Boom-Bust Cycles: Leveraging, Complex Securities, and Asset Prices

Willi Semmler
Department of Economics, NSSR, New York, NY

Email: SemmlerW@newschool.edu

Lucas Bernard
Department of Business, CUNY, New York, NY

Email: LBernard@citytech.cuny.edu

June 30, 2011

Abstract

Recent history suggests that many boom-bust cycles are naturally driven by linkages between the credit market and asset prices. Additionally, new structured securities have been developed, e.g., MBS, CDOs, and CDS, which have acted as instruments of risk transfer. We show that there is a certain non-robustness in the pricing of these instruments and we create a model in which their role in the recent financial market meltdown, and in which the mechanism by which they exacerbate leverage cycles, is explicit. We first discuss the extent to which complex securities can amplify boom-bust cycles. Then, we propose a model in which distinct financial market boom-bust cycles emerge naturally. We demonstrate the interaction of leveraging and asset pricing in a dynamical model and spell out some implications for monetary policy.

JEL classification codes: C61; C63; G21; D83; D92
Keywords: credit, leverage, mortgage, credit risk, structured finance, leveraged financing, mortgage-backed security, collateral, collateralized default obligation, booms, busts, dynamic, cycles

1 Introduction

Efficient capital markets are supposed to evaluate and price risk; but frequently, if risk assessment is measured and priced through financial market instruments, we observe significant non-robustness in risk evaluation and asset prices.[1] Moreover, markets exhibit externalities, resulting in failures, dis-inter-mediation, and meltdowns. The busts, precipitated by financial instability, usually entail contagion effects and strong negative impacts for the real side of the economy. There is some synchronized behavior of economic agents and some mechanisms, observable in boom-bust cycles, that are rather general: the boom period triggers overconfidence, overvaluation of assets, over-leveraging, and the underestimation of risk; then follows a triggering event and the market mood turns pessimistic; finally, undervaluation of asset prices and deleveraging. Most of the historically experienced boom-bust cycles exhibited such features.[2] We consider three historical illustrations.

First is the emerging-markets crisis of the 1990s. Several emerging markets experienced such cycles in the 1990s; for example Mexico (1994), Asia (1997/8), Russia (1998), and Argentina (2001). Those countries, after capital market liberalization, passed through a considerable boom period characterized by overvaluation of asset prices, the lowering of risk perceptions, foreign borrowing, and capital inflows. Yet, suddenly, the distrust of the countries' fundamentals led to a sudden reversal of these same capital flows; this triggered rapid exchange-rate depreciation, financial instability, and consequently, a sharp decline in economic activity.

Second is the information technology boom-bust cycle of the 1990s. In the US and Europe, during the period from 2001 through 2002, the financial markets experienced a significant decline in asset prices, commonly referred to as the bursting of the Information Technology (IT) stock market bubble (the dot-com bust). Overvaluation of asset prices and the lowering of risk perceptions, in combination with a decade of dubious accounting practices (see MacAvoy and Millstein, 2004) and short-sighted investment, led to a situation where, suddenly, equity valuations sharply declined.

Third is the recent financial meltdown, which began in the US sub-prime (mortgage) market in 2007, evolved as credit crisis through the US-banking system in 2008/9, and sub-

[1]Some historically important approaches to risk assessment, credit-default, etc. are gather together in Semmler and Bernard (2007).

[2]The economic literature that stress this line of thinking arises mostly in the Keynesian tradition, e.g., Minsky (1975, 1982, 1986), Tobin (1980), Kindleberger (2005) and Gallegati et al. (2011). These thinkers have been very influential in studying financially driven boom-bust cycles. There is also another important insight into this interaction as represented by Robert Shiller's (1991, 2001) overreaction hypothesis. For the most part, the above research is influenced by Keynes' view on the role of "animal spirit" in booms and busts. Another non-neoclassical tradition, also stressing those negative externalities, originates in work by Stiglitz and his co-authors. They draw upon recent developments in information economics, wherein systematic attempts have been made to describe how actual financial markets operate by referring to the concepts of asymmetric information, adverse selection, and moral hazard.

sequently spread world-wide, causing a world-wide financial panic, and staggering declines in global growth rates. This time, the usual boom-bust mechanism was reinforced by new financial innovations; specifically, the development of new financial intermediations through complex securities, e.g., mortgage backed securities (MBS), collateralized default obligations (CDO), and credit default swaps (CDS). The complex securities, which were supposed to outsource and diversify idiosyncratic risk, have, jointly with the changes in the macroeconomic environment, actually accelerated not only the boom, but also the bust, firstly through high asset prices and high leveraging and then, secondly, an asset-price collapse and credit crunch. Those innovations provided the magnification of a financial mechanism through which the asset price boom and bust became more distinct.

The Asian financial market crisis and the technology bubble of the 1990s seem to be well understood.[3] Yet, the current financial crisis is less well analyzed. It seems to be neither a financial crisis triggered by a currency run nor a technology bubble, but rather a home-made financial crisis resulting from two driving forces: macroeconomic changes (financial market liberalization,[4] low interest rates, high liquidity, easy credit, and external imbalance), and the use of new financial innovations and new tools of risk management which substantially helped to increase leveraging. Conclusive studies of the recent financial market events are still missing. Yet, there is some preliminary analysis. Popular wisdom attributes the last boom and the run-up in housing sector to Greenspan's low interest rate policy. There is evidence to suggest that interest rates had already come down significantly since the middle of the 1980s, along with the decline in inflation; the housing boom started much later. There is also some truth to the view that Greenspan has expressed: that the Fed can reduce short term interest rates, but has no power over long-term rates and, consequently, the yield curve, which also impacts mortgage rates. In fact, the yield curve, in recent years, had become rather flat or even downward sloping as the US had become a magnet for capital

[3] During the 1990s, work was done on understanding the Asian crisis. Mishkin (1998), for example, has posited an explanation of the Asian financial crisis of 1997/8 using an information-theoretic approach. A similar theory, by Krugman (1999), laid the blame on banks' and firms' deteriorating balance sheets. Miller and Stiglitz (1999) employ a multiple-equilibria model to explain financial crises in general. These theories point to the perils of too-fast liberalization of financial markets and to the consequent need for government bank supervision and guarantees. However, Burnside et al. (2001) view government guarantees as actual causes of financial crises. These authors argue that the lack of private hedging of exchange rate risk by firms and banks led to financial crises in Asia. Other authors, following the bank run model of Diamond and Dybvig (1983) argue that financial crises occur if there is a lack of short-term liquidity. Further modeling of financial crises triggered by exchange-rate shocks can be found in Edwards (1999). The latter discusses the role of the IMF as the lender of last resort. Recent work on the role of currency in financial crises can be found in Kato, Proano and Semmler (2009) and Roethig, Semmler and Flaschel (2007). The latter authors pursue a macroeconomic approach to model currency and financial crises and consider the role of currency hedging in mitigating financial crises. See also the papers by Bernanke and Mishkin, see Bernanke et al. (1983; 1994; 1998) and Mishkin (1998); on the IT bubble, see Semmler (2006, ch. 7) .

[4] Proponents of capital market liberalization cite possible benefits generated by free capital mobility such as: 1) reducing trading costs, low costs of financial transaction in particular, 2) increase of investment returns, 3) lowering the cost of capital when firms invest, 4) increasing liquidity in the financial market, and 5) increasing economic growth and positive employment effects. We do not want to deny those possible benefits, yet the proper sequencing of market liberalizations, sufficient safety precautions, and properly prudential regulations are important.

and attracted savings from the rest of the world; this kept the interest rate on the long end rather low.

Another view takes the housing sector as central. It is argued that the purchase of housing by baby-boomers led to the rise in housing prices; see Mankiw and Weil (1989), but this demographic shift seems to have occurred much earlier. Piazzesi and Schneider (2008) also refer to the housing sector. They show how baby-boomer activity forced a flow of investments out of equity and into housing. In addition to that, in their argument, inflation plays a critical role through its impact on bond prices.

Schneider et al.(2007), use a portfolio approach and argue that the fraction of housing assets in households' portfolios went down in the 1980s, whereas the fraction of equity held in those portfolios rose rapidly in the 1990s. Then, the trend reversed, starting in 2000-2001, with a rapid increase in housing assets. They attribute this to the shift in expected returns from three type of assets: fixed income, equity, and real estate. They argue that this large change in asset allocation was related to the inflation rate of the 1980s. Housing assets and equity assets show a negative co-movement which seems to arise from their different sensitivity to inflation rates. Yet, still the question remains: why equity prices and returns relatively declined as compared to housing prices and returns? Why did the housing asset boom take over the equity boom starting at the end of the 1990s? Is the answer simply a shift from Internet equities into housing?

Shiller (2006, 2007) attributes the housing boom to some overshooting mechanisms and excess volatility, first in the equity market and then, second, in the real estate sector. More specifically, Schiller points out that investors are usually not up-to-date on the latest economic models. For example, there is a money "illusion" in which investors base their decisions on nominal interest rates when real rates would be more appropriate. The phenomena is also visible in equity markets where price-to-dividend ratios can significantly overshoot their mean values.

To discuss this argument within the context of housing markets, one may have to look at how this overshooting manifests itself in terms of asset pricing. In Finicelli (2007) we see that the housing price-to-rent ratio shows a rapid upward deviation from its mean beginning in 2003. More interestingly, we see that by many other measures, e.g., the housing price-to-disposable income ratio and debt service-to-personal income ratio, have been rising as well since the mid-1990s.

