Monetary Shocks in Bounded Efficient Financial Markets
with Bounded Rational Agents

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Discussion Paper 09-12
June 2012

ISSN 1611-3837

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Abstract

During the recent US financial crisis it became evident again how fast shocks can spread in the financial system. Using the analytical framework of heterogeneous agent models, we analyze how monetary shocks are processed and dispersed across a network of financial markets. We focus on micro shocks, triggered by changes in the market liquidity, and macro shocks, caused by monetary policy decisions. Our model accounts for bounded efficient financial markets producing market anomalies and bounded rational agents, who derive their decisions based upon heuristics. Firstly, our model is able to replicate key stylized facts of asset returns in financial markets. Secondly, the intensity of shocks affects financial market stability by changing the investment strategies in asset markets. Thirdly, we identify two mechanisms of contagion effects between asset markets. The substitution mechanism is triggered by changes in market-specific variables and the sentiment mechanism is initiated by herding behavior. Fourthly, our analysis shows that market efficiency in a specific asset market does not only depend upon the condition of the particular asset market but also on the conditions of the other asset markets.

Key words: heterogeneous agent model, adaptive belief system, behavioral economics, market anomalies, contagion effects

JEL classification: C63, G02, G11

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Acknowledgements: The authors would like to thank Christian Bauer, Jane Sander and the participants of the Joint Research Seminar of the Universities of Bayreuth and Magdeburg and the 7th Research Seminar at the University of Bayreuth for useful comments.
1 Motivation

In the financial system, flows of funds are channeled through a network of financial markets and are allocated among different market participants. The crucial role of interconnected markets for the processing and dispersion of financial shocks has recently become evident again during the US financial crisis in 2007/2008. Following initial problems in the subprime segment of the mortgage markets, shock waves spread from ABS markets across the entire financial system, leading to severe turmoil and systemic problems. In efficient financial markets with rational market participants, asset prices would have adjusted instantly to the justified levels, always fully reflecting all available and relevant information (see Fama, 1970, 1991). But the financial system we know and operate with is characterized by bounded efficient financial markets with bounded rational market participants. Bounded efficient markets can produce market anomalies, such as excess volatility (see Shiller, 1981), overshooting (see De Bondt and Thaler, 1985), mean reversion (see Fama and French, 1988) and irrational bubbles (see Shiller, 2000). And bounded rational market participants can make systematic errors while attempting to reduce complexity by using simple behavioral heuristics (see Kahneman and Tversky, 1973, 1974). Both limitations can produce market inefficiencies through deviations of asset prices from the underlying fundamental value.

The existence of monetary shock waves in bounded efficient financial markets with bounded rational agents raises several research questions: how are monetary shocks processed and dispersed in financial markets? What are the underlying mechanisms of contagion effects between asset markets? And what do these mechanisms imply for the market efficiency in financial markets? We address these questions using the analytical framework of a heterogeneous agent model (HAM). In recent years, HAMs have become increasingly popular among economists, not at least due to their power to replicate important stylized facts in financial markets reasonably well (see, e.g., Lux, 1995, 1998; Lux and Marchesi, 1999, 2000; Hommes, 2002; Gaunersdorfer and Hommes, 2005).
While our HAM is related to the model class of Brock and Hommes (1998), De Grauwe and Grimaldi (2006), De Grauwe and Kaltwasser (2006, 2007) and Boswijk et al. (2007) it goes beyond this model class in a number of important aspects. Firstly, we model a number of risky assets to study the contagion effects between various asset markets. Previous models do not put focus on the interaction of risky asset markets. But for answering our posed questions, the network of asset markets is key to understanding the dispersion of shocks in the financial system. Secondly, we implement a sentimentalist strategy that factors in optimistic and pessimistic sentiment in the financial market to account for herding behavior. Herding describes the bias in the behavior of agents to anchor expectations at the behavior of other agents. Thirdly, we introduce monetary shocks to the system of financial markets in order to analyze their influence on the asset pricing in interdependent asset markets over time. Previous models do not account for monetary shocks, neither for micro nor macro shocks. We particularly distinguish between these two forms of monetary shocks and analyze their impacts. Micro monetary shocks capture events that affect only one particular asset market in the first round, e.g. changes in the market liquidity of an ABS market. In contrast, macro monetary shocks capture events that affect all asset markets in the first round, e.g. changes in the interest rate by the central bank.

The paper is organized as follows. Section 2 introduces our heterogeneous agent model mapping bounded efficient financial markets with bounded rational agents. Section 3 analyzes the underlying asset price dynamics of our model. Section 4 discusses the effects of monetary shocks in multi-asset markets. And Section 5 draws some conclusive remarks.

2 Model structure

The model economy consists of various asset markets \( a \in [1, A] \) and is populated by socially interacting, heterogeneous agents with mass 1. The timeline of the model is illustrated in Figure 1.
At the beginning of every period $t \in [1, T]$ each agent faces three investment strategies $i \in \{f; c; s\}$, i.e. the strategy of fundamentalists $f$, chartists $c$ and sentimentalists $s$. Each investment strategy builds upon a different heuristic to form expectations of asset prices (see Section 2.1). The strategy selection of each agent depends upon the expected utility of an investment strategy (see Section 2.2). After choosing an investment strategy, each agent is assigned to the corresponding type of agents, i.e. fundamentalists, chartists or sentimentalists. Each agent-type allocates its wealth among asset markets based upon a mean-variance asset portfolio optimization (see Section 2.3). The resulting demand for and supply of assets is cleared by a market maker who adjusts asset prices (see Section 2.4). The realized return on investments and forecasting errors determine the performance measure of each investment strategy for the next period. All agents act within a closed framework which is exogenously shocked by changes in the market liquidity and interest rate decisions by monetary policy (see Section 2.5).

