A Behavioral Macroeconomic Model with Endogenous Boom-Bust Cycles and Leverage Dynamics

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Abstract

We merge a financial market model with leverage-constrained, heterogeneous agents with a reduced-form version of the New-Keynesian standard model. Agents in both submodels are assumed to be boundedly rational. The financial market model produces endogenously arising boom-bust cycles. It is also capable to generate highly non-linear deleveraging processes, fire sales and ultimately a default scenario. Asset price booms are triggered via self-fulfilling prophecies. Asset price busts are induced by agents' choice of an increasingly fragile balance sheet structure during good times. Their vulnerability is inevitably revealed by small, randomly occurring shocks. Our transmission channel of financial market activity to the real sector embraces a recent strand of literature shedding light on the link between the active balance sheet management of financial market participants, the induced procyclical fluctuations of desired risk compensations and their final impact on the real economy. We show that a systematic central bank reaction on financial market developments dampens macroeconomic volatility considerably. Furthermore, restricting leverage in a countercyclical fashion limits the magnitude of financial cycles and hence their impact on the real economy.

Keywords: Behavioral economics, New-Keynesian macroeconomics, monetary policy, agent-based financial market model, leverage, macroprudential regulation, financial stability, asset price bubbles, systemic risk.

JEL classification: E31, E41, E47, E52.

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1 Introduction

The recent crisis has drastically shown the immense impact of financial instability on macroeconomic outcomes. However, models linking financial cycles and the real economy are scarce so far.[1] This triggered our motivation to construct an integrated macro-finance model which allows us to analyze the stylized impact of financial cycles on key variables such as inflation and output and to derive important implications for monetary policy and for macroprudential regulation. For this purpose we merge a financial market model with leverage-constrained, heterogeneous agents with a reduced-form version of the New-Keynesian standard model. Agents in both submodels are assumed to be boundedly rational. The financial market model produces endogenously arising boom-bust cycles. In addition, it generates highly non-linear deleveraging processes, fire sales and ultimately a default scenario as soon as the leverage constraint becomes binding.

The interaction channels between our two submodels are as follows: Asset price booms boost aggregate demand since they induce a decrease of the risk-adjusted real interest rate while a widened output gap in turn affects the perceived fundamental value of the representative asset on the financial market. Thus financial market developments are found to be the key source of economic fluctuations in our model. Asset price booms are triggered endogenously via self-fulfilling prophecies and translate into positive output gaps and upward deviations of inflation from its target rate. In turn, asset price busts are induced by agents' choice of an increasingly fragile balance sheet structure during good times. Their vulnerability is inevitably revealed by small, randomly occurring shocks which cause the need for simultaneous deleveraging or even lead to defaults. Subsequently we obtain a pronounced increase of both the macro risk premium and the risk-adjusted real interest rate and a sharp contraction of economic activity. Our setup enables us to discuss a wide range of policy measures. We show that a systematic central bank reaction on financial market developments dampens macroeconomic volatility considerably. Furthermore, restricting leverage in a countercyclical fashion limits the magnitude of financial cycles and hence their impact on the real economy.

[1] For example, the work of Cúrdia and Woodford (2009) and Gertler and Kiyotaki (2010) features sophisticated micro-founded DSGE models augmented with financial sectors. They are able to replicate the stylized pattern of a systemic crisis and its real economy-impact. However these models are silent on the endogenous build-up of financial imbalances over time. Instead, a state of financial instability is induced by exogenous shocks, for instance to capital quality or to default rates.

2 Literature

2.1 Central banks and financial procyclicality

The financial crisis not surprisingly led to a reintensification of the debate whether monetary policy should pursue a financial stability objective. The so-called 'pre-crisis consensus' stated that monetary policy should react to financial market developments only to the extent that they directly affect inflation and output (Issing, 2011). To preemptively tackle unsustainable developments via interest rate policy was regarded as theoretically questionable and practically infeasible.[2] However, the recent crisis once more demonstrated that widespread financial instability poses a serious threat to output and price stability. The ECB (2010) hence started to show some sympathy for a preemptive policy approach, even at the expense of a potential increase of short-term inflation variability. In addition, both policymakers and academics use to call for a second policy instrument. Of major importance is the concept of macroprudential regulation (Borio, 2003; BoE, 2009; ECB, 2009). It can be described as a set of supervision measures which aim to mitigate the procyclicality of the financial system as a whole, especially by employing tighter and time-varying capital requirements and higher liquidity standards. Even though there are two instruments for two policy goals, it is no longer possible to make a clear-cut distinction between monetary policy exclusively fostering price-stability and macroprudential supervision which exclusively tries to dampen financial procyclicality. Both policy fields are interdependent (Bean, 2010). Most importantly, the stance of monetary policy affects financial market developments but the stance of macroprudential regulation might also affect the real economy.

Our model accounts for both policy instruments. We allow the central bank to react to financial market developments in order to prevent adverse spillovers to the real economy. And we also include the sense of macroprudential regulation by introducing the additional instrument of countercyclical leverage caps.

2.2 Theoretical treatment of financial procyclicality

With the obvious benefit of hindsight, pre-crisis thinking and modeling of financial procyclicality in a macro context turned out to be insufficient. In our view, one can identify two major shortcomings. Firstly, the debate focused on asset price bubbles emerging in partial sectors - usually stock markets - and the difficult task of tracing out fundamental asset prices. Today, academics and policymakers

[2] Pros and contras of this view has been extensively discussed by Bernanke and Gertler (2000), Cecchetti (2000), Filardo (2001), Roubini (2006), Posen (2006), Bernanke (2010) and others.

rather focus on the broader concept of financial procyclicality.[3] Financial procyclicality means, that the financial system with its frictions endogenously amplifies or even determines business cycle dynamics in a welfare-decreasing way (Borio and Lowe, 2001). It is noteworthy that this definition includes the possibility of non-linear crisis events, but their incidence is not necessary.

Secondly, financial frictions - if they showed up in a macro model at all - were thought to lie on the borrower's side in the form of a financial accelerator mechanism (Bernanke and Gertler, 1989, 1995). During the last years the focus shifted towards the lender's side in the process of financial intermediation, that is towards banks and other intermediaries. The theory of the *risk-taking channel* postulates a systematic relationship between the stance of monetary policy, the level of economic activity and the risk attitudes of financial investors (Borio and Zhu, 2008). It is argued that expansionary monetary policy triggers endogenous responses of financial market agents, boosting their risk appetite. For example, if agents operate under sticky return targets, a policy-induced decrease of the general level of interest rates might force them into riskier engagements (Rajan, 2005). But the probably most important subchannel is determined by the *dynamics of leverage* and by an *active balance sheet management* of financial intermediaries. (See i.a. Adrian and Shin (2009a) and Adrian and Shin (2010)). Under mark-to-market accounting, rising asset prices lead to an improved equity base and hence to a lower leverage ratio. In order to entirely use their now increased balance sheet capacity, financial investors issue debt securities and use the cash inflows to purchase additional assets. This finally creates a perverse demand schedule, since demand goes up despite of increasing asset prices and decreasing returns. This mechanism implies a greater risk appetite, as financial investors are willing to hold the same assets with lower returns which implies a decrease of the desired risk compensation.

Adrian et al. (2010) indeed show, that the so-called 'macro risk premium' - which serves as a proxy for the price of a unit of non-diversifiable market risk - is inversely related to the risk appetite of financial investors. Risk appetite in turn is positively connected to variables capturing balance sheet growth, especially that of market-based intermediaries. Since the expansion of balance sheets is mainly driven by short-term collateralized borrowing, monetary policy crucially affects the conditions of these operations by setting the level of the short-term interest rate. Hence, the stance of monetary policy and financial stability are closely intertwined. The described mechanism obviously also works in an adverse way. Falling asset prices lower the capital base. In order to restore the desired leverage ratio, intermediaries have to

[3] Weber (2008:3) notes that "[t]he debate about monetary policy and financial markets is too often slanted to the question on how to deal with asset price bubbles. [...] In my opinion, the view of monetary policy and asset prices is too narrow. A more fruitful debate on appropriate monetary policy reactions to developments on financial markets would be possible if the focus were redirected from financial bubbles to the issue of procyclicality."

sell assets which drives their prices down. This puts further pressure on their capital base, creating a feedback loop of deleveraging and fire sales.[4] Financial cycles could also be aggravated by adverse incentives. Farhi and Tirole (2009) show that it is rational for all financial intermediaries to choose a risky business model with a high degree of leverage and an aggressive maturity transformation, if their exposure to liquidity risk is highly correlated. This is due to the fact that the materialization of highly correlated exposures for the whole banking system creates a systemic event, thereby forcing the central bank to step in with liquidity injections, which in turn eliminates a lion's share of the downside risk.