Though much work takes the real estate market as the underlying cause for the current boom-bust cycle, other approaches attribute the recent events to technology shocks. Several papers use as basic the dynamic stochastic general equilibrium (DSGE) model. In the context of real business cycles models, technology and technology shocks drive asset prices. Yet, usually it is hard to explain boom-bust cycles in an inter-temporal model, since, given a smooth discount factor, temporary blips or deviations of pay-offs from the trend get smoothed out. Even strong technology shocks do not deliver such results.

Therefore, there have been a few recent studies that attempt to reconstruct boom-bust cycles using RBC models with misperceived technology shocks as driving force. Here, a time-lag in the actual implementation of technology, after the perception of a technology shock is seen as the causal factor for the boom-bust cycle; see Beaudry and Portier (2004), Christiano et al. (2006, 2007) and in Lansing (2008). In most of these papers, the expectations dynamics concerns the technology shocks, which, however, is likely to explain only part of the boom-bust cycle in asset markets.

A very influential model, along the line of a DSGE model, has been proposed by Bernanke et al. (1999). This is the financial accelerator model that proposes that credit cost and credit volume move pro-cyclically, having an amplifying effect on the ups and downs of real activities. Essential, this is collateralized borrowing: with asset prices high, net worth will be high and collateralized borrowing is stimulated. The reverse is supposed to happen in downturns.[5] This approach proposes that credit cost, spread spread, and credit volume depend upon asset prices, can indeed show local amplifying effects on the ups and downs of real activities. Yet, there is some fuzziness regarding the collateral, the borrowing constraints, since they are supposed to be represented by the discounted expected pay-offs. The constraints become, in fact, some speculative constraint. Moreover, the evolution of leveraging is usually not tracked and the impact of leveraging, on asset prices, rarely studied. The interaction of asset prices and leveraging is not fully modeled in financial accelerator approach.

We here take the view — which seems to be well settled by theory and stylized facts[6] – that boom-bust cycles, e.g., the most recent, may be driven by the linkage of credit and asset prices. Yet more explicitly we want to argue that asset prices are driven by leveraging and expected pay-offs. As for borrowing, it is likely that it is not always fully covered by future asset prices and thus, not covered by collateral. Also, the inter-linkages of asset prices and leveraging may trigger – for example by some bad news on uncovered leveraging— the collapse of the self-justifying mechanism. Overall, we assume that there are non-linearities, possibly giving rise to an asset price boom and then, maybe later on, to a bust.

The recently observed amplification of the expansion and contraction of leveraging[7] is likely to be related to the way new financial instruments are employed. In the current paper, we attempt to include the new financial tools that have accelerated the rapid build-up and contraction of credit, thus triggering the collapse in asset pricing. In this context, the recent development of new financial instruments, in particular, credit derivatives and their use in securitization products, such as Mortgage Backed Securities (MBSs) and Collateralized Debt Obligations (CDOs) are of particular importance.[8] These have allowed lenders to off-load

[5]In a recent conference at the Fed on the Financial Market and Monetary Policy, a large number of papers pursuing this view have been presented and discussed, see http://www.federal reserve.gov/events/conferences/fmmp2009/default.htm

[6]See the extensive survey of the Bank of International Settlements (1998), Goodhart et al. (2003) .

[7]The observable features that were visible in the latest boom-bust cycle are well known and many papers have been put forward to explain these phenomena. A detailed discussion can be found in our working paper (same title) located at http://www.newschool.edu/nssr/cem; also see Hall (2011)

[8]A similar view on the interaction of leveraging and asset prices, recently magnified by complex securities,

risk and remove sensitivity to longer-term prospects. More specifically, by grouping large numbers of mortgages together, securitized instruments are created that are very non-robust in performance, i.e., small changes in interest rates, delinquency rates, recovery rates, and default correlations can lead to a collapse of security prices and to the bursting of the bubble.[9]

We first discuss the complex securities, which were massively found in the US real estate sector, and which involved significant leveraging build up, and then we propose a model that captures the crucial interactions of asset prices and leveraging. As starting point for our model we refer to the historical studies on financial crises by Minsky (1975, 1982, 1986) and Kindleberger et al. (2005), but also recent dynamic models such as put forward by Brunnermeier and Sannikov (2010) and Geanakoplos (2010), Miller and Stiglitz (2010), and Hall (2010, 2011).

This paper is organized as follows. In section 2 we introduce complex securities as new instruments of risk transfer and discuss of how they may have amplified boom-bust cycles. Whereas in section 2 the asset value is given exogenously by a Brownian motion, Section 3 offers a simple dynamic model with endogenous asset prices and leveraging. Section 4 concludes the paper. The appendices provide some technical background.

2 Complex Securities, Pricing, and Micro-Mechanisms

To motivate our study, we want to sketch the behavior of the Markit ABX-HE-AAA[10] index; this is illustrated in figure 1. Towards the end of 2007, along with all other ABX-HE indices, it took a steep dive. Since these indices are based on mortgage backed-securities (MBSs), which are a subclass of collateralized default obligations (CDOs), its sudden collapse just on the brink of the sub-prime disaster suggests causal connections between the housing-based securities represented by these indices and pricing problems in the housing sector. Figure 1 illustrates the phenomena - a very steep drop around mid-October 2007 for the ABX-HE-AAA

As a structural motivation for our model, we first created a Monte-Carlo simulation in which we could study the sensitivities of a securitization-structure to the variables of default rate, default correlation, recovery value, and interest rates. In this model, the short-term

can be found in the work by Geanakoplos (2009).

[9]A similar perspective that new forms of financial inter-mediation have been developed that have magnified the boom bust cycles, can be found in the work by Adrian and Shin (2009) who stress the change from bank-based to market-based inter-mediation, see also Brunnermeier (2009) and Geanakoplos (2009).

[10]Markit, Inc is a private company which owns and administers the proprietary ABX.HE index, which is a liquid, tradeable tool allowing investors to take positions on mortgage-backed securities via CDS contracts. The index became a benchmark for the performance of MBSs during the time of the housing bubble. Its liquidity and standardization allowed investors to accurately gauge market sentiment around the asset-class, and to take short or long positions accordingly. The illustrated index, ABX-HE-AAA, is a synthetic tradeable index referencing a basket of 20 AAA-rated mortgage-backed securities

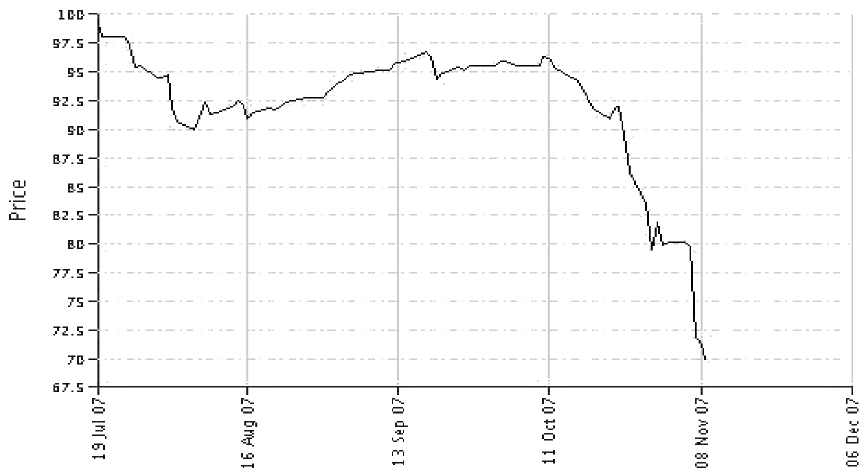

Figure 1: The Markit ABX-HE-AAA Index

valuation followed an exogenous process (in Part 3, we make the valuation endogenous). To this end, we adapted a method of CDO pricing, see Chacko, et. al, (2006), consistent with our understanding of how financing form mortgage-backed securities (MBS) actually work. Specifically, we use Merton's definition of default wherein value follows an exogenously-determined Brownian motion and default occurs when the size of the debt exceeds the value of the asset. In Merton's model, asset valuation may be expressed as follows:

$$V_t = V_0 exp^{(r-\frac{\sigma_V^2}{2})t+\sigma_V\sqrt{t}\times z}$$

where $z \sim N(\mu, \sigma)$ It can further be shown that the probability of default, given this definition, may be expressed thus:

$$Pr(default) = 1 - \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{d} exp^{-\frac{(x-\mu)^2}{2\sigma^2}}dx$$

where $d = \frac{ln(\frac{V_t}{V_0})+(r-\frac{\sigma_V^2}{2})\times t}{\sigma_V\sqrt{t}}$

Note that d is simply the upper limit of the integral shown, the cumulative normal distribution. Following the Chacko et al. (2006) approach, we assume a simple MBS structure with 5 reference assets (mortgages) and 3 tranches, equity, mezzanine, and senior, absorbing the bottom 10%, the second 10%, and the last 80% of the default risk, respectively. We assume that a default event has occurred when $V_t < V_0$. In this case, costs to the

SPV, $L_i = (1 - \delta_i)V_i$, where δ_i is the recovery rate for the ith asset, are allocated to the lower tranches first. To incorporate contagion and/or hedging effects, we assume an initial correlation matrix,

$$\mathbf{P} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \rho_{2,1} & 1 & 0 & 0 & 0 \\ \rho_{3,1} & \rho_{3,2} & 1 & 0 & 0 \\ \rho_{4,1} & \rho_{4,2} & \rho_{4,3} & 1 & 0 \\ \rho_{5,1} & \rho_{5,2} & \rho_{5,3} & \rho_{5,4} & 1 \end{bmatrix}$$

We now compute the Cholesky transformation of $\mathbf{P}$, above, which is defined as

$$\pi_{i,j} = \frac{\rho_{i,j} - \sum_{k=1}^{j-1} \pi_{i,k}\pi_{j,k}}{\sqrt{1 - \sum_{k=1}^{j-1} \pi_{j,k}^2}};$$

$1 \leq j \leq i \leq 1$

This matrix is computed using a VB program shown in Appendix 1. A convenient property of the Cholesky Transformation is that given a vector, $\mathbf{z} = (z_i)$, of n random numbers drawn from a standard Gaussian distribution, then for $\rho_{i,j} = k$, the vector $\mathbf{c}$=$\mathbf{P}\times\mathbf{z}$ is a vector of n random numbers which are correlated with $\rho_{i,j} = k$. By substituting $\boldsymbol{c}$ for $\boldsymbol{z}$ in the valuation equation above, we can generate default events with known correlation. Further, by using Monte Carlo simulation, we can determine an appropriate pricing structure for each of the tranches.