2.1 Formation of expectations

Following Kahneman and Tversky (1973) simple heuristics are generally the best way to characterize human behavior under uncertainty. A number of empirical studies found this to be also true for market participants in financial markets. For instance, Frankel and Froot (1987a,b), Taylor and Allen (1992), Menkhoff (1998) and Cheung et al. (2004) show that these market participants use heuristics, such as mean reverting trading rules (here: fundamentalist strategy) and extrapolative trading rules (here: chartist strategy). Moreover, empirical studies by Olsen (1996) and De and Forbes (1999) also highlight the
importance of herding behavior for the formation of expectations (here: sentimentalist strategy).

At the beginning of every period, agents can choose in our model between the investment strategies of fundamentalists, chartists and sentimentals.

The fundamentalist strategy $f$ takes the fundamental value of an asset $a$ into account (see also De Grauwe and Grimaldi, 2006; De Grauwe and Kaltwasser, 2006, 2007). An asset price equal to the fundamental value clears the excess demand of fundamentalists for the particular asset. Fundamentalists expect that the asset price $P_{a,t}$ will converge towards the fundamental value $F_{a,t}$, both written in natural logarithm:

$$\mu^f_{a,t} = \tilde{E}_{t-1} - \ln P_{a,t-1} = \kappa(\ln F_{a,t-1} - \ln P_{a,t-1}),$$  \hspace{1em} (1)

where $\kappa \in [0, 1]$ is the rate of convergence. The fundamentalist strategy implies positive or negative expectations. If the asset price was below (above) the fundamental value in the last period, then the strategy generates positive (negative) expectations of asset price movements for the current period. The expectations of fundamentalists of the potential of mean reversion increases with the distance between the asset price and the fundamental value.

The chartist strategy $c$ generates expectations of asset price movements without taking the fundamental value into account (see also De Grauwe and Grimaldi, 2006; De Grauwe and Kaltwasser, 2006, 2007).\(^1\) The chartists positively extrapolate the last asset price movement into the current period, expressed in natural logarithm:

$$\mu^c_{a,t} = \tilde{E}_{t-1} - \ln P_{a,t-1} = \lambda(\ln P_{a,t-1} - \ln P_{a,t-2}),$$  \hspace{1em} (2)

\(^1\)Menkhoff and Taylor (2007) list possible reasons why the chartist strategy is so frequently used in foreign exchange markets by many professional traders. Among them are as a means of profiting from monetary policy interventions, means of processing fundamental and non-fundamental information on exchange rates.
where \( \lambda \in [0, +\infty] \) denotes the degree of extrapolation. The chartist strategy implies positive or negative expectations. If the asset price movement was positive (negative) in the last period, then the strategy generates positive (negative) expectations on asset price movements for the current period. The expectations of chartists increase with the magnitude of the last asset price movement.

The *sentimentalist strategy* \( s \) takes the cross-market sentiment of all agents into account.\(^2\) The expectation of the sentimentalist strategy on the asset price movement in the current period is the weighted average of expectations of all agents-types \( i \) of the last period:

\[
\mu_{a,t}^s = \Phi_t^f \mu_{a,t-1}^f + \Phi_t^c \mu_{a,t-1}^c + \Phi_t^s \mu_{a,t-1}^s.
\]

(3)

The sentimentalist strategy captures herding behavior in financial markets. If the cross-market sentiment of the agents was positive (negative) in the last period, then the sentimentalist strategy also generates positive (negative) expectations on asset price movements for the current period. The expectations of sentimentalists increase with the average of all agents’ expectations of the last period.

2.2 Strategy selection

Market expectations can be transformed into orders in asset markets by choosing an investment strategy \( i \in \{f; c; s\} \), each representing an agent-type. After every agent has chosen an investment strategy, each agent is assigned to the corresponding agent-type, i.e. fundamentalists, chartists or sentimentalists. Following Brock and Hommes (1997, 1998), Lux (1998) and Lux and Marchesi (2000) the endogenous decision structure is formulated using a discrete-choice model with multinomial logit strategy probabilities \( \Phi_i^t \):

\(^2\)The models of Lux (1995, 1998) also account for herding behavior by using an index that describes the number of optimists and pessimists. In contrast, our sentiment measure additionally takes account of the degree of optimism and pessimism.
The performance measure $\Pi^i_t$ of investment strategy $i$ depends positively upon realized returns on investments $r^i_{a,d}$ and negatively upon squared forecasting errors $\epsilon^2_d$:

$$\Pi^i_t = \sum_{d=1}^{t} (r^i_{a,d} - \frac{\alpha}{2} \epsilon^2_d),$$

where the constant absolute risk aversion (CARA) parameter $\alpha$ describes the degree of risk aversion. In line with De Grauwe and Grimaldi (2006) the realized return on investment $r^i_t$ of each investment strategy is calculated as follows:

$$r^i_t = (\ln P_{a,t} - \ln P_{a,t-1}) \text{sgn}(\tilde{E}^i_t[\ln P_{a,t}] - \ln P_{a,t-1}).$$

Along these lines, the forecasting error is defined as the deviation of the expected asset price from its realization, written in natural logarithm:

$$\epsilon^i_t = (\tilde{E}^i_t[\ln P_{a,t}] - \ln P_{a,t}).$$

---

3The sign function $sgn$ takes the values according to the following case distinction:

$$\begin{cases} 
+1, & \text{for } x > 0, \\
0, & \text{for } x = 0, \\
-1, & \text{for } x < 0. 
\end{cases}$$
2.3 Portfolio optimization

Following Brock and Hommes (1998), Chiarella et al. (2005) and De Grauwe and Grimaldi (2006) each agent-type adjusts its asset portfolio allocation in every single period. The underlying utility function depends positively upon the conditional expected returns $\mu_{i,t}$ and negatively upon the unconditional market risk $\sigma_{a,t}$. $ER^i_t$ is the $A \times 1$ vector of expected returns, $V_t$ is the $A \times A$ variance-covariance matrix and $w^i_t$ is the $A \times 1$ vector of portfolio weights:

$$ER^i_t := \begin{pmatrix} 1 + \mu^i_1,t \\ \vdots \\ 1 + \mu^i_A,t \end{pmatrix}; \quad V := \begin{pmatrix} \sigma^2_{1-1} & \cdots & \sigma^1_{1-A} \\ \vdots & \ddots & \vdots \\ \sigma^1_{A-1} & \cdots & \sigma^2_{A-A} \end{pmatrix}; \quad w^i_t := \begin{pmatrix} w^i_1,t \\ \vdots \\ w^i_A,t \end{pmatrix}.$$