2.3 Are financial investors behaving non-rational?

It is important to stress that the new line of research summarized above does not consider financial market agents to be non-rational. Nor is it necessary to make stark assumptions such as cyclical developments of risk preferences. Adrian et al. (2010) argue that an outsider looking at the patterns of financial market activity might be tempted to reach such conclusions. However, they emphasize that the driving force of financial procyclicality is not a shift in fundamental preferences but rather an outcome of several frictions, e.g. sticky leverage targets and procyclical risk management methodologies. They come into place as soon as, for whatever reason, interest rates and/or asset prices change. They indeed affect the risk appetite as an important force in determining risk premia, but this has to be distinguished from the more fundamental concept of risk aversion. We rather think of these frictions as a behavior which can be regarded as bounded rationality in the sense of Tversky and Kahneman (1974). For instance, risk management techniques such as Value-at-Risk (VaR) and internal rating approaches can be regarded as biased heuristics in a complex world, which have obvious methodological drawbacks but which deliver an acceptable performance under usual circumstances. Hence, we believe that models with heterogeneous agents acting under bounded rationality are a reasonable alternative to model financial cycles and their stylized facts.[5]

3 The Model Set-up

In this section, we describe our modeling strategy. Our model consists of two submodels. One describes an extended behavioral macroeconomic model. The other one provides the law of motion and dynamics of the financial market. We take the existence of heterogeneous agents and bounded rationality seriously in

[4] Fire sales according to Shleifer and Vishny (2011) can be understood as a process where simultaneously finance-constrained investors face the urgent need to sell off assets, (or the inability to buy them respectively) which finally leads to a depression of asset prices below their fundamental values. Usually, this is supplemented by sharply rising collateral rates. See Brunnermeier (2009) for an insightful description of these mechanisms during the current financial crisis.

[5] See Hommes (2006) for an insightful survey.

the spirit of an adaptive belief system (ABS, Brock and Hommes, 1997, 1998). For our purpose, the ABS implies that (i) the population of agents differ in the real and financial markets (ii) agents do not possess a full information set nor full knowledge of the economy, nor adequate information processing capacities in order to form rational expectations (iii) in each market, agents interact through an evolutionary strategy switching process. Each agent uses an heuristic that guides her behavior and her forecasting rule. Moreover, following Lengnick and Wohltmann (2010), we assume that the frequency of trading on the financial market is higher than the frequency of transactions taken place in the goods market. Agents of the real sector, therefore, are not able to engage in high frequency trading; nor are financial market participants in the position to be actively engaged in goods markets transactions. Financial agents can be best seen through the lense of institutional investors allocating wealth of ultimate savers.

However, what all agents have in common is that they use simple heuristic rules to make forecasts of the relevant state variables. The population of agents endogenously chooses among those rules that forecast best in the past. Since agents use different heuristics, the expectation formation is heterogeneous.

3.1 The Macroeconomic Model

The macroeconomic model resembles the three-equation representation of the New-Consensus model economy where output dynamics are described by an aggregate demand equation, inflation dynamics by an aggregate supply equation and monetary policy is conducted according to an interest rate reaction function (Allsopp and Vines, 2000; Woodford, 2003; Goodfriend, 2007).

We part with the paradigm of starting from the 'top-down' perspective, where agents fully understand the complexity of the system; instead, we apply the 'bottom-up' approach where agents are incapable to understand the system as a whole (De Grauwe, 2010; DeGrauwe, 2011).

The output gap is specified in the reduced-form way

$$x_q = a_1 \tilde{E}_q[x_{q+1}] + (1 - a_1)x_{q-1} - a_2(i_q - \tilde{E}_q[\pi_{q+1}] + \zeta_q) + u_q \tag{1}$$

where x_q is the output gap which depends on its own forward-looking expectation, denoted by $\tilde{E}_q[x_{q+1}]$, on its own lag, x_{q-1}, on the ex-ante risky real interest rate, $i_q - \tilde{E}_q[\pi_{q+1}] + \zeta_q$ and on a disturbance term u_q.[6] In this respect, the short-term nominal policy rate is denoted by i_q.

Compared to the reduced-form representation of the prototype New-Keynesian aggregate demand equation, two modeling issues are fundamentally distinct. Firstly, despite being in their nature forward-

[6] For example, small New-Keynesian models with both leads and lags are Clarida et al. (1999); Cho and Moreno (2006). Typically, the ex-ante real interest rate enters the demand function through the consumption Euler relation and the lag term is derived from some form of habit formation in the consumption process of the representative household (Fuhrer, 2000; Woodford, 2003).

looking, expectations in this model specification are non-rational (denoted by the tilde above the expectations operator). Expectations on the future output gap and expected inflation, $\tilde{E}_q[\pi_{q+1}]$, are build as the average forecast of a set of heterogeneous agents applying different heuristic forecasting rules (more on that later).

Secondly, we allow for a modified financial propagation effect following the risk-taking channel of monetary policy transmission (Borio and Zhu, 2008). Instead of using the financial accelerator model of Bernanke et al. (1999) which has recently been applied to the New-Keynesian model economy by Castelnuovo and Nistico (2011), in our model, financial market activity affects real outcomes by the risk taking capacity of financial agents. As already sketched out, Adrian and Shin (2009b) and Adrian et al. (2010) highlight the close relationship between rapid growth of financial actors' balance sheets, lower risk premia, and higher real activity. We implement this channel in the aggregate demand equation by introducing a risky real interest rate that determines the output gap. It is defined as $r_q^r = i_q - \tilde{E}_q[\pi_{q+1}] + \zeta_q$ with ζ_q describing the spread between the riskless and the risky ex-ante real interest rate. The risk premium, in turn, depends on the risk appetite of the financial sector and on macroeconomic conditions; the latter imbed lagged variables of output and policy rate dynamics. Risk appetite is determined in the financial market; a complete characterization of the risk premium is, thus, given in Section (3.2).

Inflation dynamics are specified by a conventional hybrid New-Keynesian Philips curve with inflation π_q being influenced by its own lead and lag, by the current output gap as well as a disturbance term v_q.[7] Again, expectations are non-rational; they denote the average forecast of the projections of the population of heterogeneous agents.

$$\pi_q = b_1 \tilde{E}_q[\pi_{q+1}] + (1 - b_1)\pi_{q-1} + b_2 x_q + v_q \tag{2}$$

Finally, the model is closed by a standard interest-rate reaction function for the short-term nominal policy rate with monetary policy reacting to the current inflation gap $(\pi_q - \pi_q^*)$ and to the output gap. Here, the central bank's inflation target is denoted by π_q^*. Moreover, monetary policy has the degree of freedom to respond to an additional set of variables (denoted by the vector χ_q). These variables may reflect financial market or other policy-relevant dynamics. As will be discussed later on, there might arise a rationale for monetary policy to directly address the emergence of financial cycles.

$$i_q = c_1 i_{q-1} + (1 - c_1)[c_2(\pi_q - \pi_q^*) + c_3 x_q + c_4^\top \chi_q] + w_q \tag{3}$$

[7] For a review of price-setting equations, the reader is referred to Mankiw and Reis (2010).

Market forecasts of the macro state variables are derived from simple heuristic rules. Agents permanently update their forecasting rules in order to make optimal forecasts by means of minimizing forecast errors.[8] In this respect, following Brock and Hommes (1997); Branch and Evans (2011), this 'learning' mechanism is generated by switching between a pre-defined set of forecasting rules which perform best in the recent and past market environment. Despite the use of biased forecasts, agents act rational as they rank their forecasting models in accordance with their mean squared error (MSE).[9] We assume that agents forecast the set of macroeconomic variables $y_{q+1} = (x_{q+1}, \pi_{q+1})$ by pre-specified forecasting rules $g_q^{i,j}$ with $j = \{x, \pi\}$ and i denoting the number of forecasting rules. Notice that these rules are exogenously fixed in the model, thereby reflecting bounded rationality. In its general form, the market forecast for a state variable, i.e. the market state of belief, can be derived as the first moment of the aggregate distribution of individual beliefs. It holds that $\tilde{E}_q y_{q+1} = N^{-1} \sum_{i=1}^{N} g_q^i$ (Kurz, 2011).

Output forecasts. We apply two types of forecasting rules, that shape agents' individual market belief $g_q^{i,x}$ with $i = \{f, ad\}$. The first rule is labeled the fundamentalist rule where agents estimate, eventually by good luck, the steady state value of the output gap which is normalized to zero (see also on this account DeGrauwe, 2011). The second rule is associated with adaptive expectations where agents form expectations about the output gap in period $t + q$ based on the realized output gap of period $q - 1$. It holds that

$$g_q^{f,x} \quad : \quad \tilde{E}_q^f[x_{q+1}] \quad = 0 \tag{4}$$

$$g_q^{ad,x} \quad : \quad \tilde{E}_q^{ad}[x_{q+1}] \quad = x_{q-1}. \tag{5}$$

Inflation forecasts. Forecasts for the inflation outlook are produced in a similar vein with two forecasting rules; the first rule, again, is a fundamentalist rule that captures agents' belief in monetary policy credibility; it relies on the central bank's announced inflation target π_q^* where the inflation target is normalized to zero. The second rule belongs to the adaptive forecast according to which inflation expectations are built upon realized inflation. The rules are written as

$$g_q^{f,\pi} \quad : \quad \tilde{E}_q^f[\pi_{q+1}] \quad = \pi_q^* \tag{6}$$

$$g_q^{ad,\pi} \quad : \quad \tilde{E}_q^{ad}[\pi_{q+1}] \quad = \pi_{q-1}. \tag{7}$$

[8] Unpublished work by Lengnick and Wohltmann (2011) is using the same forecast rules. As we do, they rely on the work of De Grauwe (2010) and DeGrauwe (2011). We consequently obtain similar macro setups. However, the interaction channels between financial market and real economy differs substantially.

[9] For a methodological discussion on the different concepts of rational expectations, rational beliefs, diverse beliefs and the presence of private vs. public information, the reader is referred to Kurz (2011).

