck

Working Papers in Economics and Statistics

2016-06

Michael Razen, Jürgen Huber, Michael Kirchler

Cash inflow and trading horizon in asset markets

Abstract

It is conjectured that one of the major ingredients of historic financial bubbles was the inflow of money in various forms. We run 36 laboratory asset markets and investigate the joint effect of cash inflow and trading horizon on price efficiency. We show that only markets with cash inflow and long trading horizon exhibit bubbles and crashes. We also observe that markets with extended trading horizon but without cash inflow and markets with shorter trading horizon do not trigger bubbles. Finally, we report that beliefs about prices and, importantly, about (constant) fundamentals follow bubble patterns as well.

ISSN 1993-4378 (Print)

ISSN 1993-6885 (Online)