An efficient portfolio is determined by maximizing the utility function $U^i_t$ with respect to the portfolio weights $w^i_t$:

$$\max_{w^i_t} U^i_t[w^i_tER^T_t - \alpha \frac{1}{2} w^i_t V w^i_t] \quad \text{with} \quad \left\| w^i_t \right\|_1 = 1. \quad (8)$$

The risk aversion is needed to find an efficient investment portfolio on the capital market line, but plays no role for the determination of the market portfolio. The general solution of the portfolio optimization for $n$ risky assets is given by the following equation system:

$$\begin{pmatrix} \sigma^2_1 & \sigma_2 \sigma_1 \rho_{1,2} & \cdots & \sigma_n \sigma_1 \rho_{1,n} \\ \sigma_1 \sigma_2 \rho_{1,2} & \sigma^2_2 & \cdots & \sigma_n \sigma_2 \rho_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_1 \sigma_n \rho_{1,n} & \sigma_2 \sigma_n \rho_{2,n} & \cdots & \sigma^2_n \end{pmatrix} \begin{pmatrix} w^i_1,t \\ w^i_2,t \\ \vdots \\ w^i_n,t \end{pmatrix} = \begin{pmatrix} \mu^i_1,t - r_0 \\ \mu^i_2,t - r_0 \\ \vdots \\ \mu^i_n,t - r_0 \end{pmatrix}. \quad (9)$$

In every period the outcome of portfolio optimization fully materializes in the aggregated excess demand of all agent-types:
The aggregated excess demand $D^{EX}_{a,t}$ is determined by the strategy probability of each agent-type $\Phi^i_t$, i.e. how many agents choose the specific investment strategy $i$, and the portfolio weights of the assets for each agent-type $w^i_{a,t}$, i.e. how much money is allocated by each investment strategy $i$ to an asset market $a$.

2.4 Market outcome

The market design is chosen to follow a market maker framework since in reality asset prices are also adjusted with finite speed in contrast to the modeling of a perfect Walrasian market (see Beja and Goldman, 1980). For instance, market makers in corporate equity markets at the NASDAQ also process the order flow sequentially. In general, market makers are obligated to make two-sided quotes and set bid and ask prices in accordance with the supply and demand in the market.\textsuperscript{4} Our market design focuses on the middle price, i.e. the average price between the bid and ask prices. The market maker clears the market by compensating excess demand and supply through offsetting positions.\textsuperscript{5} This mechanism ensures that the market equilibrium condition holds since the aggregated excess demand $D^{EX}_{a,t}$ of all agent-types is equivalent to the net supply $S^{MM}_{a,t}$ of the market maker (MM):

\begin{equation}
D^{EX}_{a,t} \equiv S^{MM}_{a,t}.
\end{equation}

Following Day and Huang (1990) and Brock and Hommes (1997, 1998) asset prices are adjusted according to the aggregated excess demand of all agent-types. We distinguish

\textsuperscript{4} The market maker buys assets at the lower bound (bid price) and sells assets at the upper bound (ask price) of the bid-ask-spread.

\textsuperscript{5} A positive (negative) asset demand reflects the desire to buy (sell) the asset by agents and is compensated through the selling (buying) of the market maker.
the price function of the market maker into two cases to exclude negative asset price outcomes:

\[
P_{a,t} = \begin{cases} 
0, & \text{for } t \leq 0, \\
P_{a,t-1} + \beta D_{a,t}^{EX}, & \text{for } t > 0,
\end{cases}
\]  

with \( \beta > 0 \). The adjustment parameter \( \beta \) determines the price reaction of the market maker in the wake of an excess demand or supply. A high adjustment parameter goes along with a strong price reaction and vice versa.

2.5 Monetary shocks

We distinguish between two types of monetary shocks, namely micro and macro shocks. Micro shocks capture events that affect only one particular asset market in the first round, such as changes in the market liquidity of an ABS market (see section 2.6). In contrast, macro shocks capture events that affect all asset markets in the first round, such as interest rate decisions by monetary policy (see section 2.7).

2.6 Market liquidity

Market liquidity describes the ability of a market to absorb temporary imbalances between the demand and supply side without any excessive price reactions (see Baks and Kramer, 1999). In illiquid markets, assets are not readily tradable due to a lack of sufficient supply for or demand of assets, respectively. For instance, a sudden drying up of market liquidity took place at ABS and interbank markets at the outset of the US financial crisis in 2007/2008. In the following period, financial shock waves spread through the financial system and it became evident how contagion can spread from illiquid asset markets even to fundamentally sound asset markets. The crucial links between these asset markets are agents who operate in several asset markets (see, e.g., Adrian and Shin, 2008b,a; Brunnermeier and Pedersen, 2009).
Market liquidity shocks are mirrored in the liquidity premia which are idiosyncratic components of the discount factor for each asset’s expected stream of income. We introduce market liquidity shocks in our heterogeneous agent model via shocks to the fundamental value. In line with the present value theory, the fundamental value $F_{a,t}$ of a risky asset $a$ in period $t$ is defined as the expected stream of income $E_t[Y_{t+d}]$ with $d \in [1, +\infty]$ discounted by the appropriate interest rate $i_t$ and $p_t$ representing the market-specific market liquidity premium:

$$F_{a,t} = \sum_{d=1}^{\infty} \frac{E_t[Y_{a,t+d}]}{(1 + i_t + p_t)^d}. \tag{13}$$

For instance, a sudden increase (decrease) in the market liquidity decreases (increases) the market liquidity premium that compensates for the risk of illiquidity. The decrease (increase) in the market liquidity premium leads to a fall (rise) in the discount rate. In turn, the fall (rise) in the discount rate results in a higher (lower) fundamental value of the asset.