We suppose, for this simplified MBS, that the attachment points for each of the tranches are as follows:

Equity	0, C
Mezzanine	C, D
Senior	D,

So, for example, the Mezzanine tranche, *g(L(t))* = Loss/Default can be written,

$$g(L(t)) = min\{max\{D - L(T), 0\}, D - C\}$$

And the resulting spread, for a given time period,

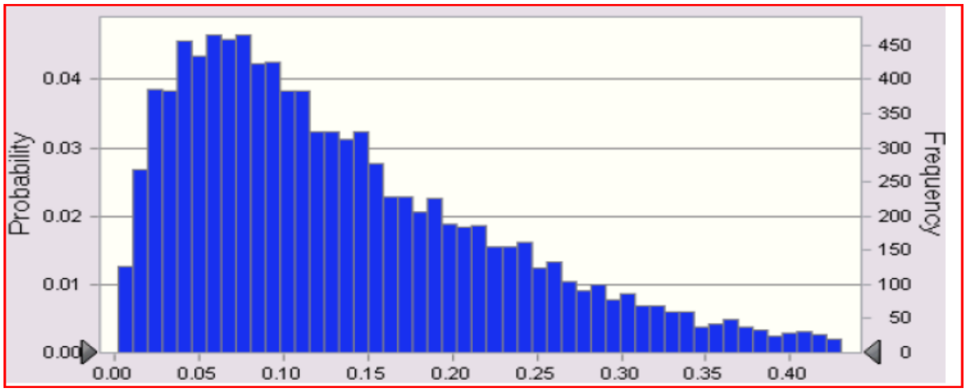

Figure 2: Implied Default Rate Distribution ($\rho = 0.75$)

$$\text{spread} = \frac{\sum_{i=1}^{k} exp^{-rt}(L(t)-L(t-1))}{E^P\left(\int_0^T exp^{-rt}(L(t))dt\right)}$$

Using the above, we can determine, when a hypothetical SPV is profitable and when it is not. In other words, when the amount demanded by potential holders of the different tranches exceeds the anticipated cash flows, the SPV is no longer profitable. When SPVs are losing money, this is likely to entail a liquidity or credit crisis. A sudden decrease in liquidity squeezes buyers out of the market in ways that may be highly dependent upon the locality or other local specifics. This model allows us to explore the sensitivity of the regime-change event (credit crisis) to changes in the default correlation of the component assets of the MBS. Depending upon different assumptions regarding the correlation implicit in mortgage products, we obtained reasonable calibration of our method with empirically determined results, as shown in the following graphs. Our model produced the distribution shown first, in Figure 2. It is a calibration exercise in which 10,000 random trials were simulated. The implied default probability, as given by the equation shown earlier, resulted in the illustrated distribution. That is, we see that default probabilities are right-skewed with a density shown below. This is similar to the empirically-determined density of default probabilities appearing next in Figure 3, which was constructed by the PMI Mortgage Insurance Company.[11]

Text placed here for no reason.

Thus, this model is able to generate appropriate distributions of default. Further, we can simulate joint-distributions of varying default-correlations by using the Cholesky transformation. However, a change in the correlation between default probabilities has radical effects on the distribution of default rates. The following graph illustrates the distribution for a correlation coefficient of 0.40, as opposed to the value of 0.95, as shown in the calibration exercise above. This is not unexpected. If we assume that some local economic conditions are powerful influences on home sales and/or on the ability to pay mortgage debt, we would expect default rates to be somewhat correlated in that region. On the other hand, if it is supposed that markets are fragmented, perhaps by geographic region, then a broad-based MBS

[11] For details, see Akkeren and Hansen (2004).

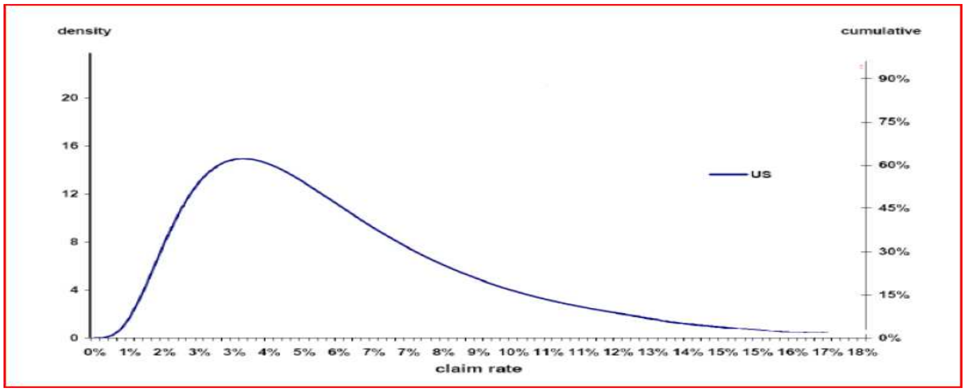

Figure 3: Impact of Geographic Diversification

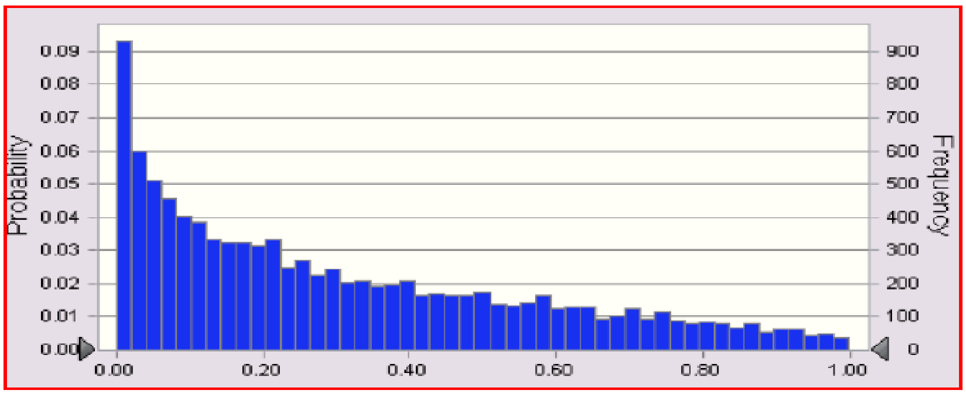

Figure 4: SPV Profitability; $\rho = 0.40$

would have less correlation between assets. The change in the implied default distribution is shown in Figure 4.

We can also illustrate the distribution of profit/loss for a typical SPV as shown below. The distribution of success/failure of SPVs is, of course, directly impacted by correlation through the mechanism described. This is shown below for a 10,000-run simulation with $= 0.40$. In this step, we do not consider the valuation process, but rather use the default probability directly. Also, since we are not interested in investigating the effect of correlation here, we leave it fixed at 0. In this step, a MBS security consisting of 100 iid mortgages as reference assets is divided into tranches of size 3% each. Each investor is supposed to have put up \$1000 each 1% position. Thus, the expected loss for each tranche is approximated by:

$$\sum_{i=k}^{k+2} \binom{100}{i} p_{default}^{i}(1-p_{default})^{100-i} \times 1000(i-k+1) + \sum_{i=k+3}^{100} \binom{100}{i} p_{default}^{i}(1-p_{default})^{100-i} \times 3000$$

So, for example, if the $Pr(default) = 0.05$, the expected loss for the mezzanine level

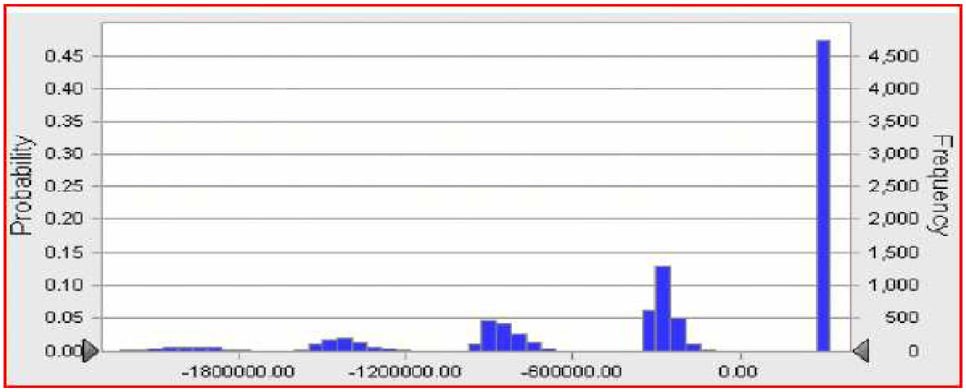

Figure 5: SPV Probability; $\rho = 0.95$

tranche (6% - 8%) will be ~$640 or ~21%. This anticipated loss is the minimum compensating interest rate that an investor will demand for purchasing this position. Thus, it is a cost to the SPV. This distribution is shown in Figure 5.