Agents choose from this set of different beliefs/rules for future macroeconomic variables. This predictor selection depends on the fitness and performance measures based on the MSE of the forecasting rules. The utility, as measured by the sequence of MSEs, of applying one of the forecasting rules is specified as

$$U_q^{i,j} = -\sum_{k=1}^{\infty} \omega_k \left[y_{j,q-k} - \tilde{E}^i_{q-k-1} \right]^2 \tag{8}$$

where ω_k are geometric declining weights (De Grauwe, 2010). The weights attached to the MSEs over time decline with the effect that the most recent forecast errors exhibit a greater impact on utility than errors made in the distant past. According to discrete choice theory, the proportion (and probability) of agents choosing one of the two forecasting rules for the expected output gap and inflation is determined by a multinormal logit distribution of the form

$$\alpha_q^{i,j} = \frac{\exp(\gamma U_q^{i,j})}{\exp(\gamma U_q^{f,j}) + \exp(\gamma U_q^{ad,j})}. \tag{9}$$

The agent's individual belief represents a random draw with $\Pr[g_q^{i,j} = f, j] = \alpha_q^{f,j}$ and it holds that $\alpha_q^{f,j} + \alpha_q^{ad,j} = 1$ for $j = x, \pi$. Consequently, the market forecast (belief) is the pair of the proportions with

$$\tilde{E}_q[x_{q+1}] = \alpha_q^{f,x} \tilde{E}_q^f[x_{q+1}] + \alpha_q^{ad,x} \tilde{E}_q^{ad}[x_{q+1}] \qquad \text{with } \alpha_q^{f,x} + \alpha_q^{ad,x} = 1 \tag{10}$$

$$\tilde{E}_q[\pi_{q+1}] = \alpha_q^{f,\pi} \tilde{E}_q^f[\pi_{q+1}] + \alpha_q^{ad,\pi} \tilde{E}_q^{ad}[\pi_{q+1}] \qquad \text{with } \alpha_q^{f,\pi} + \alpha_q^{ad,\pi} = 1. \tag{11}$$

As highlighted by Kurz (2011), such a model specification allows for diverse beliefs according to the forecast classes. Within each class, agents are identical; across classes their expectations diverge.

Equation (9) describes the choice for a forecasting rule. Consider the case of $i = ad$ and $j = \pi$. With increased utility (and therefore greater fitness) of inflation forecasts based on adaptive expectations, the share of agents selecting the rule $g_q^{ad,\pi}$ increases. In this respect, the parameter γ is the intensity of choice. It measures how fast agents switch between different forecast strategies. If the intensity of choice approaches infinity, the entire population applies that forecasting rule that performs best over the time horizon. In contrast, if γ is set to zero, the choice for a prediction strategy is entirely stochastic implying that agents distribute themselves evenly across the set of strategies. Then, the probabilities of forecasting inflation and output according to the fundamental and adaptive rule each take on values of exactly 0.5.

3.2 The Financial Market Model

In order to guarantee consistency of modeling the economy, we likewise apply the agent-based approach to the financial market. Work on agent-based financial models shares in common that the presence of heterogeneous and boundedly rational agents triggers complex and adaptive endogenous dynamics arising from non-linearities in the financial market (Brock and Hommes, 1998; Hommes, 2006; LeBaron, 2006). In our model, the financial market is populated by interacting agents trading a representative real asset; its gross price is denoted with S_t. Agents are supposed to align their physical asset orders in accordance to expected asset price changes (Westerhoff, 2008; Lengnick and Wohltmann, 2010). Moreover, we assume that the fraction of agents following an adaptive trading strategy is balance sheet constrained implying that leveraged asset purchases may provoke asset price reversals in the case the constraint becomes binding (Thurner et al., 2010).

We start by describing the heuristic trading rules agents are equipped with in order to predict the future asset price. In general, these rules rely on a mispricing signal upon which agents base their positive or negative asset demand, where negative asset demand corresponds to selling assets in the market.

Noise traders: The first forecasting rule is based on the concept of noise where investors base their asset demand simply on a white noise process. Economic news and past information on asset price dynamics do not play a role at all.[10] The expected asset price change is calculated as

$$g_t^N: \quad E_t^N[S_{t+1} - S_t] = k^N[\epsilon_t^N] \tag{12}$$

where k^N denotes the strength of the influence of the noise term on the expected price change. Since the expected price development is positively related to the order demand, the demand function of agents pursuing a noise strategy can be written as

$$D_t^N = lE_t^N[S_{t+1} - S_t] = a\epsilon_t^N \quad \text{with } a = lk^N. \tag{13}$$

The parameter l is a positive reaction parameter mirroring the aggressiveness of the trading strategy.

Fundamental traders: Within this class, agents expect that the asset price may diverge from its fundamental value F_t but the misalignment is going to be corrected with the market price converging to its long-run, fundamental value. The mispricing signal governs the expected price change according to

$$g_t^F: \quad E_t^F[S_{t+1} - S_t] = k^F[F_t - S_t]. \tag{14}$$

[10] Alternatively, the existence of noise traders in the market can be justified by limits of arbitrage (Shleifer and Vishny, 1997). For a more general perspective on various aspects derived from behavioral finance, in particular on the effects of market psychology for market dynamics, the reader is referred to Barberis and Thaler (2003).

Notice that F_t denotes the perceived fundamental value on part of the fundamentalist. It does not need to be equal to the true fundamental value $\bar{F}$ (for the difference see Section (3.3), and in particular Lengnick and Wohltmann (2010)). The order demand then follows

$$D_t^F = lE_t^F[S_{t+1} - S_t] = b(F_t - S_t) + \epsilon_t^F \quad \text{with } b = lk^F \tag{15}$$

where a noise term is added to the demand equation. A fundamental trading rule implies that order demand is positive whenever the fundamental value of the asset exceeds the current market value. Conversely, asset demand becomes negative if fundamentalists perceive the asset price to be over valued.

Momentum traders: Agents rely on technical analysis trying to extrapolate observed price patterns. There are various specifications to apply technical analysis; we rely on a trend-following strategy of the form

$$g_t^M: \quad E_t^M[S_{t+1} - S_t] = k^M[S_t - S_{t-1}] \tag{16}$$

where the memory factor is characterized by only one lag. Again, order demand can be expressed as

$$D_t^M = lE_t^M[S_{t+1} - S_t] = c(S_t - S_{t-1}) + \epsilon_t^M \quad \text{with } c = lk^M \tag{17}$$

with the most recent past price trend being extrapolated. A random term, ϵ_t^M, is added to the asset demand to account for a variety of possible momentum strategies that are not captured by the simple form used here (Westerhoff, 2008).

Agents choose between the specified strategies g_t^z with $z = \{N, F, M\}$ according to the corresponding fitness. In this respect, the attractiveness of a strategy is determined by a performance measure that calculates the realized profits of trading rule z

$$A_t^z = (S_t - S_{t-1})D_{t-2}^z + gA_{t-1}^z. \tag{18}$$

The higher the weighted average of realized profits, the higher the attractiveness of the trading rule. This can be modeled by two components. The first component of Equation (18) reflects the profit of orders which are submitted in period $t - 2$. The profit is evaluated with a lag of one period. The second component captures the memory factor g which measures how fast the attractiveness is discounted for strategy selection.

Like in the macroeconomic model, discrete choice theory gives an answer how beliefs are updated over time and how the proportions of agents using one of the pre-defined trading rules evolve. It holds that

$$W_t^z = \frac{\exp(eA_t^z)}{\exp(eA_t^N) + \exp(eA_t^F) + \exp(eA_t^M)}. \tag{19}$$

Again, the fractions W_t^z add up to 1 and e is the intensity of choice parameter.

The price adjustment process is modeled as a price-impact function where the quantity of physical excess demands (D_t^z) are related to the price change. The price function is given by

$$S_{t+1} = S_t + d\{\sum_{z=1}^{3} W_t^z D_t^z\} \tag{20}$$

with prices adjusted according to observed excess demand (Kyle, 1985). The parameter d measures the adjustment speed how fast excess demands are translated by the market maker setting the price.[11]

Balance sheet constraint of the momentum trader: We model the chartist to be balance-sheet constrained. This restriction allows us to draw implications of asset price dynamics when the balance-sheet constraint is hit. As will be shown in Section (4), the modeling specification generates pronounced non-linear price movements. In order to keep model dynamics tractable, we let the constraint bind only for the proportion of agents following the momentum strategy.[12] This is important because if we let the fundamentalists be likewise constrained in leveraged asset purchases, they may have not enough balance-sheet capacity to generate asset orders that push the asset price back towards its fundamental value.

In what follows, we apply the market environment of Thurner et al. (2010) who model leveraged asset purchases for a multi-agent hedge fund market with value investors. The fraction of momentum traders is equipped with an initial cash position C_0 that is equal to their capital position. Most generally, asset purchases are financed by cash or by loans leading to a negative cash position; the total amount of loans outstanding is calculated as $L_t = \max[-C_t, 0]$. The asset side is written as the identity

$$W_t = S_t N_t + C_t \tag{21}$$

[11] Notice that our price impact function is based on the gross asset price S_t. Market maker models with the gross price are specified in Kyle (1985); Day and Huang (1990); Chiarella (1992). In these models, "the market maker mediates transactions on the market out of equilibrium by providing liquidity" (Hommes, 2006:1135). The market maker services excess demand by supplying stock out of his inventory (et vice verse when there is excess supply). In contrast, the literature we rely on to build the financial market model usually takes a log-linear approximation of the market maker's price formation rule. Then, the price impact function refers to the log price (Farmer and Joshi, 2002; Westerhoff, 2008; Lengnick and Wohltmann, 2010).