2.7 Monetary policy

The decision parameter of monetary policy is the interest rate. We assume that the economy’s yield curve is flat, reflecting implicit expectations of all agents of non-varying future interest rates. Monetary policy is able to affect fundamental values via the discount rate as both are inversely related to each other:

$$F_{a,t} = \sum_{d=1}^{\infty} \frac{E_t[Y_{a,t+d}]}{(1 + i_t)^d}. \tag{14}$$

Monetary policy decisions can trigger changes in the economy’s discount rate. These changes in the discount rate modify the fundamental values of all assets. For instance, an interest rate cut by monetary policy lifts the fundamental values of all assets in the economy.
3 Financial Shocks

3.1 Stylized Model Dynamics

To give some intuition for our heterogeneous agent model, we first briefly discuss the stylized asset price dynamics. Let us assume that the model economy is in global equilibrium in the period $t_0$. To disturb the global equilibrium, exogenous forces have to come into play. For instance, an interest rate cut by monetary policy in the period $t_1$ would immediately lift the fundamental values of all assets. The upward shift of the fundamental value creates excess demand from fundamentalists in order to drive asset prices towards the higher fundamental value. The excess demands of chartists and sentimentalists remain unaffected at zero. This is because asset prices have not moved yet and expectations of all agent-types were zero in the last period. In sum, the market opinion turns slightly positive in period $t_1$. The asset price is only pushed upward due to the excess demand from fundamentalists. Let us assume that despite excess demand from fundamentalists, asset prices are still below the new fundamental value in the period $t_2$. In this case, fundamentalists still create excess demand, but now chartists and sentimentalists additionally join in and also create excess demands. Chartists extrapolate the last asset price movement upward, whereas sentimentalists map the last average expectations of all agents. In sum, the asset price is pushed upward in the period $t_2$. The market opinion is strictly positive as it is driven by the positive excess demands of fundamentalists, chartists and sentimentalists. The further market dynamics depend upon whether the asset price is already above, equal to or still below the fundamental value. If the asset price is below the fundamental value, then the market opinion remains strictly positive. If the asset price is above the fundamental value, then the number of optimists decrease while pessimists increase. This is because expectations of fundamentalists turn negative whereas expectations of chartists and sentimentalists remain positive. Whether the asset price overshoots, undershoots or directly converges to the fundamental value.
in the short-term and reaches an equilibrium point or behaves chaotic in the long-term depends among other things upon the initial conditions of the equation system.

3.2 Calibration of the Model

The initial conditions of the equation system are given by the initial values of variables and the constant parameter values. Initial values are set to ensure that the model economy begins in global equilibrium. The global equilibrium makes it easier to illustrate and understand the ongoing adjustment processes.

<table>
<thead>
<tr>
<th>Initial value</th>
<th>Calibration</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_a$</td>
<td>1</td>
<td>market price of risky asset a</td>
</tr>
<tr>
<td>$F_a$</td>
<td>1</td>
<td>fundamental value of risky asset a</td>
</tr>
<tr>
<td>$\phi$</td>
<td>1/3</td>
<td>strategy probabilities</td>
</tr>
</tbody>
</table>

Table 1: Calibration of initial values

Table 1 shows our calibration of the initial values and Table 2 lists the calibration of the parameter values. We choose parameter values that are similar to the parameter settings of related HAM literature (see, e.g., De Grauwe and Grimaldi, 2006; Boswijk et al., 2007).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Calibration</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>2</td>
<td>degree of risk aversion</td>
</tr>
<tr>
<td>$\beta$</td>
<td>1</td>
<td>market adjustment</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>1</td>
<td>rate of convergence</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>1</td>
<td>intensity of extrapolation</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>1</td>
<td>unconditional market risk</td>
</tr>
<tr>
<td>$\chi$</td>
<td>1</td>
<td>intensity of strategy revaluation</td>
</tr>
<tr>
<td>$i$</td>
<td>0</td>
<td>return on cash</td>
</tr>
</tbody>
</table>

Table 2: Calibration of parameter values

Moreover, we analyze the sensitivity of our HAM for different parameter settings by using bifurcation analysis. In general, bifurcation analysis focuses on changes in the qualitative behavior of a particular variable in the wake of different parameter calibrations (Kulenović and Merino, 2002). From the analysis follows that within the reasonable parameter range between 0 and 2 as suggested by similar HAM literature, the quanti-
tative behavior changes but the qualitative behavior remains the same for all of these parameters.

3.3 Basic Model Dynamics

To analyze the basic model dynamics we begin with a model economy consisting of one riskless asset, such as cash, and one risky asset, such as corporate equities, bonds, real estate or commodities. In this case, the market portfolio is equal to the one risky asset so that the efficient frontier runs between the risk-return profiles of the riskless asset and the one risky asset. We know from portfolio optimization that the portfolio weights for the riskless asset \((a = 0)\) and the risky asset \((a = 1)\) are given by:

\[
w_{0,i,t} = 1 - w_{1,i,t} \quad \text{and} \quad w_{1,i,t} = \frac{\mu_{1,i,t} - r_0}{\alpha \sigma_{1,i,t}}.
\]

(15)

In period \(t_0\), our model is in global equilibrium. In period \(t_1\), we introduce a monetary shock implying positive information for the fundamental value. For instance, this could plausibly be a micro shock, in terms of an increase in the market liquidity, or a macro shock, in terms of an interest rate cut by monetary policy. The subsequent evolution of asset prices is characterized by complex nonlinear dynamics. We study these dynamics for different time horizons by using simulation methods.