We can approximate the loss of a tranche, with attachment points a and b, using a normal approximation:

$$E\left[Loss\right] = \frac{1}{\sqrt{2np(1-p)\pi}} \int_a^b exp^{-\frac{x-np}{2np(1-p)}} \delta(x) dx$$

where

$$\delta(x) = \begin{cases} 0; & x \leq a \\ \Phi\textbf{int}(x); & a \leq x \leq b \\ \Phi\textbf{int}(b-a); & b \geq x \end{cases}$$

and Φ is the amount invested in 1% of the MBS. We assume that defaults above the upper attachment point result in a total loss to the tranche-holder. The cost to the MBS is then simply

$$\frac{\sum E\left[Loss\right]}{\sum \text{interest payments}}$$

When the MBS becomes unprofitable, there is a corresponding drop in prices driven by the difficulty of obtaining financing. This, in turn drives mortgage rates up, which increases the default rate: a vicious cycle. Figure 6 illustrates the effect of the MBS financing mechanism operating underneath the housing market. In this section, we use the short-term cyclicality[12]

[12]Later, in the dynamic model, we will see that this occurs naturally

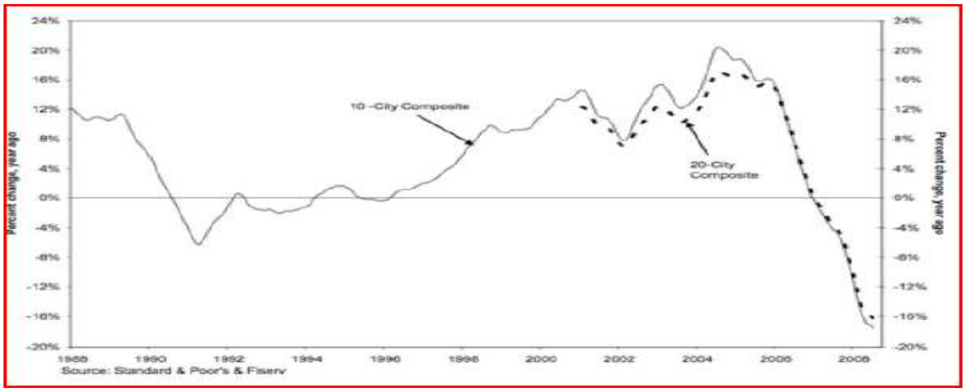

Figure 6: Collapse of Actual House Prices

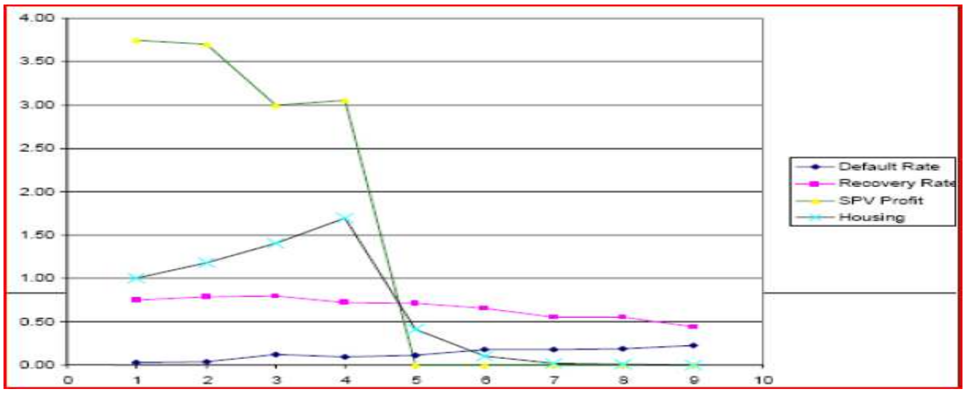

Figure 7: Monte-Carlo Results

to set indicator variables. Also, graphical analysis suggests over/under shooting. However, at each step, the implied default rate is recalculated. If the recalculated default rate is such that the SPV financing mechanism becomes less profitable, there is a corresponding decrease in value. Then, a new sequence is initiated and the process repeats. Large negative shocks to the implied default rate, which initiates a negative-feedback into the system, cause rapid declines in prices due to a sudden decrease in market liquidity. This is shown below for the actual house price in Figure 6 and the simulated price in Figure 7.[13]

We see that our model is well able to explain the stylized facts that were presented in Figures 1 and 6. A few remarks can be made on monetary policy. In the context of our model, we can see that the Federal Reserves monetary policy, setting the interest rate, is a relatively weak instrument in controlling this market. Consider the following graph (Figure 8):

This graph shows the rapid escalation in demanded compensation due to increasing default rates. This means that the spread of premia over the risk free rate, or other bonds, will rapidly go up, and the ABX index representing the underlying bonds will rapidly decrease. Both

[13]See Figure 1 of this section.

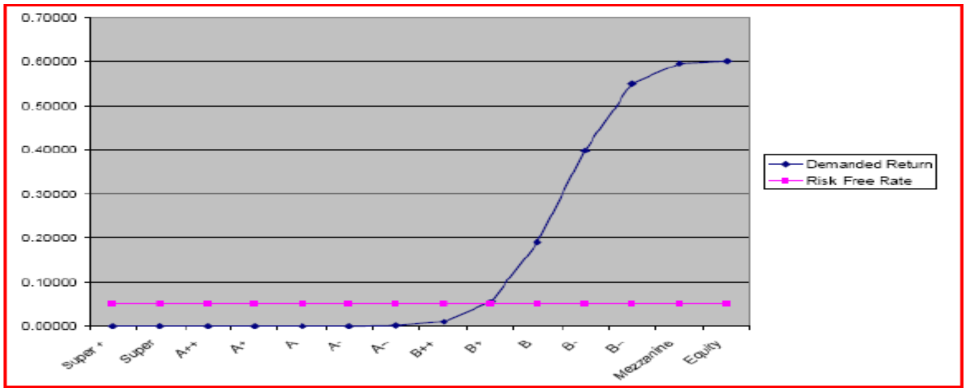

Figure 8: Impact of Federal Reserve Policy

were actually very much observable during the financial market melt down.[14] We can see that the Federal Funds rate can only influence, perhaps, players considering B-level tranches. However, changes in the default rate, and the consequences of this and the decline of the ABX index make this only a minor influence. Further, reducing this same interest rates also reduces SPV income. Thus, while it may have some salutary effect on the default rate, it seems not likely to make a huge difference for a crisis regime triggered by the required rates demanded by the lower tranches of an MBS. Furthermore, correlation and contagion effects reinforce each other. For example, in a rising market, recovery values may exceed the size of the loan. In such an environment, investors will actually favor a higher default rate because they can obtain property at a discount. On the other hand, in a declining market, recovery values will decrease as the default rate increases. Thus, when overshooting has occurred and defaults are triggered, the effects may be exaggerated.

In addition, the critical variable, the variable that drives the process, is default probability. This is an information asymmetry issue as buyers and sellers have different information with respect to default rates. Such informational asymmetries often emerge in places of financial stress[15]. So, overall, the above pricing model and its results illustrate the non-robust character of these new financial instruments of intermediation: change in interest rates, delinquency rates, recovery rates, suddenly rising default risk and default correlations, and rising information asymmetry may make prices of those new complex securities very volatile, leading to sudden and sharp rises or collapses.

[14] In particular, the repo rate (unsecured), short term loans from the money market, and what is termed the "hair cut" went up dramatically, see Adrian and Shin (2009). Curdia and Woodford (2009) also point to the sudden rise of the spread. Also see the accompanying sudden decline of the ABX index, which is an accurate reaction of the risk of the underlying sub-prime bonds; see Gorton (2009).

[15] See USFSI, 2010, for more on this.

3 A Model of Asset Pricing and Leveraging

Above, in our study of complex securities, the asset price, V_t, was given exogenously and modeled assuming Brownian motion; the leveraging involved was not explicitly modeled. This was sufficient to study behavior of the phenomena posed there, namely the sensitivity of the value of complex securities to delinquency rates, default correlation, and recovery rates. These aspects of mortgage-backed securities played an important role in the 2007-9 meltdown. We now want to make the asset prices endogenous and their interaction with leveraging explicit.

A number of papers, published by the authors, relate asset prices and debt dynamics in a rather complex way.[16] Here, we propose a simpler version that captures the intuition of the more complex models and may better explain the current financial market meltdown. The guiding approaches for linking asset prices and leveraging are work by Geanakoplos (2010), Brunnermeier and Sannikov (2010), Miller and Stiglitz (2010), and Hall (2010).

As in that literature, we want to relate expected payoffs and asset prices to borrowing. When the expectations of payoffs are stimulated by a borrowing boom, this often works hand-in-glove with an asset-price boom; this occurs because asset-price rises will stimulate borrowing. So, while there will be some asset price rise, due to its interaction with borrowing, some "bad" events, e.g., a collapse in the value of some complex security, may also lead to a sudden decline in asset prices and, hence, borrowing. Since asset prices are essentially determined by discounted future pay-offs, leverage can be, alternately, undercovered or overcovered by asset prices.

Note that there might be locally-arising externalities: higher asset prices allow, through higher collateral valuations, increased leveraging. Higher leveraging means more household and firm expenditures, reduced borrowing constraints, and liquidity constraints for agents: One agent‘s reduction of liquidity constraints means more spending; more spending relieves the borrowing and liquidity constraints of other agents. Although our proposed mechanism will, at some level, accelerate borrowing and increase expectations, later, it is likely to lead to a slowdown and may trigger rapid declines.