[12] To be clear, in reality, agents are not able to instantaneously switch between a fundamentalist strategy and a leveraged strategy in the presence of funding constraints. However, in our model, we can still rely on this switching mechanism by making the assumption that changing weights in the population likewise reflects reallocations of funds by ultimate savers to those agents that turn out to be most successful in terms of profits in the recent past.

where N_t represent the total amount of the asset hold on the balance sheet. Therefore, the laws of motion for asset holdings and the cash position are

$$N_t = N_{t-1} + D_t^M \tag{22}$$

$$C_t = C_{t-1} - (N_t - N_{t-1})S_t. \tag{23}$$

Our leverage ratio is given by

$$\lambda_t = \frac{S_t N_t}{S_t N_t + C_t}. \tag{24}$$

Notice that the ratio changes due to (i) a pure valuation effect, i.e. an increase in the asset price and (ii) a balance sheet expansion/contraction through asset purchases/sales and a corresponding change in the cash or loan amount.[13]

Momentum traders are required to maintain a maximum permitted threshold $\lambda_t^{\max}$. One can think of this threshold as either (i) fixed by funding suppliers (which we do not explicitly model here) or (ii) fixed by a regulatory agency. Moreover, maximum leverage can be pure exogenous to the market environment or it can be adjusted endogenously to market conditions. The insights of macroprudential regulation indicate that it is advantageous for policymakers to apply time-varying instruments conditioned on market dynamics (Borio, 2010). Therefore, the endogeneity is achieved by allowing the maximum leverage to increase in times of low market volatility. In contrast, maximum permitted leverage decreases when asset volatility picks up speed. It holds that

$$\lambda_t^{\max} = \max\left[1, \frac{\lambda^{\max}}{1 + \varrho\sigma_t^{2,S}}\right] \tag{25}$$

where $\sigma_t^{2,S}$ measures the variance of the asset price over an observation period of τ time steps. The parameter ϱ is the strength of response by the regulator when volatility changes.

In order to reveal the implications of balance sheet effects of momentum traders, we set up a coordination game between the 'balance sheet risk manager' and the 'trading strategist'. The risk manager's task is to permanently evaluate the balance sheet position on a mark-to-market basis in order to ensure that the maximum permitted leverage is not exceeded. The trading strategist has the aim of buying or selling the asset on the basis of the mispricing signal she receives. The coordination can best described by a sequence of actions to be taken within one period.

[13] A small drawback of this measure is its somewhat unintuitive behavior if the cash position is positive. A rising asset price and the associated positive valuation effect lead to an increase of the leverage ratio which is at odds with basic balance sheet arithmetics. With a negative cash position, the ratio behaves correctly.

At the beginning of period t, the risk manager arrives with the following asset position from the 'evening' of the previous period $t-1$:

$$W_{t-1} = N_{t-1}S_{t-1} + C_{t-1}. \tag{26}$$

When starting her trading portal, the risk manager observes the new traded price S_t.

At the same time, the trading desk opens with traders likewise observing the new price S_t upon which the trading strategy is based upon. In particular, following the momentum strategy, the trader articulates the additional physical asset demand N_t^{add} for the current day t based on the observed price S_t. She communicates the desired volume of additional physical asset demand to the accountant.

The risk manager calculates the new desired balance sheet position which involves (i) considering the desired asset demand of the trader and (ii) valuing total desired asset holdings (holdings of the previous period N_{t-1} plus the desired asset demand N_t^{add}) marked-to-market at the observed asset price S_t.

$$\begin{aligned} W_t &= N_{t-1}S_t + N_t^{add}S_t + C_t \\ W_t &= N_tS_t + C_t \end{aligned} \tag{27}$$

with

$$N_tS_t = (N_{t-1} + N_t^{add})S_t \tag{28}$$

$$C_t = C_{t-1} - N_t^{add}S_t. \tag{29}$$

In a next step, the risk manager needs to calculate the leverage ratio based on the desired balance sheet:

$$\lambda_t = \frac{N_tS_t}{N_tS_t + C_t}. \tag{30}$$

Now, the she compares the desired leverage λ_t with the maximum permitted leverage $\lambda_t^{\max}$.

If λ_t does *not* exceed $\lambda_t^{\max}$, then there is leeway to leverage up and asset demand is realized according to the trading rule D_t^M. The balance sheet is set up according to Equation (27) at the end of period t (evening).

If λ_t exceeds $\lambda_t^{\max}$, the accountant must calculate the required amount of asset demand to restore $\lambda_t^{\max}$. She then submits a binding command to generate exactly the asset demand by the trader.[14]

[14] A situation may arise where a very strong positive mispricing signal leads to a large desired additional demand of the trading strategist. It is now however possible that the risk manager refuses to confirm the order in its entire amount, since a very large amount of credit-financed additional demand might produce a violation of the leverage constraint.

The required amount of additional physical asset demand q_t in case of the binding constraint can be calculated by the balance sheet identity.

$$
\begin{aligned}
\lambda_t^{\max} &= \frac{N_t S_t}{N_t S_t + C_t} \\
\lambda_t^{\max} &= \frac{N_{t-1} S_t + q_t S_t}{N_{t-1} S_t + q_t S_t + C_{t-1} - q_t S_t} \\
\lambda_t^{\max}(N_{t-1} S_t + q_t S_t + C_{t-1} - q_t S_t) &= N_{t-1} S_t + q_t S_t \\
q_t &= N_{t-1}(\lambda_t^{\max} - 1) + \lambda_t^{\max} \frac{C_{t-1}}{S_t}. \qquad (31)
\end{aligned}
$$

Therefore, if the asset price falls, Equation (31) predicts that q_t becomes negative for a negative cash position, i.e. a positive amount of outstanding loans, and becomes even more negative with a higher $\lambda_t^{\max}$.

Finally, we allow for the possibility of default on part of the class of momentum traders. Whenever the valuation effect leads to a negative net worth position with $W_t < 0$, we model a stylized default. Momentum traders are removed from the market with the effect that their proportion W_t^M shrinks to zero and they are reintroduced in the next period with the initial cash position C_0.

3.3 Market Interconnections, the Risk Premium and Solving the Model

Like in Lengnick and Wohltmann (2010), both submodels operate on different time scales. The financial market model is supposed to be set up on a daily basis t; whereas the macroeconomic model exhibits a quarterly frequency q; quarter q is assumed to contain 64 trading days. Each variable derived from the financial market model is transferred to the quarterly model by simple taking the mean of the daily realizations for one quarter. For instance, for the quarterly asset price, it holds that

$$
S_q = \frac{1}{64} \sum_{t=64(q-1)+1}^{64q} S_t. \qquad (32)
$$

The question is now how both models are interconnected to each other. The macroeconomic model affects the financial market in terms of the perceived fundamental price F_t. Although the true, steady state fundamental value $\bar{F}_t$ is a constant, trader's perception about the fundamental value depends on the most recent real activity, i.e. the output gap. It holds that

$$
F_t = h \exp(x_q) \qquad \text{for } t = 64(q-1) + 1 : 64q. \qquad (33)
$$

In our model, the perceived fundamental price diverges from the true fundamental value for a number of reasons. According to the no-arbitrage pricing theory, an asset's price reflects expectations about the future underlying payments generated by the asset, discounted to the present. The discount factors, in turn, are determined by the future path of interest rates with the relevant maturities augmented by a risk premia compensation whose size depends on the riskiness of the respective asset Cochrane (2001). Due to the presence of bounded rationality, we assume that agents are not equipped with the objective probability distributions of future cash flow streams and the path of discount rates. Therefore, agents try to approximate the fundamental value by the recent real activity.

The dynamics within the financial market flip back to the real economy by the presence of the macro risk premium ζ_q that enters the aggregate demand equation. Motivated by the insights of the risk-taking channel and the interplay of asset price, balance sheet as well as leverage dynamics, our macro risk premium reflects the degree of expansion in the financial market. As Adrian et al. (2010) make clear, risk appetite highlights both (i) the constraint in the financial sector and (ii) preferences of agents who actively trade in the market. In their model, active management of balance sheets by means of meeting a target Value-at-Risk (VaR) triggers portfolio choices that lead to fluctuations in the market price of risk in the economy.

From an asset pricing perspective, the risk premium on a specific asset is composed of two components, i.e. the quantity of risk and the market price of risk. The quantity of risk describes the covariation between the stochastic discount factor and the expected return on the asset; whereas the market price of risk measures the required risk compensation per unit of risk; it is the same for all assets and equals the reciprocal of agents' risk appetite. Overall risk appetite depends on agents' reluctance towards uncertain outcomes and the level of aggregate, non-diversifiable, macroeconomic uncertainty. The latter typically relies on the macroeconomic environment and moves periodically in response to macroeconomic factors (Gai and Vause, 2006). For our modeling purposes, we model the risk premium, i.e. the credit spread, as a linear combination of both financial market and macroeconomic variables

$$\zeta_q = m_1 \Delta s_q + m_2 x_q + m_3 i_q + m_4 \sigma_q^{2,x} + m_5 \sigma_q^{2,\pi} + m_6 \sigma_q^{2,i}. \tag{34}$$

The balance sheet expansion of the financial sector and hence its risk appetite is measured by the change in the (log-) asset price between two quarters. This change reflects both the heterogeneous trading strategies of the population of agents and the possibility that the leverage constraint of the momentum traders binds. The endogeneity of trading weights and the existence of an adaptive trading strategy generates a positive feedback loop of rising asset prices and amplifying fluctuations in the real economy. If there is a strong expansion of financial market activity, this should be reflected in higher asset price growth. However, if the leverage constraint is hit due to valuation effects and momentum traders are forced to de-lever, asset demand plumps and the credit spread increases. Risk appetite, thus, determines the macro risk premium of the economy. Like in Adrian et al. (2010), changes to risk appetite are not triggered by varying risk preferences, but the apparent change emanates from the strength of trading and the leverage constraint.[15] To account for other aspects of the risk-taking channel, we allow for lagged values of the output gap and the interest rate to enter the risk premium equations. In particular, Gambacorta (2009) has shown that a lower level of the policy rate induces increased risk-taking which manifests itself in a compression of required risk compensation. Finally, overall macroeconomic uncertainty as measured by the volatility of the output gap, the inflation rate and the policy rate affects the macro risk premium.