3.4 Market dynamics

The analysis focuses on the first periods after the monetary shock. We shock the fundamental value with different intensities to simulate the resulting quantitative and qualitative microeconomic dynamics in the asset market.
We begin with an analysis of the influence of different shock intensities on the composition of agent-types. Any shock to the fundamental value modifies the realized returns on investments and forecasting errors. These changes cause adjustments in the performance measures and hence motivate all agents to reevaluate the investment strategies. These revaluations ignite agents to now choose among the investment strategies with different strategy probabilities. As a result, the different strategy probabilities lead to a different composition of agent-types.

Figure 2: Composition of agent-types

Figure 2 illustrates a three-dimensional coordinate system with the axes time, market share and shock intensity. The development of each area illustrates the development of the market shares of agent-types in the asset market over time for different shock intensities. The blue area represents the chartists, the red area the sentimentalists and the green area the fundamentalists. The figure shows that the higher the intensity of shocks, the more fundamentalists exit asset markets while chartists and sentimentalists enter asset markets. Given our standard model calibration, the shock to the fundamental value causes sudden changes in the composition of agent-types which then stabilize in
the following periods. The dynamics in the composition of agent-types in the wake of a
shock to the fundamental value has consequences for the financial market stability. That
is because the exit of fundamentalists increases the vulnerability of financial markets to
instabilities since the asset price is less anchored to the fundamental value. Nevertheless,
it is striking that the exit of fundamentalists from the asset market increases nonlinearly
with the intensity of shocks. This observation implies that a sequence of small shocks
is more preferable for reasons of financial market stability than a big shock of equal
size. But how do the different compositions of agent-types influence the quantitative
and qualitative asset price dynamics?

\[ \Phi_f^0 = 0.8, \quad \Phi_c^0 = 0.1 \text{ and } \Phi_s^0 = 0.1 \]

\[ \Phi_f^0 = 0.1, \quad \Phi_c^0 = 0.8 \text{ and } \Phi_s^0 = 0.8 \]

\[ \Phi_f^0 = 0.1, \quad \Phi_c^0 = 0.1 \text{ and } \Phi_s^0 = 0.1 \]

\[ \Phi_f^0 = 0.1, \quad \Phi_c^0 = 0.8 \text{ and } \Phi_s^0 = 0.8 \]

\[ \Phi_f^0 = 33.3, \quad \Phi_c^0 = 33.3 \text{ and } \Phi_s^0 = 33.3 \]

\[ \Phi_f^0 = 33.3, \quad \Phi_c^0 = 33.3 \text{ and } \Phi_s^0 = 33.3 \]

Figures 3-6 illustrates four three-dimensional coordinate systems with the axes time,
price and shock intensity. The blue area represents the development of asset prices and
the red area represents the development of fundamental values over time for different shock intensities. The red area shows that the fundamental value increases with the intensity of shocks and is identical for each asset market. The model calibrations for the four cases differ only with respect to the initial composition of agent-types. At first glance, all figures demonstrate that the asset price dynamics do essentially depend upon the composition of agent-types in each asset market. In asset markets that are dominated by fundamentalists, the asset prices approach the fundamental value within a few periods (see Figure 3). This is because the expectations of most agents in the market are anchored to the fundamentals so the asset price is driven by fundamentalists towards the fundamental value. In asset markets that are dominated by chartists, the asset prices approach the fundamental value slowly (see Figure 4). The reason is that the share of fundamentalists is small so that the initial asset price movement is triggered by only a few fundamentalists. In asset markets that are dominated by sentimentalists, the asset prices approach the fundamental value at some point in time between (see Figure 5). In fact, there are still few fundamentalists but now there are a lot of sentimentalists in the asset market that mimic the past expectations of fundamentalists and chartists. And finally, a balanced composition of agent-types results in quantitatively and qualitatively different asset price dynamics with over- and undershooting (see Figure 6). This can be explained by the enormous influence of the shock intensities on the initially balanced composition of agent-types. The composition of agent-types changes depending on the shock intensities and so do asset price dynamics.

Now, what do these findings imply for the market efficiency in an asset market? We follow Fama (1963) and define asset markets to be market efficient when asset prices fully reflect all available and relevant information. In our model, all agents have access to the full information set. Agents are only different in the way they make use of this information by choosing an agent-type and thereby an investment strategy. Given the full information set of our agents, asset markets are market efficient when asset prices are
equal to the fundamental values. Our model shows that the degree of market efficiency in an asset market depends among other things upon the composition of agent-types in the particular asset market. Specifically, the degree of market efficiency increases with the share of fundamentalists in an asset market. Moreover, sentimentalists foster the market efficiency more than chartists do. This comes as no surprise since sentimentalists mimic the past expectations of fundamentalists and chartists. Moreover, it is worthwhile noting that chartists are nevertheless useful, apart from reasons of market efficiency, in providing market liquidity.

3.5 Validity of the Model

Although every asset class has specific characteristics, the statistical properties of most asset returns are quite similar over long periods of time. These properties constitute the stylized facts of asset markets. Following Pagan (1996) and Cont (2001), asset returns are often characterized by a (1) non-Gaussian distribution with a (2) negative skewness and a (3) positive kurtosis. Moreover, asset returns often show (4) insignificant autocorrelation, (5) mean reversion and (6) conditional heteroscedasticity.

In general, the ability to duplicate these stylized facts is an indicator for the validity of theoretical models and for the robustness of conclusions. We evaluate the power of our HAM to replicate these stylized facts. In doing so, the fundamental value is continuously shocked over 10,000 periods with a white noise process that follows a Gaussian distribution with the mean $\mu = 0$ and different shock intensities ranging from $\sigma_1 = 0.01$ to $\sigma_{10} = 0.1$. The initial composition of agents in the asset market are chosen to be equally balanced with a market share of one-third for each agent-type.