The above mentioned models by Brunnermeier and Sannikov (2010) and Geanakoplos (2010) have those features. The Brunnermeier and Sannikov model works with flows and stocks of capital assets and liabilities, the latter representing debt and (outside) equity. In that model, the excess of consumption and investment over income encourage borrowing and investment in capital assets, thus driving the evolution of capital assets and asset prices. But, on the downside, there could be externality and contagion effects (for example, through a "fire sale" of assets). Thus, it is also possible that there could be a negative feedback effect arising from falling asset values: falling valuations of collateral triggers rising borrowing costs

[16] See Semmler and Sieveking (2000), Semmler and Sieveking (2004), Gruene, Semmler and Bernard (2007), and Gruene, Chen, and Semmler (2008); a more behavioral foundation of the involved asset pricing theory is given in Gruene and Semmler (2008), where asset pricing with loss aversion is studied.

and credit constraints; this implies less demand for credit and more falling asset prices, etc.[17] This can, in turn, destabilize firms, financial intermediaries, and lead to a macroeconomic meltdown. In contrast to common DSGE models, this model is locally unstable, possibly leading to accelerated downturns.

Geanakoplos (2010) employs a similar positive feedback mechanism. His main construction is also a leverage cycle, but one defined in terms of flows. If, for example, someone wants to borrow an initial amount of $100 (maybe a home owner, a hedge fund, or an investment firm) but can pay $20 in cash, then we say that the margin is 20 percent. The leverage ratio is 5. So, the lower their own cash, or equity, contribution, the higher is the leveraging. In the housing sector a leverage ratio of 20 was common before the meltdown 2007-2009 and for investment firms a leverage ratio of 40 to 60 was not unusual.[18] The leverage ratio is the reciprocal of the margin, in this case: $100/20 = 5$. The same happens in the money market, when the investment firm is borrowing at a lower margin, the leveraging rises and vice versa.

Geanakoplos argues that during a boom, the margin is lowered and leverage rises. As the margin falls, borrowing increases along with profit expectations. In a recession, the margin is rapidly rising and the reverse happens. This would predict that in booms, leveraging and profit expectations[19] are rising while in recessions, both are falling. This prediction of pro-cyclical leveraging appears to be in contrast to empirical results, see Gilchrist et al. (2009), which seems to show a falling leveraging in the boom and a rising leveraging in the recession. Yet, as Geanakoplos convincingly argues this stems from a measurement problem, namely that fact that the value of the equity rises in the boom and falls in the recession.

Geanakoplos' theory has immediate implications for asset pricing. Lower margins and higher leveraging takes place in a climate of optimistic expectations and both will drive up asset prices. In recessions there is a pessimistic climate, lower profit expectations as well as lower leveraging and asset prices are falling. Geanakoplos sums up his theory by stating :

> "... variation in leveraging has a huge impact on the price of assets, contributing to economic bubbles and busts... ...leveraging becomes too high in boom times and too low in bad times. As a result, in boom times asset prices are too high, and in crisis times they are too low. This is the leverage cycle"; see Geanakoplos (2010)

He also presents some empirical work where he shows that the margin requirements have been varying in the financial market, in particular for financial firms, ranging from 10 to 70 percent, the former, for example, until 2007 and the latter in 2009.

[17] For further details of such a mechanism, see Brunnermeier (2009).

[18] See Geanakoplos (2010).

[19] The nexus of leveraging and the profit expectations is expressed in the following statement, Geanakoplos (2010) says, there is "... the expectation by the leveraged ... that good times are coming", so leveraging is accompanied by over-optimism in profit expectations.

The paper by Miller and Stiglitz (2010) is another work in this direction. As in Geanakoplos, they illustrate the inter-linkages of borrowing in a two period model, in discrete time fashion. By assuming credit restrictions in borrowing, where by the borrowing is constrained by net worth, next period's discounted value of asset income, which forms the asset value, will constrain current period borrowing. They sketch the relation of borrowing and asset prices in the two period model as:

$$b_t = E_t q_{t+1} k_t / R$$

with b_t representing borrowing, and $E_t q_{t+1} k_t / R$, the the value of capital asset next time period. R is a gross return which acts as the discount rate used to obtain the present value of the expected capital value of next time period. Given fully collateralized borrowing, where borrowing is constrained by the given (expected) collateral value, empirically this would predict a high correlation of borrowing and the discounted expected pay-offs of capital investments. This is a relation that is also used in our model below. Thus, for both the lender as well as the borrower, the collateral value is often quite fuzzy, and subject to speculation. So, we want to note that borrowing is not always fully covered by collateral value. Leveraging may sometimes be over-covered by the value of collateral and sometimes under-covered.

Further interesting work in our context is found in Hall (2010, Ch. 7). Additionally he sketches a model of debt-to-capital asset interaction. His model is a discrete time infinite horizon model, with household preferences in the objective function, consumption as a dynamic decision variable, the evolution of capital stock as the first state variable and the evolution of debt (as long as there is non bankruptcy) as the second. Our model has similarities with his model. We will work with an infinite time horizon but use a continuous time set-up.

Employing the basic elements in the construction of the leveraging - asset price interaction, as proposed in the above mentioned work, we want to sketch a model that works with flows and stocks, exhibits one dynamic decision variable (investment), but also exhibits, as in Hall (2010, Ch. 7) two state equations: The dynamics of capital assets and the dynamics of debt. Here, then, borrowing and the evolution of debt is driving asset prices and rising asset prices may feed back into borrowing. Yet, realism suggests that one should avoid a completely unstable mechanism through positive feedback effects; therefore, we will keep the dynamics bounded through some reasonable constraints. We will also allow the leverage either not to be fully covered by collateral value or to be over-covered.

As is the case in most of the above literature, we concentrate on firms (real firms, financial firms) that are allowed to borrow and to leverage their activities. In a traditional model of asset pricing the limit of the leveraging is the value of the firm. Usually, since Merton (1974), it is assumed that the asset value of the firm is given by a Brownian motion when the firm's debt is priced, as also assumed in the prior section. Then the adding-up theorem, namely $V = S + b$ is supposed to hold where V is the asset value, S the value of stocks and b the value of bonds. The distance of the value of the firm to the debt is called the distance to default, commonly employed in the KMV model. Yet, we not only want to determine the value of assets endogenously, but also show how it might be impacted by leveraging.[20]

Let us first focus on the typical firm's inter-temporal investment strategy to accumulate capital assets. For the debt equation we assume, that debt can be continuously issued and retired. We can interpret the firm as real company producing output, or as a financial intermediary producing financial services and buying assets through borrowing. In both cases, the firm borrows to invest in capital assets and the expected cash flows determine its asset value. As in the traditional model, the value of the firm represents its debt capacity, but in our model there are also feedback effects from leveraging to the value of the firm. If the debt is equal to the value of the firm, there is likely to be a default even if only small shocks occur. Yet, if the debt taken on by the firm is lower than the value of the firm there is a positive distance to default and shocks to the value of the firm may not lead to defaults. Such distance-to-default models have found wide-spread acceptance in the industry, e.g. the KMV model, which has become popular among financial market practitioners.[21]

Since we want to use stocks and flows, we employ a model that is similar to Brunnermeier and Sannikov (2010) and Mittnik and Semmler (2010) where there are two state equations.[22] Employing the above sketched theory by Geanakoplos (2010), we can study the following dynamic-decision problem of a firm[23]

$$V(k) = \underset{j}{Max} \int_0^\infty e^{-rt} f\left(k(t), j(t)\right) dt \tag{1}$$

$$\dot{k}(t) = j(t) - \sigma k(t), \quad k(0) = k. \tag{2}$$

.

$$\dot{b}(t) = r(b(t)/k(t))b(t) + \phi(b/k)b - g\left(k(t), j(t)\right), \; b(0) = b_0 \tag{3}$$

The (expected) cash flow to be managed by the firm is composed of net income and expected profit flows. As we will show below the latter will be a function of the distribution of the borrowing to capital ratio. We thus define:

[20] A more detailed proof that leveraging impacts asset value is given in Gruene, Semmler, and Sieveking (2005).

[21] For a further discussion of the distance to default, or KMV, models, see Semmler (2011, ch. 19).

[22] We note that one could also turn the subsequent model into a model with households that make inter-temporal consumption decisions, see Appendix 3. So, in the subsequent model, asset pricing is studied without reference to utility theory. In Gruene, Semmler, and Sieveking (2005) an analytical treatment is given of why and under what conditions the subsequent dynamic decision problem of a firm can be separated from the consumption problem. In Brunnermeier and Sannikov (2010) and Mittnik and Semmler (2010) household behavior is included in the model.

[23] Note that we do no have here a usual optimization problem, since we do not have linear credit cost, we state our optimization problem in a way that it has state-dependent credit cost. Our numerical procedure, as briefly summarized in appendix 2, can also solve difficult problems where there are state-dependent default premia.

$$f(k(t), j(t)) = ak(t)^{\alpha} + \theta(b(t)/k(t))b(t) - j - \varphi(k(t), j(t)). \tag{4}$$

The flow $f(k, j)$,[24] is discounted to obtain the asset value of the firm. It is generated from production function, Ak^{α}, minus investment, j, and minus the adjustment cost of capital $\varphi(k, j) = j^{\beta}k^{-\gamma}$ plus the expected profit flow, $\theta(b/k)b$, related to borrowing,[25] Investment is the choice variable in order to maximize the present value of the total cash flow of (4). Note that $\sigma > 0, 0 < \alpha < 1, \beta > 1, \gamma > 0$, are constants.

Equ. (2) represents the equation for accumulation of capital assets. The equ. (3) represents the second state variable, the evolution of the debt of the firm, with the primary deficit

$$g(k, j) = ak^{\alpha} - j - \varphi(k, j). \tag{5}$$

Equ. (4) shows that the primary deficit of a firm, $g(k, j)$, is equal to total income, generated by the production function, minus investment (including adjustments costs); if there is negative primary deficit, debt can be retired.