To provide the laws of motion for the macroeconomic variables, the model is solved by first writing the model equations in a structural matrix form. With the coefficient matrices appropriately chosen, the model takes the form of

$$\Xi X_q = \bar{\Omega}\tilde{E}_q X_{q+1} + \bar{\Psi} X_{q-1} + \bar{\Lambda}\varepsilon_q \tag{35}$$

where the variable vector X_q consists of $X_q = [x_q, \pi_q, i_q, \zeta_q]^\top$. Macro shocks, the (log-) asset price and the volatility measures are stacked into the vector $\varepsilon_q = [u, v, w, \Delta s_q, \sigma_q^{2,x}, \sigma_q^{2,\pi}]^\top$. These variables are purely exogenous to the endogenous state variables of the quarterly model. The reduced-form solution is then given as

$$X_q = \Omega\tilde{E}_q X_{q+1} + \Psi X_{q-1} + \Lambda\varepsilon_q \tag{36}$$

with $\Omega = \Xi^{-1}\bar{\Omega}, \Psi = \Xi^{-1}\bar{\Psi}, \Lambda = \Xi^{-1}\bar{\Lambda}$

4 Simulation Dynamics

4.1 The Benchmark Simulation

The implications of the model dynamics can be revealed when calibrating the model to fit basic moments and cross-correlations of state variables. As emphasized by Hommes and Wagener (2009), an important problem arises within the behavioral approach due the presence of the many degrees of freedom. Heterogeneity in expectations formation inevitable increases the number of parameters which need to be

[15] To make the point clear, in our model, risk preferences (risk aversion) of agents remain constant as measured by the aggressiveness parameters of the trading rules. However, when the population of momentum traders dominates the market, strong momentum of the asset price generates the positive feedback loop that spills over to the real economy. In so far, the time-varying weights of traders reflect changes in the measured aggregate risk appetite.

Table 1: Parameter Calibration

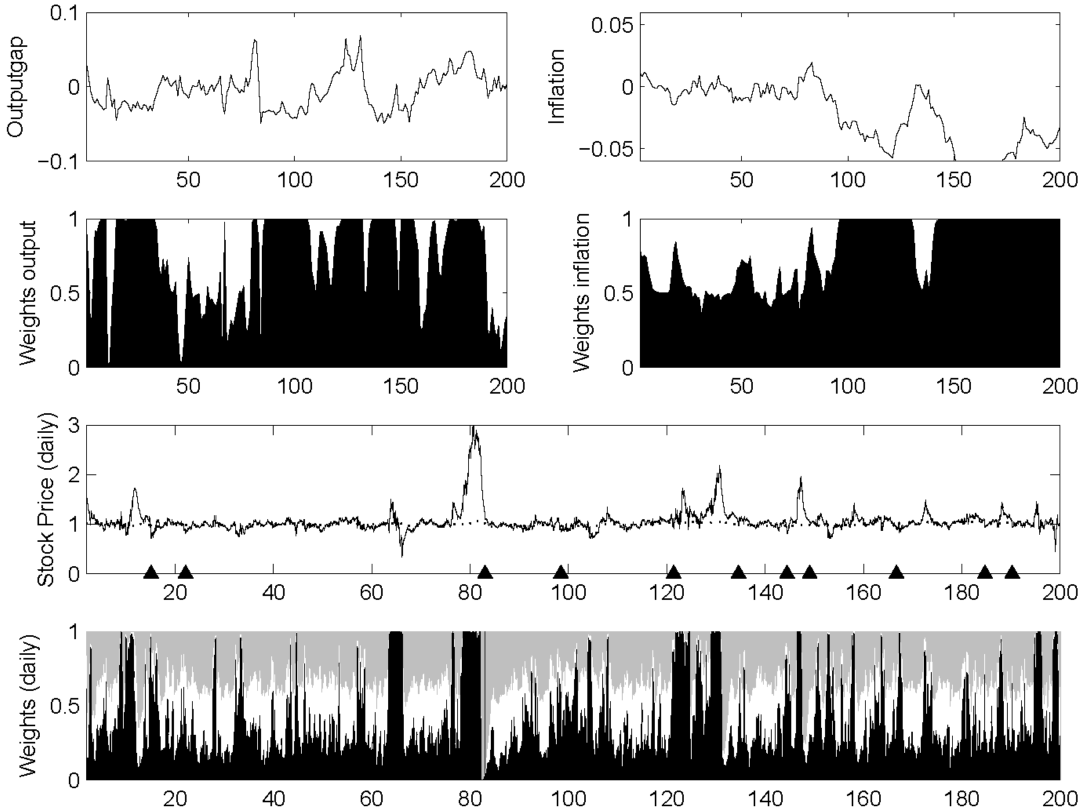
Calibration Values					
macro model		financial market model			
a_1	0.5	k^N	0.04	m_3	0.01
a_2	0.2	k^F	0.04	m_4	0.2
b_1	0.5	k^M	0.08	m_5	0.2
b_2	0.05	l	1.0	σ^N	0.01
c_1	0.5	g	0.975	σ^F	0.01
c_2	1.5	e	300	σ^M	0.05
c_3	0.5	d	1.0		
$c_4^\top$	$0_{N\times 1}$	ϱ	0		
ρ	0.5	λ^{max}	10		
γ	10000	m_1	-0.5		
$\sigma^{x,\pi,i}$	0.005	m_2	-0.01		

quantified. However, in our opinion, the insights of this modeling strategy by allowing diverging expectations to be a major source of business and financial cycle fluctuations outweighs the obvious drawback of restricting the parameter set a-priori and somewhat ad-hoc. Since our macroeconomics model mainly relies on the work of De Grauwe (2010); DeGrauwe (2011), except the macro risk premium, and the financial market follows partly the line of Westerhoff (2008), we stick to their parameter calibration whenever possible.

Table (1) reports the calibration for the benchmark simulation; the parameter values of the macroeconomic model are those typically found in reduced-form New-Keynesian model estimates as in (Clarida et al., 1999; Cho and Moreno, 2006). The financial market model is calibrated to fit basic properties of empirical financial times series data; they include period of booms and busts. Moreover, the benchmark simulation is conducted with the specification that the it entails an exogenous leverage constraint with $\varrho = 0$. The maximum permitted leverage $\lambda_t^{\max}$ is set at a constant value with the consequence that most recent financial market conditions do not enter the leverage constraint. Moreover, it is assumed that monetary policy follows a conventional Taylor-type interest-rate reaction function with positive reactions coefficients for the inflation gap and output gap.

Figure (1) shows one 'prototype' simulation with one sequence of random draws for the stochastic shocks. The time period covers 200 quarters or 12800 days, respectively. It covers the time series dynamics for the output gap, inflation and the asset price as well as the degree of heterogeneity of agents prevailing in the goods and financial market. The sub-figures of the macro variables are quarterly; whereas asset price movements are depicted as the daily realizations of trading activity scaled to the quarterly abscissa.

Figure 1: Baseline Simulation



First of all, what appears eye-catching is the strong cyclical behavior of the output gap and inflation for the simulation period. In particular, between quarter 85 and 110, output persistently is below its steady value. The same holds for the inflation rate which deviates from the target for a prolonged period of time. The sub-figures below the output gap and the inflation figures display the corresponding proportion of agents following either the fundamentalist or the adaptive forecasting strategy for building output and inflation expectations. In this respect, the black areas denote the proportion of agents who use the concept of adaptive expectations formation. It becomes clear that in those states of the economy that are dominated by type $g_q^{ad,x}$-agents, the output gap becomes either positive or negative. In turn, the latter depends on the market environment whether there are optimistic or pessimistic views on the future path of the output gap. What is striking is the existence of a reinforcement learning process of boundedly rational agents throughout the course of the business cycle. Agents switch to the forecasting strategy that performed best in the recent past (Hommes and Wagener, 2009; De Grauwe, 2010). Expectations now become self-fulfilling in the sense that a small sequence of random shocks or one single large shock to the endogenous state variables in one direction makes it attractive to switch to the adaptive rule. The more agents rely on this rule, the more likely the output gap or inflation moves in exactly the same direction, thereby strengthening cyclical fluctuations. The business cycle then becomes increasingly expectations driven and it is the outcome of endogenous waves of different kinds of expectations formations. For agents permanently searching for the optimal forecasting rule, a reduction of the macro risk premium by means of a financial market expansion can just represent a market scenario that induces them to switch to the $g_q^{ad,x}, g_q^{ad,\pi}$-rules. Consequently, even if the macro risk premium has already adjusted towards its fundamental value, macroeconomic expectations continue to push output and inflation away from their steady state values. This holds particularly for the inflation rate where the size of the output gap movements and the exogenous supply shock are not sufficient to initiate a negative feedback effect that allows for an endogenously changing share of inflation expectations in favor of the perceived inflation target π_q^*.