1) The non-Gaussian distribution of asset returns is well documented in empirical literature (see, e.g., Fama, 1963; Mandelbrot, 1963). We test the distribution of asset returns in our model using the Jarque-Bera (JB) statistic (Bera and Jarque, 1980), which measures the difference of the skewness and kurtosis between the underlying distribution and Gaussian distribution:
\[ JB = \frac{T}{6} \left( S^2 + \frac{(K - 3)^2}{4} \right), \]  

(16)

where \( T \) is the number of periods, \( S \) the measure of skewness and \( K \) the measure of kurtosis. The null hypothesis of the JB statistic states the existence of a Gaussian distribution, whereas the alternative hypothesis claims the existence of a non-Gaussian distribution. The JB statistic is \( \chi^2 \)-distributed with 2 degrees of freedom.

<table>
<thead>
<tr>
<th>( \sigma )</th>
<th>0.01</th>
<th>0.02</th>
<th>0.03</th>
<th>0.04</th>
<th>0.05</th>
<th>0.06</th>
<th>0.07</th>
<th>0.08</th>
<th>0.09</th>
<th>0.10</th>
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<td>73.9</td>
<td>92.1</td>
<td>108.9</td>
<td>1152</td>
<td>1897</td>
<td>3526</td>
<td>4998</td>
<td>13106</td>
<td>13235</td>
</tr>
<tr>
<td>p-value</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 3: Results for the tests on normal distribution

The Jarque-Bera statistics consistently indicate that the Gaussian distributed shocks to our HAM produce non-Gaussian distributed asset returns. The \( p \)-values show that our empirical results are highly statistically significant for all shock intensities. The higher the shock intensities, the more distinctive are the results for the JB statistics.

2) The unconditional distribution of asset returns is often found to have a negative skewness (see, e.g., Fama, 1965; Cont, 2001). We use the third central moment \( S \) to measure the degree of asymmetry around the mean. The third central moment is typically defined through the third power of variability:

\[ S = \frac{1}{T} \sum_{t=1}^{T} \left( \frac{y_t - \bar{y}}{\hat{\sigma}} \right)^3, \]  

(17)

where \( y_t \) denotes the time series, \( \bar{y}_t \) its arithmetic mean and \( \hat{\sigma} \) is the estimated standard deviation. In the case of symmetry the measure depicts the value \( S = 0 \). In the case of a positive skewed distribution \( (S > 0) \) the right tail is longer than the left tail. In the case of a negative skewed distribution \( (S < 0) \) the left tail is longer than the right tail. The null hypothesis states that the distribution of
asset returns is symmetric, whereas the alternative hypothesis claims that the distribution of asset returns is asymmetric.

<table>
<thead>
<tr>
<th>$\sigma$</th>
<th>0.01</th>
<th>0.02</th>
<th>0.03</th>
<th>0.04</th>
<th>0.05</th>
<th>0.06</th>
<th>0.07</th>
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<th>0.09</th>
<th>0.10</th>
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<tr>
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<td>-0.50</td>
<td>-0.44</td>
<td>-0.34</td>
<td>-0.77</td>
<td>-1.21</td>
<td>-0.60</td>
<td>-1.35</td>
<td>-1.66</td>
<td>-1.92</td>
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<td>$p$-value</td>
<td>0.00</td>
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Table 4: Results for the tests on skewness

The null hypothesis is significantly rejected for all shock intensities towards an asymmetric distribution. The empirical results point to a negative skewness of the return distributions indicating that the mode and median lie right to the mean.

3) The unconditional distribution of asset returns is often characterized by an excess kurtosis (see, e.g., Mandelbrot, 1963; Fama, 1965; Cont, 2001). The analysis uses the fourth central moment to evaluate the kurtosis of the return distributions in our HAM. The fourth central moment $K$ measures the distribution density around the peak and in the tails. Typically, the fourth central moment is defined through the fourth power of variability:

$$K = \frac{1}{T} \sum_{t=1}^{T} \left( \frac{y_t - \bar{y}}{\sigma} \right)^4.$$  \hspace{1cm} (18)

In the case of a Gaussian distribution, the measure of kurtosis is $K = 3$. The distribution is called leptokurtic for high peaks and heavy tails ($K > 3$), whereas it is called platykurtic for low peaks and thin tails ($K < 3$).

<table>
<thead>
<tr>
<th>$\sigma$</th>
<th>0.01</th>
<th>0.02</th>
<th>0.03</th>
<th>0.04</th>
<th>0.05</th>
<th>0.06</th>
<th>0.07</th>
<th>0.08</th>
<th>0.09</th>
<th>0.10</th>
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<tr>
<td>Test stat.</td>
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<td>3.88</td>
<td>4.19</td>
<td>4.46</td>
<td>8.02</td>
<td>9.30</td>
<td>12.13</td>
<td>13.62</td>
<td>20.43</td>
<td>20.72</td>
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<tr>
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</table>

Table 5: Results for the tests on kurtosis

Our model produces distributions of asset returns that are leptokurtic and statistically significant throughout. These empirical results imply that in the underlying distribution, asset returns are more frequently found in the tails than in the Gaussian normal distribution.
4) Most time series of asset returns show no statistically significant autocorrelation (see, e.g., Fama, 1970; Pagan, 1996). To test the autocorrelation of returns we use the Durbin-Watson (DW) test statistic (Durbin and Watson, 1950, n.d.):

\[ DW = \frac{\sum_{t=2}^{T} (\hat{\epsilon}_t - \hat{\epsilon}_{t-1})^2}{\sum_{t=1}^{T} \hat{\epsilon}_t^2}, \]  

where \( \hat{\epsilon}_t \) are the residuals of an AR(1) process of asset returns. The null hypothesis claims the absence of first-order autocorrelation, whereas the alternative hypothesis claims the existence of first-order autocorrelation.

<table>
<thead>
<tr>
<th>( \sigma )</th>
<th>0.01</th>
<th>0.02</th>
<th>0.03</th>
<th>0.04</th>
<th>0.05</th>
<th>0.06</th>
<th>0.07</th>
<th>0.08</th>
<th>0.09</th>
<th>0.10</th>
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<tbody>
<tr>
<td>Test stat.</td>
<td>2.10</td>
<td>2.15</td>
<td>2.08</td>
<td>2.10</td>
<td>2.14</td>
<td>2.22</td>
<td>2.19</td>
<td>2.13</td>
<td>2.13</td>
<td>2.14</td>
</tr>
<tr>
<td>p-value</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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Notes: The critical values are taken from (Savin and White, 1977).