Furthermore, as both Brunnermeier, Sannikov, and Geanakoplos argue, if asset values are high, the margin requirements will be low and the borrowing high. So, if the firm will raise additional funds from the credit market in the amount $\phi(b/k)b$, which will increase its debt, it will also increase the profit expectations, and the present value which is to be obtained through an optimal investment strategy j.[26]

Thus the borrowed funds, which relaxes the constraints for investment, will indirectly also impact the investment strategies and the asset price. So, the raised funds are, as in Geanakoplos (2010), flows in equ (4) which will drive up investment into capital assets and asset prices. On the other hand, as we will show, the increase of asset prices will lead to a higher leverage so that $\phi(b/k)b$ will go up too. As we will demonstrate this will not go on indefinitely, there will be constraints for this dynamics which we will discuss below. Of course, the borrowing term $\phi(b/k)b$, which raises the expectations of higher cash flows, from which investment into assets can be undertaken, also increases debt.[27]

As mentioned above one can think of the term $\theta(b/k)b$ in (4) as capturing some expectation dynamics.[28] Geanakoplos (2010) has given a justification of this term as an expectation

[24] We leave out the time index.

[25] Note we are using here the argument by Geanakoplos (2010) that there is "... the expectation by the leveraged ... that good times are coming", so leveraging is accompanied by optimism in profit expectations, see our justification below.

[26] Note that Geanakoplos (2010) would have in the leverage function (4) and (5) the time rate of change of debt over assets, namely$\theta(\dot{b}/\dot{k})$ and $\phi(\dot{b}/\dot{k})$. Yet since we need to work with the evolution of stocks, we use the ratio of debt-to-stock, $\theta(b/k)$ as argument. This is reasonable, since eventually the flows will effect this ratio. We also tried the formulation of using flows, employing our dynamic programming algorithm, the results for the value function, and the dynamics of capital assets and debt came out are roughly the same in the flow version of Geanakoplos as compared to our proposed version using stocks in the equs (4) and (5).

[27] For a similar formulation of the asset accumulation-leverage dynamics, see Brunnermeier and Sannikov (2010).

[28] One could introduce here, some heterogeneous agents. If we have a mixture of optimists and pessimists

term.[29] It encompasses expectations of payoffs originating in leveraging: higher leveraging does not only mean the expansion of credit, but also the rise of optimism and expectations of higher payoffs, entailing higher investment. Higher leveraging and higher investment relaxes borrowing and liquidity constraints for other agents and other agents can spend more. The expected payoff of one firm is validated through credit expansions and expenditures by other firms and households.[30] This can continue for a considerable time period and a credit expansion might even go on without collateral-secured loans, or without margin payment at all. Thus, we might want to perceive $\theta(b/k)$ as representing a movement that is for a considerable time period above its mean, or below its mean. It cannot be ignored or included as simply "noise." We will also assume that expected future asset prices might under-cover or over-cover leveraging.

Our postulated positive correlation of profit expectations and leveraging resembles the Miller and Stiglitz (2010) idea. We can maintain the following: as anticipated profit potential increases, so does the degree of leveraging that a firm is willing to take on– and the financial intermediaries are willing to grant. The main measure of leverage is the debt to capital ratio. This is also a measure of the riskiness of a loan. Thus, the higher the debt to capital ratio, the higher the borrowing costs, as appearing in equ (3), yet associated with it is also a higher anticipate profits. For the borrowing cost, there may be limits. On the down side, there is a certain rate, the risk free rate, below which no firm can borrow. Similarly, there is an upper limit to the rate that may be charged. This defines the shape of our borrowing cost, $r(b/k)b$, in equ. (3)

Now, clearly, no firm knows for sure what the profit level associated with a particular degree of leverage. However, there are expectations associated with the degree of leveraging. In other words, a bank would probably assume that the high degree of leveraging associated with a debt-to-capital ratio implies high profit expectations on the part of the firm's managers, but the profit expectations might not be linear. This the higher leveraging implies a high degree of risk to the bank. Thus, the profit expectations of the firm are proxied by the debt-to-capital ratio, but with a declining increase as the leveraging goes up. Though in absolute terms in may hold that the larger the debt taken on, the higher the profits expected.

Now we have to make explicit our functions employed. We suppose that a credit manager would reason that the relevant factors in his analysis would be (1) the probability that the firm's debt-to-capital ratio remains below some threshold, (2) the actual size of the debt taken on, and (3) some industry or firm-specific factor(s). The expected value of additional profits due to borrowing might thus be stylized as follows:

they could start to synchronize on one side or the other, so that overall the profit expectations would be driven up or down.

[29]A profit-expectations term, such as the one we use in equ (4), is also used in Adams and Marcet (2010). Note that our term is discounted to obtain the asset value. In Adams and Marcet, the mean profit expectations term is stylized as a result of a learning process involving economic agents, i.e., as the persistent component of their expectations. However, the agents do not consider leveraging.

[30]This idea goes back to Kalecki (1937a, 1937b), though there in a zero horizon model.

$$E\left[profits\right] = \theta\left(\frac{b_t}{k_t}\right) b_t \qquad (6)$$

where $\theta\left(\frac{b_t}{k_t}\right)$ is the probability of the debt-to-capital ratio remaining below $\frac{b_t}{k_t}$. Obviously, as this ratio increases, the riskiness, and hence the risk premium, will also climb. But this, in fact, occurs with a delay, so we will stylize its instantaneous impact as small.

The reason for this is as follows. If one looks at the data from 2000-2007, we can observe (slightly disrupted through 2001) two major stylized facts:

- Investment and Commercial banks, private investors, and mortgage buyers face, since 2000, exceptional funding conditions, not only concerning low interest rates, but because of over-optimism and underestimation of risk. Thus, they pay also low credit spreads for the riskier borrowing. Not only is the Baa-Aaa spread very low but also the financial stress index provided by the KCFED[31] is at historical low levels, and so are the credit constraints[32]. Both declined markedly between 2002 and 2007.
- Yet, at the same time investment and commercial banks with high profit expectations become more leveraged. For example, Blundell-Wignal and Atkinson (2008) demonstrate rising debt levels for US banks‘s balance sheets. According the Fed, the debt of commercial banks rose from 59 percent of GDP in 1999 to 76 percent at the end of 2007. A similar rise of households‘debt could be observed.[33]

Thus, in spite of high leveraging during this period, we might observe an optimistic view of profit expectations, low risk premia and low credit spreads, and few credit constraints. So, in our model the instantaneous impact of the debt-to-capital ratio on the premium will be low (see below).

Finally, we should not assume that the actual debt-to-capital ratios would be normally distributed around some target value, as has been common in many financial studies. In light of recent financial history, it would seem that a leptokurtic (fat-tailed) distribution would be more appropriate. In our model, therefore, we suppose that the debt-to-capital ratio follows a hyperbolic-secant distribution:

$$f(x) = \frac{1}{2} sech\left(\frac{\pi}{2}x\right) \qquad (7)$$

This distribution is almost identical to the Standard Gaussian Normal distribution, $\mu = 0$, $\sigma = 1$, but with a kurtosis of 5 instead of 3. This seems a more appropriate choice than

[31] See the KCFSI (2010)
[32] See the Fed survey on loan officers, Fed web-site.
[33] See Hudson (2005), see also Hall (2010) & Semmler and Bernard (2009)

either a uniform or a normal distribution. The hyperbolic-secant distribution is known to have a cdf given by

$$F(x) = \frac{2}{\pi} arctan \left[exp \left(\frac{\pi}{2} x \right) \right] \tag{8}$$

Thus, we stylize our cdf as

$$\theta \left(\frac{b}{k} \right) = \upsilon arctan \left(\frac{b}{k} \right) \tag{9}$$

The function (6) has the following properties. It is locally, at a mean level of leveraging, rather steep and may show a 45 degree angle. That means that locally as (b/k) is going up actual leveraging is going up in the same way. This is what Geanakoplos (2010) has assumed. But we note that the function implies some boundedness, where $\nu > 0$ as constant. Similar sigmoid functions are often found in asset price and portfolio models[34]

For the profit expectation dynamics we thus take

$$\theta(\frac{b}{k}) = \kappa \; arctan(\frac{b}{k}). \tag{10}$$

Taking (9) and (10) in this way, avoids the extreme instability arising in the asset price leveraging dynamics in Geanakoplos (2009) and Brunnermeier and Sannikov (2010). It also keeps the cash flow expectation dynamics bounded. So, as we can observe (9) and (10) are closely related, here in a linear fashion.[35]

The economic interpretation is that financial agents are likely to become more cautious in their expectations of profit flows or in the actual amount to be borrowed as the ratio of b/k rises. In terms of the expected profits, for example, that means that an already high expected cash flow might deter agents to expect this to prevail at such a level for too long.

As to our above mentioned state-dependent risk premium and credit cost, $r(b/k)$, we have taken a similar function, which is calibrated in a way that reflects a risk free interest rate in the limit (that of no debt). Thus, here we consider a case where the firm has to pay a default or finance premium, but the impact on the debt dynamics is initially kept low, as justified

[34]Earlier use of it in finance can be found in Beja and Goldman (1980), for a recent use see Chiarella et al. (2002), and Chiarella (2009, ch. 6 and 8, where extensions to heterogeneous agents and the stochastic case are provided.

[35]Other (nonlinear) relationships could be introduced between the leveraging and expected cash flow, but in order to demonstrate the mechanics of this basic model, our above formulation is sufficient. Note that in the numerical solution procedure, we do not extend the *arctan* function to the negative region. This is avoided by using our DP algorithm in the positive state space.

above.[36] We restrict our considerations here to the simplest case, as in equ (3), where the firm pays a risk premium formulated in a simple way.[37]

If the interest rate, r, is a constant[38], and the debt dynamic term, $\phi(b/k)b$, and profit expectations dynamic term, $\theta(b/k)$, drop out then we have a simple case: it is then easy to see the debt capacity is $V(k)$, the present value of k.[39] For any value of debt, b, below V, holds that $V - b > 0$ and the residual remains as equity of the firm.[40] Yet, for studying the inter-linkages between leveraging and asset prices a constant interest rate is an unrealistic formulation.