Turning to the financial market, the presence of heterogeneous traders likewise matters for booms and busts in the representative asset price. Whenever momentum traders, denoted by the black-shaded area, dominate the market, the asset price decouples from its fundamental value.[16] For instance, around quarter 80, the asset price dynamic can be clearly interpreted as a boom period before it crashes back to its fundamental value. The evolutionary switching between the two trading strategies produces these 'speculative' bubbles. What is worth mentioning is the fact that their existence is the result of individual rational choice rather than the outcome of pure irrational behavior. Agents in the financial market choose

[16] For the sake of completeness, the sub-figure at the bottom of Figure (1) depicts the weights of momentum traders (black), fundamentalists (gray) and noise traders (white).

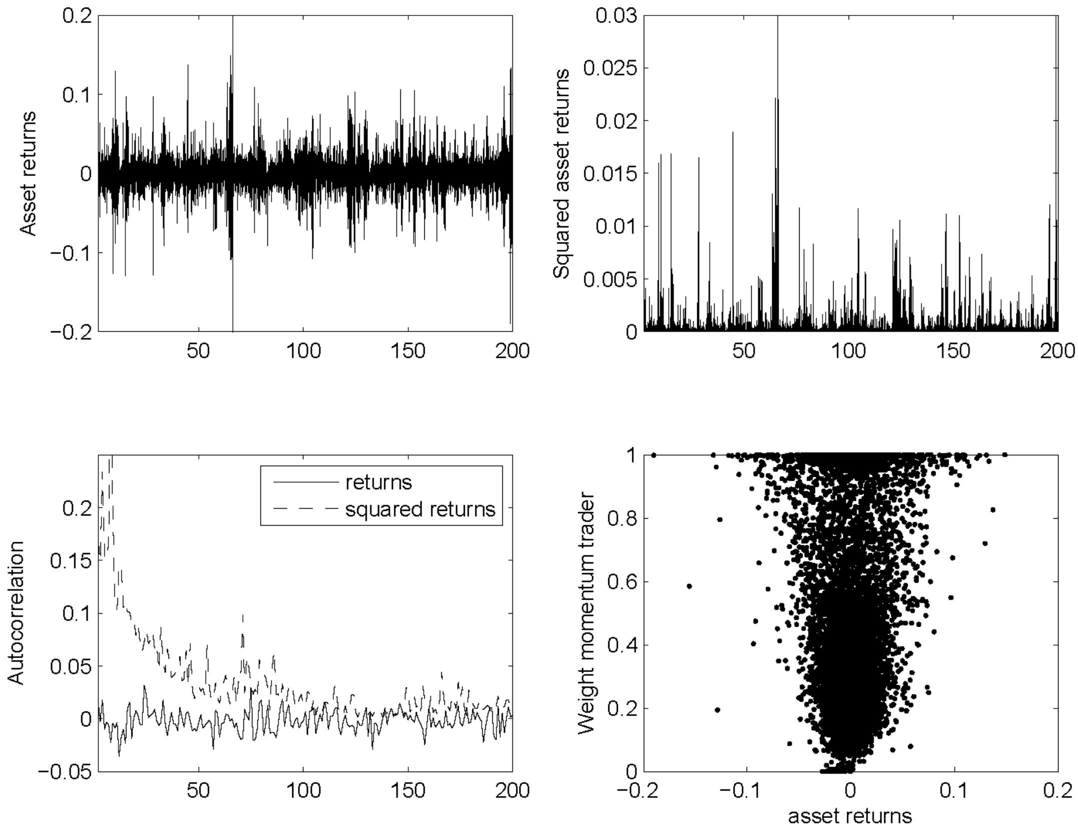
the strategy which maximizes their utilities being determined by gross profit flows and measured by their fitness functions. In so far, from time to time, the asset price is driven by *rational animal spirits* (Brock and Hommes, 1998). From a technical perspective, what is happening is that the occurrence of a small and positive random shock of the uninformed noise trade pushes the asset price away from its fundamental. If, by chance, the momentum trader realized a positive gross profit based on the latest asset demand, the fitness function ensures that the fraction of momentum traders in the trading population increases which results in a widening of the mispricing signal. As a consequence, a self-reinforcing asset price boom occurs with the fundamental strategy not being strong enough to counteract momentum in the financial market. The turning point is reached whenever a negative shock generated by the noise trader is strong enough to let the asset price drop. Then, trading opportunities based on a bullish market are erased and the momentum as well as the fundamental strategy pushes the price back to its fundamental value. In the worst case, the falling asset price can make the momentum trader force to deleverage which produces a highly non-linear asset price reaction and the possibility of default. The black triangles mark market events in which momentum traders default on their assets with their asset demands becoming nil and their net worth position approaching zero.

Most interestingly, our macro-finance model is capable of replicating stylized facts and statistical properties of price and return dynamics of a variety of asset classes. They include (i) asset prices follow a near unit root process with prices persistently being decoupled from fundamentals, (ii) returns are not predictable with no autocorrelation, (iii) the distribution of asset returns display fat tails and (iv) asset returns exhibit excess volatility and clustered volatility.[17] This implies on the one hand that in an arbitrage-free market, price changes, i.e. returns, exhibit essentially no correlation indicating to the property that expected returns are not predictable under the risk-neutral measure (Singleton, 2006). On the other hand, however, during some periods of time, it appears that high volatility events tend to cluster in time; high price changes tend to be followed by high price changes (et vice versa).

Figure (2) plots the basic return characteristics of the asset. The upper sub-figures represent the log returns and the squared log returns for the simulation exercise. As suspected, returns follow a random walk character with hardly any predictable component for the underlying data-generating process. The lower left figure shows the autocorrelation function of log returns; evidently, autocorrelations show no significant fluctuations around zero. However, the return process is characterized by fat tail events: a simple test on the probability distribution of returns clearly dismisses the assumption of a normal distribution. More probability mass is located in the tails and in the center of the distribution as measured

[17] See for an overview of stylized facts Mandelbrot (1963); Ding et al. (1983); Pagan (1986); Cont (2001).

Figure 2: Return Distribution



by excess kurtosis.[18] When turning to squared returns, we can identify the existence of clustered volatility as measured by the autocorrelations of squared returns for the simulation run. They are positive and exhibit a high degree persistence for a prolonged period of time. Finally, to shed light on the sources of these observations, the lower right sub-figure shows a scatter plot for log returns in the dimension size of returns and the weight of momentum traders in the market. There is a clear concentration of returns around $+-0.05$ for momentum weights between 10% and 60%. Weights between 60% and 90% are associated with returns with the same size, but with a much lower frequency. Only if the market essentially is dominated by momentum traders, returns blow up in either one direction. The fact that weights between 60% and 90% are less frequent comes from the non-linearity of the reinforcement process. Whenever momentum picks up speed, the fraction of agents applying the g_t^M-rule increases almost by a jump process.[19] All in all, the endogeneity of switching between forecasting rules produces the observation of clustered volatility and fat tail outcomes.[20]

Whether non-fundamental asset price movements, de-leveraging processes and default events spill over to the real economy via the macro risk premium mostly depends on the current macroeconomic condition itself. In times of optimistic expectations concerning the future output gap, negative shocks from the financial market are of minor importance, if at all. However, if output gap expectations are pessimistic, contractive financial developments amplify pessimist views on the economy, thereby pushing the output gap to even worse negative values. Due to the presence of endogenous expectations building on part of the agents on both goods and financial market, the model is not capable to fully isolate the effect of financial market activity on the real economy. Or to put it in on a nutshell, persistent and cyclical output gap movements could be the outcome of either waves of adaptive macro expectations or financial market developments or the combination of a self-reinforcing process of both components.[21]

[18] Kurtosis κ is the fourth moment of a distribution and it measures how much of the variance is the result of infrequent extreme deviations from the mean of the distribution. Here, the kurtosis takes on a value of $\kappa = 17.8$ which is clearly higher than the kurtosis of a normal distribution with $\kappa_n = 3$.

[19] Rational asset pricing models typically find it hard to replicate all the stylized facts. Only recently, some literature has made progress to resolve the asset pricing anomalies. Time-variation in discount rates due to time-varying risk aversion or time-varying aggregate macroeconomic uncertainty with changing conditional volatility and long run risks are used as explanation attempts to resolve the puzzles (?Bansal and Yaron, 2004; Lettau and Ludvigson, 2005; Bansal and Shaliastovich, 2010). In a recent asset pricing survey, Cochrane (2011:28) makes the point that theories based on behavioral finance and bounded rationality can be likewise explained within the discount rate approach where distorted expectations are captured by the difference between the risk-neutral and the historical probabilities of asset prices. To him, it is rather a convention with "[...] the line between recent 'exotic preferences' and 'behavioral finance' [being] so blurred that it describes academic politics better than anything substantive."

[20] For the sake of competentness, various other model specifications based on agent-based modeling or based on the existence of learning agents using Bayesian updating generate boom-bust dynamics with excess as well as clustered volatility (Lux and Marchesi, 2000; Cont, 2007; Branch and Evans, 2010; Bansal and Shaliastovich, 2010; Adam and Marcet, 2011).