Table 6: Results for the tests on autocorrelation

The DW test statistics confirm for different shock intensities the stylized fact of no first-order autocorrelation, implying that the residuals of asset returns are serially independent from each other. Otherwise, serial dependence of asset returns would be immediately used to arbitrage as the realizations of asset returns could be predicted to some extent.

5) As documented by Fama and French (1988) and Poterba and Summers (1988) asset prices are typically characterized by mean reversion in the long-term. We test the property of mean reversion by using unit root tests. We use the Augmented Dickey-Fuller test (Dickey and Fuller, 1979, 1981) with a constant and a maximum lag length of 4 selected by the Schwarz information criterion (Schwarz, 1978):

\[ \Delta y_t = \alpha + (\rho - 1)y_{t-1} + \sum_{i=1}^{k} \theta_i y_{t-i} + v_t. \]  

(20)
The null hypothesis states that the times series has a unit root, whereas the alternative hypothesis claims stationarity. A unit root implies that asset prices drift away from the mean, whereas stationarity implies mean reversion behavior.

\[
\sigma = 0.01 \quad 0.02 \quad 0.03 \quad 0.04 \quad 0.05 \quad 0.06 \quad 0.07 \quad 0.08 \quad 0.09 \quad 0.10
\]

| Test stat.  | -18.0 | -18.2 | -18.3 | -16.4 | -16.0 | -16.0 | -15.3 | -16.5 | -14.8 | -19.0 |
| p-value     | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |

Note: One-sided critical values are taken from MacKinnon (1996).

Table 7: Results for the tests on mean reversion

The unit root test statistics indicate that all time series are stationary, independent of the underlying shock intensity. The stationarity implies the property of mean reversion for asset prices which again fits the stylized facts.

6) Most time series of asset prices show conditional heteroscedasticity, i.e. the clustering of volatility (see, e.g. Pagan, 1996; Cont, 2001). These findings imply that events of high volatility tend to be followed by periods of high volatility and vice versa. We test for conditional heteroscedasticity using Lagrange Multiplier tests for ARCH(1) (Engle, 1982):

\[
\epsilon_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i \epsilon_{t-i}^2 + \psi_t. \tag{21}
\]

The null hypothesis claims that the magnitude of the current square of errors does not depend upon the magnitude of the past square of errors. The alternative hypothesis states that the magnitude of the current square of errors does depend upon its lagged realizations.

| Test stat.  | 2103 | 2228 | 2107 | 2636 | 3451 | 4004 | 3191 | 3766 | 5834 | 3364 |
| p-value     | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table 8: Results for the tests on conditional heteroscedasticity
The ARCH tests give highly statistically significant evidence for the existence of conditional heteroscedasticity. These empirical results imply that our HAM is able to produce volatility clusters which match stylized facts.

Taken together, the empirical evaluation of our HAM indicates its power to replicate several stylized facts. The implementation of white noise shocks drawn from the Gaussian normal distribution to the fundamental value produces non-Gaussian distributed asset returns. These findings provide an argument for the validity of our heterogeneous agent model and for the robustness of our findings.

4 Financial Contagion

The previous analysis focused on the effect of monetary shocks in a single risky asset market without taking account of any interdependencies between multiple risky asset markets. To analyze the contagion effects between risky asset markets in general we extend our model economy by one additional risky asset. The portfolio optimization for one riskless and two risky assets yields the following portfolio weights:

\[ x_{1,i,t} = \frac{\sigma_2 \mu_{1,i,t} - \sigma_1 \mu_{2,i,t} \rho_{1,2} - (\sigma_2 - \sigma_1 \rho_{1,2}) r_0}{\sigma_1^2 \sigma_2 (1 - \rho^2)}, \]  \hspace{1cm} (22)

\[ x_{2,i,t} = \frac{\sigma_1 \mu_{2,i,t} - \sigma_2 \mu_{1,i,t} \rho_{1,2} - (\sigma_1 - \sigma_2 \rho_{1,2}) r_0}{\sigma_1 \sigma_2^2 (1 - \rho^2)}. \]  \hspace{1cm} (23)

The contagion effects between asset markets can be analytically distinguished into two separate effects — the substitution and sentiment mechanism. The substitution mechanism captures those contagions between asset markets that are caused by fundamentalists and chartists due to changes in market-specific variables. In contrast, the sentiment mechanism captures those contagions between asset markets that are caused by sentimentals due to herding behavior towards the cross-market sentiment.
We analyze the impact of the contagion effects in both risky asset markets for micro shocks, such as a sudden increase in the market liquidity, and macro shocks, such as an interest rate cut by monetary policy. In the case of micro shocks, the fundamental value of one asset market is affected, whereas the other one remains unaffected at first. A sudden increase in the market liquidity causes the market-specific market liquidity premium to fall so that the fundamental value increases due to the accompanying fall in the discount rate. In the case of macro shocks, all fundamental values are affected in a similar way. A sudden interest rate cut by monetary policy causes all fundamental values to increase due to the accompanying fall in the discount rates for all assets.

4.1 Micro shock

We induce a permanent and positive micro shock to one risky asset market in order to analyze the mutual contagion effects between both risky assets. For instance, one can think of an increase in the market liquidity for risky asset 1 and an unchanged market liquidity for risky asset 2. In the following, the fundamental value of risky asset 1 increases whereas the fundamental value of risky asset 2 remains unaffected.