Next we solve the model of equs. (1)-(10) using our dynamic programming algorithm as sketched in Appendix 2. The solution gives us the asset value as the maximum debt capacity that the agents can take on; note that the asset value is affected by leveraging through profit expectations. Also, we solve the above model with the terms $\phi(b/k)$ and $\theta(b/k)$ in equs. (3) and (4). Overall we have a dynamic decision problem with one decision variable and two state variables; thus, the model is highly non-linear. This can be turned into a dynamic programming problem. Gruene and Semmler (2004) have developed an algorithm to solve such dynamic programming problems with a numerical algorithm. Our DP method, sketched in Appendix 2, goes back to papers by Capuzzo-Dolcetta (1983), Falcone (1987), and Gruene (1997).

We first want to study a benchmark case where there may be past debt but no new leveraging, so the terms $\phi(b/k)b$, and $\theta\,(b/k)\,b$ are zero. As the results of our solutions show, the value of the firm is low, see Figure 9, and moves in waves, due to the risk premium's moving with the debt to capital stock ratio.

The results of our exercises of solving the asset pricing model with no new borrowing and profit expectations terms provides us with the following graph.

[36]We will stylize our slow influence of the debt to capital ratio on the risk premium by using a small coefficient and thus a long adjustment time; introducing an actual delay here would give rise to a delay model, which is complicated to solve - see Maurer and Semmler (2010).

[37]As mentioned above, we use the same *arctan* function-type for the risk premium. This has a lower limit, the risk free rate, and an upper limit. The upper limit of a premium charged is justified, since, as Stiglitz has always argued, with higher default premia, the lender might have loan losses at greater credit spreads.

[38]As aforementioned, in computing the present value of the future net income, we do not have to assume a particular fixed interest rate. In an even more general setting than is used in our formulation above, the present value, $V(k,b)$, can also, for the optimal investment decision, enter as an argument in a more general credit cost function $H\,(k, V(k))$; see Gruene, Semmler and Sieveking (2005).

[39]This is the standard case in which it holds that sustainable leverage is $\lim_{t\to\infty} e^{-rt}b(t) = 0$, as the non-explosiveness condition for debt, to close the model. But note that our model is more complex.

[40]The more general case, however, occurs when there is an endogenous default premium. If we have a more general form of $\phi\,(b,k)$, then the creditworthiness itself might become difficult to treat. Pontryagin's maximum principle is not suitable to solve the problem with endogenous default premium and endogenous net worth and we thus need to use special numerical methods to solve for the present value and investment strategy of a levered firm (see Gruene, Chen, and Semmler (2008).

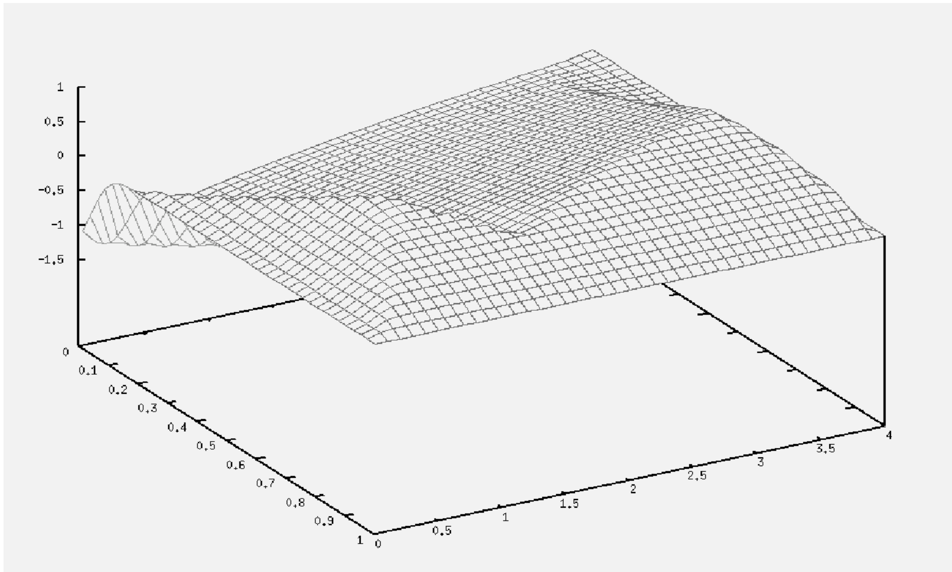

Figure 9: Value function representing the asset value of the firm for the benchmark case

Figure 9 shows a screen plot of the value function. The front axis represents the size of leveraging, b, going from 1-4 and the axis going to the back denotes the accumulated capital assets, going from 0 to 1. The value function represents the value of the capital assets. It obtains a maximum height at roughly 1.0

Note, however, looking at Figure 9, if the debt is rising (see the horizontal axis), then debt eventually becomes higher than the value of the firm and bankruptcy will occur, since the distance to default has become zero.[41] For any smaller amount of debt there would be a positive distance to default and the firm could pay its liabilities, keeping the remaining part as equity, as the Merton model suggests.

We also present the vector field of the benchmark model; this is shown in Figure 10. As the figure shows, there are regions of the state space that are stable, capital stock shrinks, and debt goes to zero and there appears to be an attracting point at capital stock roughly $k^* = 0.5$, except debt is already too high.

As one can observe from figure 10 there is a large region of stability where capital stock and debt contract. There is also a size of initial debt where debt will not shrink, but rise, due to payment of the risk premium. With high debt, the debt is driven up further because of the high risk premium.

Next we want to introduce the impact of new leveraging and profit expectations on asset prices. Thus, the terms $\phi(b/k)b$, and $\theta\,(b/k)\,b$ will be positive, but first we assume that the

[41] This is identical to the case in the Hall (2011:p.100) model: if there, z‘=1, bankruptcy occurs, all the previously held debt by creditors is lost.

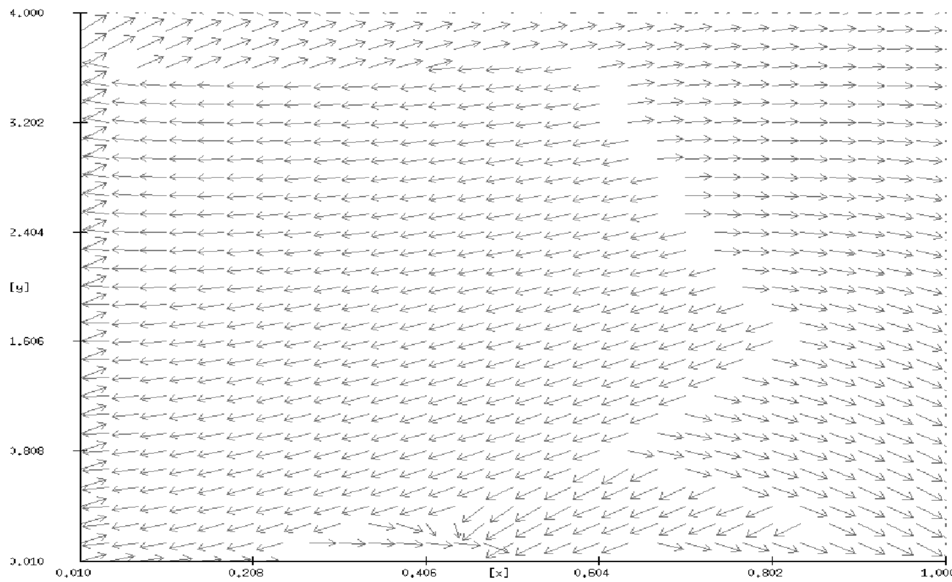

Figure 10: Vector field for the benchmark case

leveraging has a low impact on profit expectations, so $\theta\,(b/k)\,b < \phi(b/k)b$, and .[42] This could roughly represent the case where, though there is borrowing, there is no euphoria in profit expectations and thus borrowing is not fully covered by collateral values. For this scenario we obtain the following value function as shown in figure 11

Since now there is a leverage effect on profit expectations, though to a limited extent, the value function is higher than in the case of Figure 9. Also, when debt is built up (see the debt is going up roughly to 1.2) the asset value is represented by the value function and thus the asset value is higher as compared to the case of no new borrowing. Thus the asset value is going up with borrowing. But, of course, also the debt is rising faster, since fresh borrowing occurs– and with fresh borrowing there is a rise in asset value. Since the dynamics is roughly the same as in the case of Figure 9 we will forgo the presentation of the figure. Yet, whereas in Figure 9 the debt below 1 already is a problem (since the asset value is much too low), in the case of Figure 11 there is a bankruptcy risk when the debt reaches roughly 1.

In the next case we want to allow high leveraging and high profit expectations.[43]

In the case of Figure 12, as one would expect, the value function and thus the value of the firm becomes larger and the build up of debt becomes less of problem since the distance to default is still positive, at least for a debt going up roughly to 1.4. Here too the dynamics in debt and capital assets is roughly the same as in Figure 3 except that the separation line of attracting and repelling dynamics moves further inward.

[42]This is achieved by choosing the coefficient in front of $\phi(b/k)b$ as 0.3 and for $\theta\,(b/k)\,b$ as 0.1.

[43]Here we take the coefficient in front of $\phi(b/k)b$ as 0.3 and for $\theta\,(b/k)\,b$ also as 0.3.