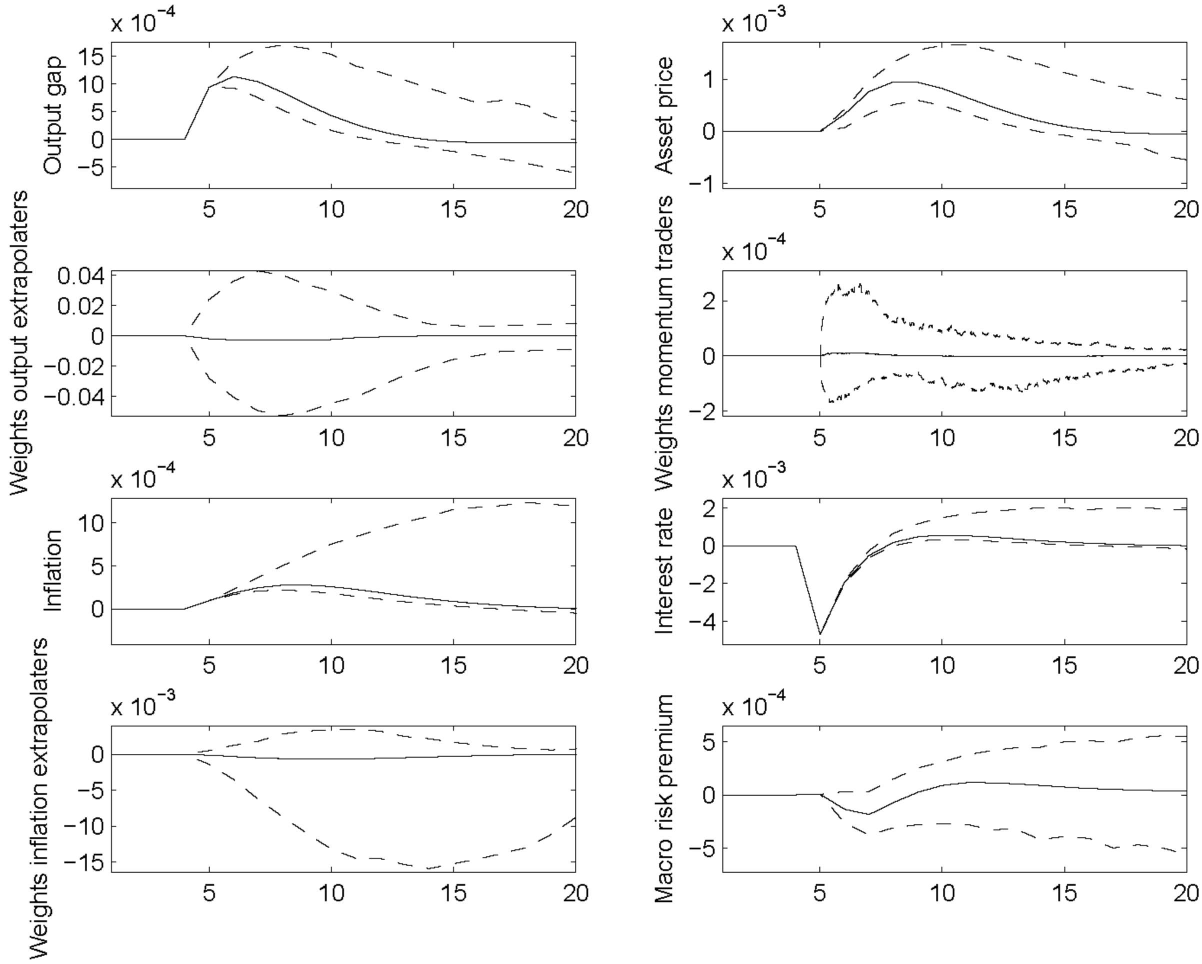
[21] In the model economy of Lengnick and Wohltmann (2010), these effects can be to some extent separated from each other because they equip agents on the goods market with rational expectations.

4.2 Isolating Macro Impacts

This section further elaborates on the implications of the benchmark model specification. One decisive distinction compared to the rational expectations paradigm is that for the same parameter calibration setup, the responses of the endogenous state variable differ depending on the current market environment. The latter, in turn, is determined by the weights of macro fundamentalists and adaptive agents as well as the fraction of momentum, fundamental and noise traders. In order to isolate the effects of macroeconomic shocks, we follow the procedure of Lengnick and Wohltmann (2010) of calculating the impulse responses of selected macro and finance variables. In this respect, the model is simulated 2000 times for 2000 different realizations of the financial market random shocks; whereas the macro shocks are set equal to zero. In each simulation run, we generate two model dynamics; the first by setting $u_q, v_q, w_q = 0$ and the second by setting the shocks likewise to zero except one particular macro shock that is supposed to take on a value of one standard deviation at a particular time during the simulation process. Notice that the random shocks associated to the financial market in each simulation are exactly the same. By calculating the differences of the evolution of state variables between the two simulation runs, it becomes possible to detect the isolated impact of macro shocks. It allows to analyze how a macroeconomic shock affects the financial market and how resulting changes in asset price and leverage dynamics spill over again to the real economy.

Figure (3) displays impulse responses for a negative policy rate shock, i.e. the central bank lowers its rate by one standard deviation. The solid lines represent the mean responses of selected variables and the dashed lines are the corresponding 95% quantiles. The model produces variable dynamics that are mostly in line with stylized facts on business cycle dynamics (see for an empirical overview Taylor, 1995). A fall in the policy rate is associated with a boost of aggregate demand as captured by a widening of the output gap and an increase in inflation. In accordance with the risk-taking view, a fall in the short rate triggers a fall in the macro risk premium which can be amplified by subsequent asset price dynamics following the initial policy shock. However, the bandwidth of possible adjustments widely varies due to the presence of market sentiment on the goods and financial market, even in the long-run, there remains a persistent effect on the economy, particularly on the inflation rate. Inflation inertia is central in agent-based, behavioral macro models; this has also been found by De Grauwe (2010). This becomes clear when observing the 95% quantiles outcomes of the state variables. For instance, the asset price can significantly rise with the effect of compressing the macro risk premium further which produces exactly the procyclicality of the system we are looking for. The state variables heavily depend on the initial market environment concerning market expectations. Each simulation run with different random draws generates different market expectations that have build up in the past. Consequently, there is some sort of path dependency

Figure 3: Impulse Response Function to Interest Rate Shock



in the evolution of the economy which can either act as a dampening effect on the macro shocks or it can amplify shocks in terms of cyclical fluctuations and persistent deviations from the steady state. The confidence intervals also confirm that the effectiveness of policy-rate changes on the financial market heavily depend on market sentiment. High weights of trend-chasers and expectations extrapolators can bring about a macro and finance response that is essentially 'immune' to unanticipated policy moves. As the same should hold in case monetary policy raises its policy rate, interest-rate increases to fight asset price bubbles might be ineffective - the proposition put forward by the proponents of the benign-neglect view of how monetary policy should deal with asset price bubbles (Greenspan, 2002).

5 Monetary Policy and Macroprudential Policy

The exercise of the benchmark simulation pursues the aim of presenting the evolution of endogenous waves of output expansion and contraction generated by market beliefs on both financial and goods markets. In this section, we explore recent advances in both academia and policy institutions towards dealing with procyclicality and financial market dynamics from a policy perspective. As already illustrated in Equation (3), monetary policy is implemented by the appropriate setting of the short-term policy rate. Notice, however, that in this section, we allow monetary policy to react to the macro risk premium that ensures a negative feedback between inflation and output as well as financial market dynamics. Such reaction is not the outcome of an explicit financial stability objective. Monetary policy is yet advised to change the conventional Taylor rule in response to a varying risk spread by a way of increasing the policy rate whenever the spread shrinks (et vice versa). Such policy response is welfare-improving since it acknowledges that the relevant interest rate is not only the risk-neutral part but it is also affected by variations in the risk premium. Consequently, it is an optimal response in order to shield the goods market from financial procyclicality for the purpose of stabilizing inflation and output.[22] The reaction parameter χ_q is, thus, equal to ζ_q.

Ultimately, macroprudential policy has the aim of addressing the systemic risk component in financial markets and the possible associated real disruptions. It includes (i) a time dimension, i.e. the evolution of risk over time and its implications for procyclicality and amplification effects of the financial system, and (ii) a cross-section dimension that describes the interlinkages between financial agents, how aggregate common risk is distributed among them and how this common source of risk makes them vulnerable to joint failures (Borio, 2010; Geiger, 2011). In our model, procyclicality is most pronounced when momentum trades follow their trading strategy without bounds in a self-fulfilling way and with a positive

[22] For a theoretical and rule-based explanation of this result see McCulley and Toloui (2008); Taylor (2008); Cúrdia and Woodford (2009); Giavazzi and Giovannini (2010).