Figures 7 and 8 each illustrate a three-dimensional coordinate system with the axes time, price and shock intensity. The blue area represents the development of asset prices and the red area represents the development of fundamental values over time for different micro shock intensities. The substitution mechanism allocates asset demand from risky
asset 2 towards risky asset 1. This shift in the asset demand is caused by the relative increase in the market-specific expected returns of agent-types in favor of risky asset 1 compared to risky asset 2. In contrast, the sentiment mechanism allocates asset demand equally towards both risky asset markets. The reason is that the return expectations of sentimentalists for each asset market are anchored at the increased cross-market expectations of all agents. As a result, the substitution and sentiment mechanisms cause asset demand to increase for risky asset 1, but cause asset demand to be adversely allocated for risky asset 2. The reaction of the risky asset 1 is strictly positive, whereas the reaction of the risky asset 2 depends upon the specific model calibration. But no matter whether the effect of the substitution or sentiment mechanism outweighs in this asset market, it should be noted that the asset price of the initially unaffected risky asset market 2 responds to the micro shock in the risky asset market 1.

What do these findings on contagion effects imply for the market efficiency in both asset markets? In general, monetary micro shocks cause the substitution and sentiment mechanisms to rebalance asset portfolios. The rebalancing of asset portfolios is followed by reactions of the asset prices. These reactions cause temporary or permanent deviations of asset prices from fundamental values, even in fundamentally unrelated asset markets. Following this finding, we have to acknowledge that the market efficiency in an asset market depends, next to the conditions in the particular asset market, also upon the conditions in other asset markets. The reason is that asset markets constitute a network of flow of funds that is interlinked through the market operations of market participants.

4.2 Macro shock

Monetary macro shocks differ from micro shocks in their effects on asset markets. We induce a permanent and positive macro shock in order to analyze the mutual contagion effects between asset markets. For instance, one can think of an interest rate cut by monetary policy. In the following, the fundamental values of both risky assets increase.
Figures 9 and 10 each illustrate a three-dimensional coordinate system with the axes time, price and shock intensity. Again, the blue area represents the development of asset prices and the red area represents the developments of fundamental values over time for different shock intensities. In symmetric asset markets, macro shocks do not cause any market-specific changes in the variables so that the substitution mechanism does not reallocate asset demand between the risky asset markets. In asymmetric asset markets, the substitution mechanism does reallocate asset demand between the risky asset markets. That is because macro shocks are differently processed in asymmetric markets so that the market outcome varies across asset markets. For instance, asymmetric asset markets can differ in the market size, the market maker’s adjustment parameter or the unconditional risk. Nevertheless, the sentiment mechanism contributes to changes in asset prices as long as sentimentalists participate in asset markets. The sentiment mechanism always drives asset prices in the same direction.

And again, what can we learn from these findings on contagion effects for the market efficiency in both asset markets? The influence of contagion effects on the market efficiency of other asset markets in the wake of monetary macro shocks depends upon whether asset markets are symmetric or asymmetric. In the case of symmetric asset markets, the contagion effect does not influence the market efficiency in other asset markets. The reason is that the market-specific orbits of asset prices in the two risky asset case do not deviate from those in the one risky asset case. In the case of asymmetric
asset markets, the contagion effect does influence the market efficiency. That is because the different processing of asset markets causes substitution and sentiment mechanisms to unfold effects that let asset prices deviate from their original orbits.

5 Conclusions

We analyze the impact of monetary shocks on asset price dynamics using a heterogeneous agent model. The innovative aspect of our analysis is the focus on the processing and dispersion of monetary shocks in interconnected asset markets. Our heterogeneous agent model incorporates bounded rational agents and bounded efficient financial markets. Agents are modeled to be bounded rational in order to incorporate insights from behavioral economics on the inherent limitations of market participants. Financial markets are modeled to be bounded efficient in order to account for the empirical evidence of market anomalies. We address the following research questions: how are monetary shocks processed and dispersed in financial markets? What are the underlying mechanisms of contagion effects between markets? What do these mechanisms imply for the market efficiency in financial markets? Our analysis yields the following conclusions.

Firstly, our model is able to replicate several stylized facts of asset returns in financial markets. We test this ability by shocking the fundamental value continuously with a white noise process. The model transforms the shocks from a Gaussian distribution into asset returns that follow a non-Gaussian distribution with a negative skewness and a positive kurtosis. Moreover, asset returns are insignificantly autocorrelated, have the mean reversion property and show conditional heteroscedasticity. These properties of asset returns are totally in line with stylized facts in financial markets and underpin the validity of our model.

Secondly, the intensity of shocks influences financial market stability by changing the composition of agent-types. The higher the intensity of shocks, the more fundamentalists exit asset markets while chartists and sentimentalists enter asset markets. This
shift in the composition of agent-types increases the vulnerability of financial markets to instabilities since the asset price is less anchored to the fundamental value. Nevertheless, it is striking that the exits of fundamentalists from the asset market increases nonlinearly with the intensity of shocks. This finding implies that a sequence of small shocks is more preferable than a big shock of equal size. Hence, monetary policy should conduct interest rate smoothing and steer market expectations using the expectation channel also for reasons of financial market stability.

Thirdly, we identify the substitution and sentiment mechanisms as two components of contagion effects between asset markets. The substitution mechanism captures those contagions between asset markets that are caused by asymmetric shifts in market-specific variables. The sentiment mechanism captures those contagions between asset markets that are caused by herding behavior towards the market sentiment. The analysis demonstrates that the substitution mechanism works asymmetrically and the sentiment mechanism works symmetrically. If the substitution and sentiment mechanisms amplify and compensate each other in an asset market depends upon whether the asset market is subject to the shock or not.

Fourthly, our analysis shows that the market efficiency in an asset market depends not only upon the condition in the particular asset market but also on the conditions in the other asset markets. Asset price dynamics in one asset market can ignite asset price dynamics in other asset markets through market operations of market participants even if the fundamentals are completely unrelated. In our model, market inefficiencies are defined as existing when asset prices deviate from the fundamental values. Following this rationale, a market inefficiency in one asset market can ignite market inefficiencies in other asset markets by causing their asset prices to also deviate from fundamental values. But contagion effects influence the market efficiency in other asset markets only when asset markets are asymmetric and not when they are symmetric.
References


Hommes, C. H., “Modeling the stylized facts in finance through simple nonlinear


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