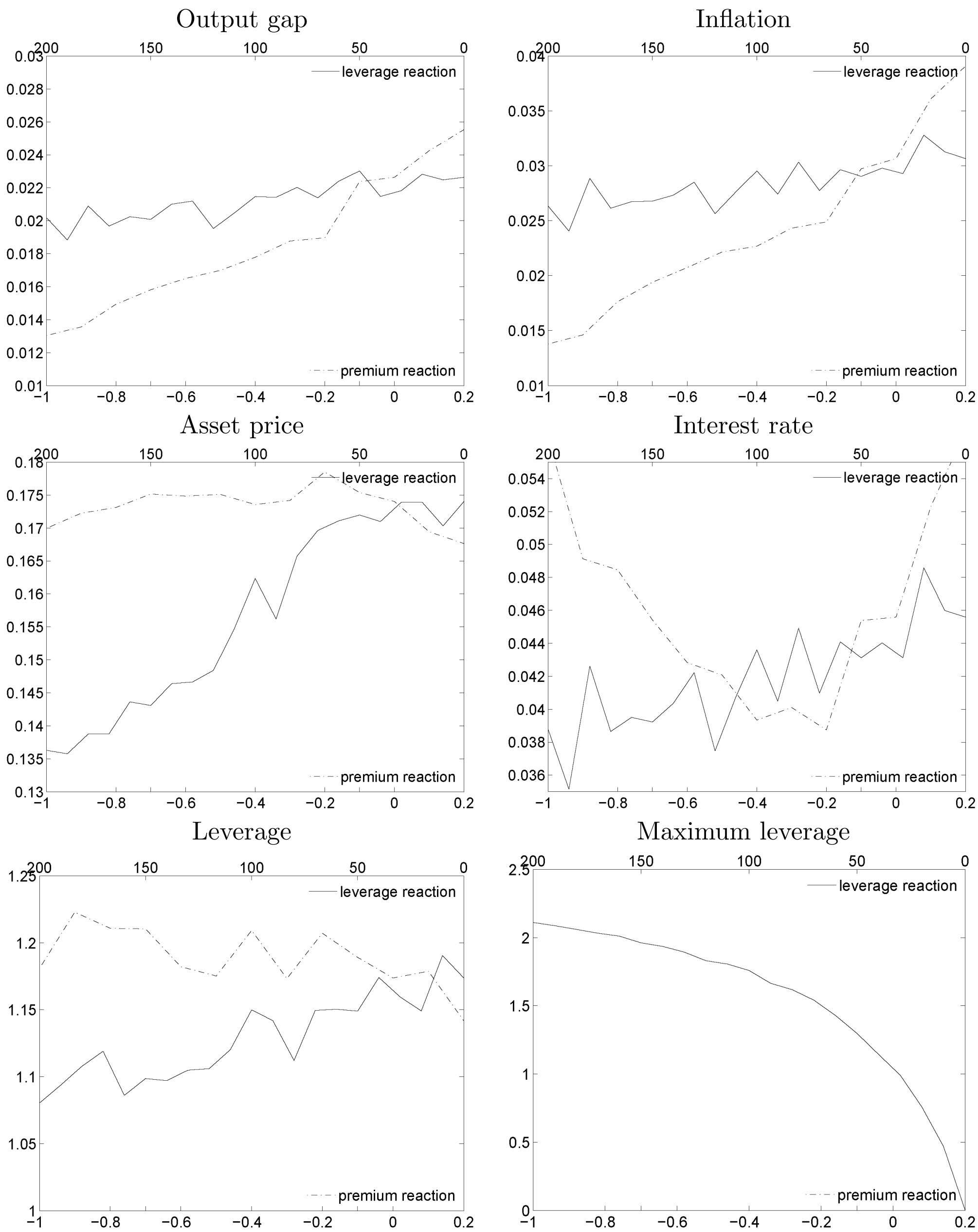
feedback loop on asset price dynamics. The danger of non-linearities in the asset price and in the macro risk premium are, thus, greater the higher is the fraction of momentum traders in the market. At the same time, the more leveraged those trades are, the more likely is the presence of fire sales. Due to the leverage constraint and marked-to-market valuation, traders are forced to sell the stock of assets which can trigger a severe asset price bust with adverse effects on output. From a regulator perspective, the objectives of minimizing financial and real procyclicality then is equivalent to minimizing volatility of the asset price and the output gap. As already sketched out, the macroprudential regulator tries to achieve this by varying the maximum permitted leverage inversely to the observed asset price volatility.

Figure (4) plots the standard deviations of the objective variables in the parameter space $\{c_4, \varrho\}$. The parameter c_4 captures the strength of the monetary policy reaction to the macro risk premium; whereas the parameter ϱ mirrors the macroprudential policy's aggressiveness to asset price volatility. In the respect, the lower abscissa draws the c_4 space and the upper abscissa draws the ϱ space. Notice that the standard deviations are calculated as the outcome of a non-cooperative policy game implying that monetary policy's reaction function is altered taking macroprudential policy as completely inactive, i.e. $c_4 = [-1, \ldots, 0.2]$ and $\varrho = 0$ (et vice versa with $\varrho = [200, \ldots, 0]$ and $c_4 = 0$).[23] The values for the unconditional second moments are the outcome of simulating the system for 100 different realizations of the random generator with each simulation run consisting of 500 quarters.

With an increasing negative reaction to the macro risk premium, monetary policy is successful in shielding output and inflation from financial procyclicality. The stronger the inverse policy response, the lower are the macro standard deviations. At the same time, monetary policy indirectly may affect asset price dynamics. A fall in the macro risk premium and an appropriate increase in the policy rate may lead to changes in the perceived fundamental asset price such that pronounced asset price dynamics led by trend-chasing strategy can be smoothed by increasing the mispricing signal on part of fundamental traders so that actual asset price does not deviate too much from its fundamental value. However, this part of monetary policy transmission in our model seems rather weak. Monetary policy is incapable of changing asset price and leverage volatility by means of reacting to the macro risk premium. In contrast, changing the maximum permitted leverage dependent on the current market environment is a powerful instrument to stir asset price dynamics. As illustrated by the standard deviation of both the asset price and leverage, macroprudential policy can dampen financial procyclicality without increasing the standard deviations of the macro variables. Indeed, it supports stabilizing inflation and output though the macro effects are less pronounced than an adequate monetary policy reaction. Turning to the policy instruments,

[23] The choice for the parameter space for c_4 comes from the observation, that with $c_4 > 0$, monetary policy itself generates positive feedback between the real economy and the financial market. For a sufficiently large value of c_4, a generalized Taylor principle does not hold anymore so that the asset price as well as the other state variables explode.

Figure 4: Standard Deviations of Policy Variables



it is clear that macroprudential policy increases its instrument volatility the more aggressively it reacts to market conditions. This is shown by the convex pattern of the maximum permitted leverage when plotting against ϱ. What is worth mentioning, however, is that it enables monetary policy, on average, to react less volatile by its short-rate instrument in order to stabilize inflation and output. In this respect, macroprudential supports monetary policy. Monetary policy, itself, is faced with a U-shaped pattern of interest-rate volatility when reacting to the macro risk premium. This comes from the fact that a highly negative macro risk premium reaction generates sharp interest reversals; along similar lines, a positive response to the risk premium leads to an amplification of macro procyclicality which requires sharp interest rate responses in opposite direction in order to stabilize inflation and output.

6 Conclusion

We constructed a model which integrates the real economy and the financial market. Our transmission channel of financial market activity to the real sector embraces a recent strand of literature shedding light on the link between the active balance sheet management of financial market participants, the induced procyclical fluctuations of desired risk compensations and their final impact on the real economy. Our financial market submodel generates pronounced boom-bust cycles and - mainly due to the presence of leverage - we obtain episodes of highly non-linear asset price reversals triggered by simultaneous fire sales. The cyclical behavior of the model has to be mainly attributed to the abandonment of the rational expectation assumption. It might appear somewhat inconsistent that we assume bounded rationality. We indeed stress that financial market behavior can be viewed as rational under certain severe frictions instead of assuming wildly irrational agents. But the emerging patterns of asset prices and discount rates might not look rational at all. In our view, this comes from important frictions such as limited time horizons in risk management models, and sticky return and leverage targets. They might literally force fundamentally rational agents to behave as if they were not - from an outsider's perspective. So, the most sophisticated research strategy would be to explicitly model frictions for financial market agents and to construct a micro-founded general equilibrium model with endogenous financial procyclicality. But to our knowledge, all of the attempts undertaken in this direction (i) do not capture yet the entire characteristics of endogenous financial procyclicality and (ii) are restricted to a two-period setup and therefore unable to produce macro time series e.g. for policy analysis.[24] Hence, we believe it is a pragmatic and sufficiently reasonable modeling strategy to assume bounded rationality on financial markets. This assumption essentially serves as a 'proxy' for the frictions which turn out to be very difficult to model. Furthermore, the tractability of our setup allows as to generate simulated time series. Nevertheless, we acknowledge that an explicit modeling of these mentioned frictions in a general equilibrium setup would be crucial for a deeper and more comprehensive understanding of the various feedback mechanisms and spillovers.

Concerning policy analysis, it becomes clear that a systematic and inverse central bank reaction to changes of the macro risk premium is highly effective in shielding the real economy from boom and bust episodes on the financial market. Macroprudential regulation in turn is well suited to smooth asset price dynamics, since a countercyclical leverage regulation dampens debt-financed booms. However, we do not formulate an optimal policy conclusion. It would be interesting to specify loss functions for both the central bank and the macroprudential authority and to minimize them over the space of possible parameter constellations, most likely with a numerical grid search. This procedure could also shed light

[24] See for instance Cúrdia and Woodford (2009), Gertler and Kioytaki (2010) and Phurichai and Rungcharoenkitkul (2010).

on the issue of optimal coordination between both policies. See Angelini et al. (2011) for an approach heading in this direction. We leave this as a question for future research.

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