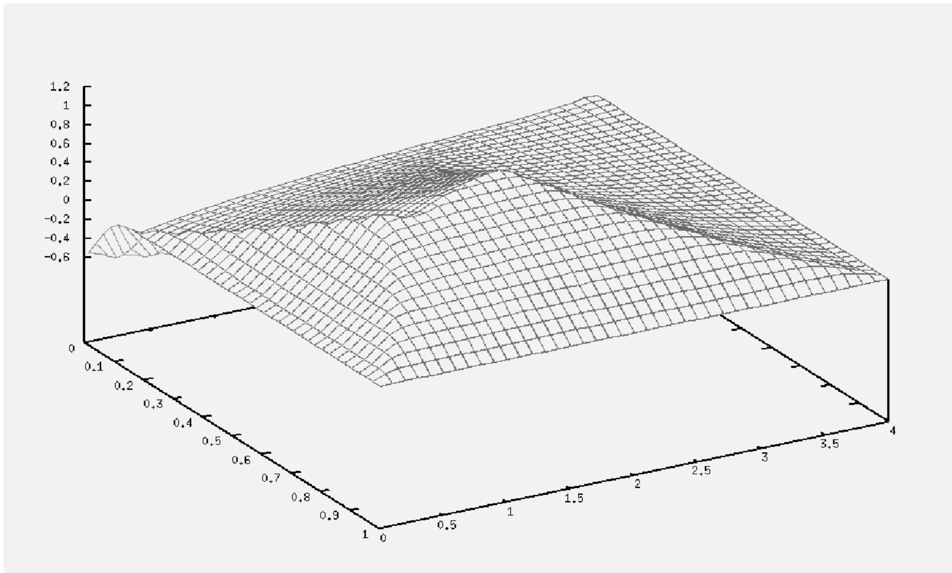

Figure 11: Value function for leveraging, but limited profit expectations

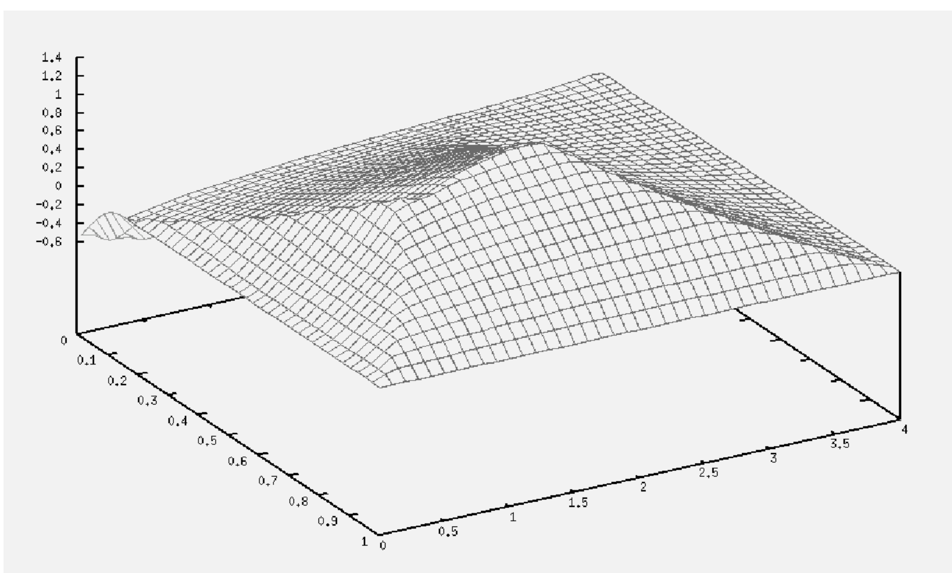

Figure 12: Value function for large borrowing and large effect on profit expectations

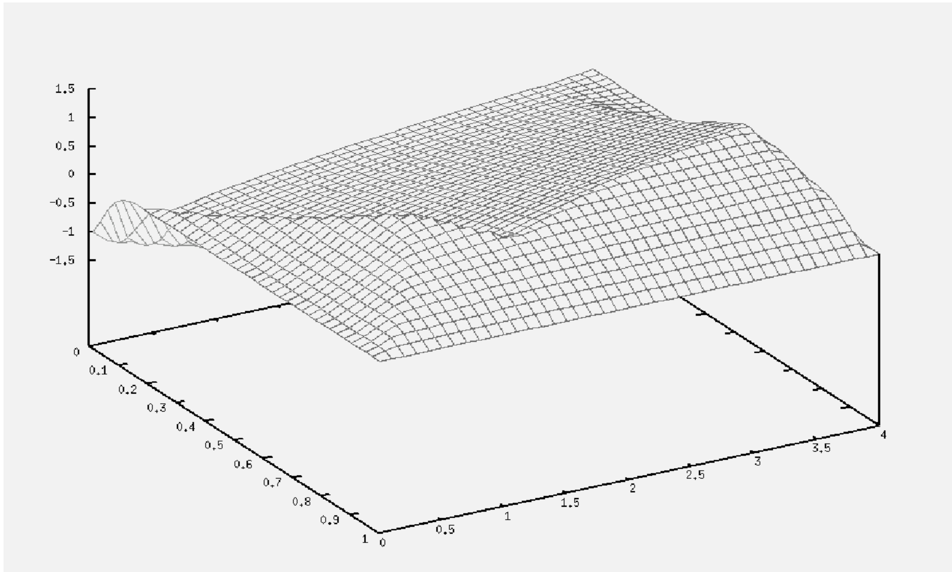

Figure 13: Value function resulting from overly optimistic profit expectations

Above we see also another effect mentioned above. The asset value of the firm rises faster if there is borrowing, at least up to a point, then the debt dynamics takes over, the asset value falls fast, and the distance to default quickly shrinks leading to the bankruptcy case with asset value smaller than the liabilities.

In the next case we evaluate what happens if the agents become over-optimistic in terms of profit expectations, as compared to the actual leverage undertaken.[44] In this case borrowing could be lower than the actual value of collateral.

In Figure 13 we can see slow debt build up with a coefficient of debt-value build up of 0.05 in the leveraging. This leads to slow asset build up through the profit expectation function, but it also can lead to insolvency. The value function in principle can go up to 1.5 but the second region of attraction for a high value of the firm is at about a size of a debt approximately close to 3.5, thus the second region of attraction is clearly a bankruptcy region.

Next we introduce a consumption out of net income. Let us say there are bonus payments out of net income, $d(b/k)b$[45]

Then the equ. (5) would read:

$$g(k,j) = ak^{\alpha} - j - \varphi(k,j) - d(b/k)b$$

[44]Here we take the coefficient in front of $\phi(b/k)b$ as 0.05 and for $\theta\,(b/k)\,b$ as 0.3.

[45]We assume bonus payments are a fraction of total borrowing. The bonus payment could also take the form of dividend payment if executives obtain equity shares, or at least a fraction of the bonus payment could be deferred as equity holdings, as for example the EU has suggested in 2010.

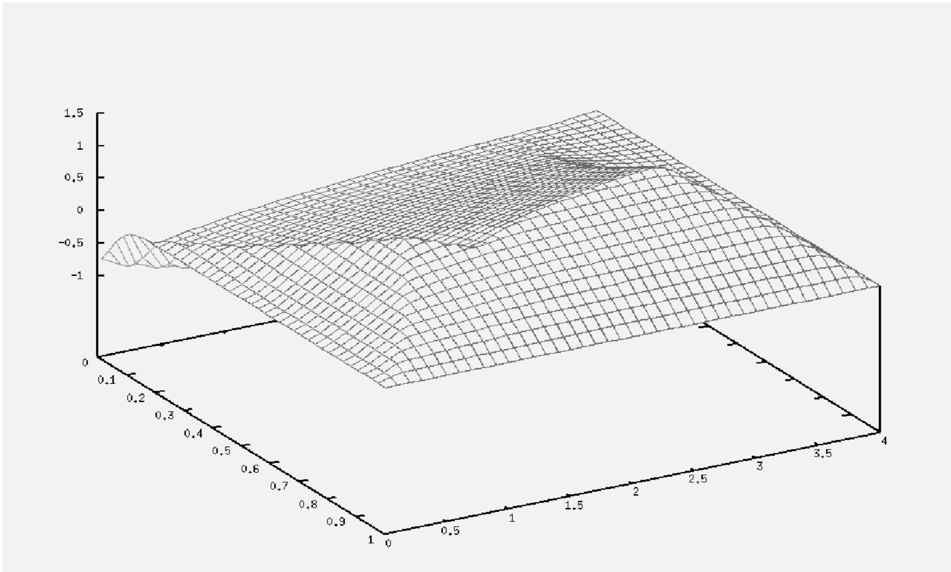

Figure 14: Value function with bonus payments

For reason of simplicity we define the bonus payment simply also as nonlinear fraction of leveraging, defining $d(b/k)$ as fraction.[46] The intuition here is that with the rise of bonus payment the debt will rise faster.

As we can observe there is not so much difference with Figure 13, there are two effects working: if debt rises relative to asset value, due to bonuses, that increase debt burden and credit spread, but if the profit expectations rises too, asset value will rise, see Figure 14. The the increase of debt due to bonus payments comes from the fact that the bonus payments will reduce net come available for debt repayment.

If we rotate the value curve we can see another effect.

As Figure 15 shows if one slices the value function along the dynamics of debt, the value function obtains a changing form.

Though the previous figures have shown the ups and downs in the value of the firm as a function of both the size of capital assets and leveraging, Figure 15 shows the further rotated value function clearly exhibiting a movement of the asset value as a function of the capital assets, k : first rising with the level of capital assets and then falling.[47] But there is also

[46]We hereby pre multiply the bonus payment function by a coefficient of 0.1.

[47]In a previous version of the paper we had made the boom-bust cycles in asset prices solely dependent on the size of the capital assets. This has been criticized by one of the referees. Yet we can see here that this case is included in a 3 dim representation of the problem. The value function can, here depicted in a third dimension, be thought to be given for each value of leveraging, and with leveraging changing the asset value of the capital assets are changing.

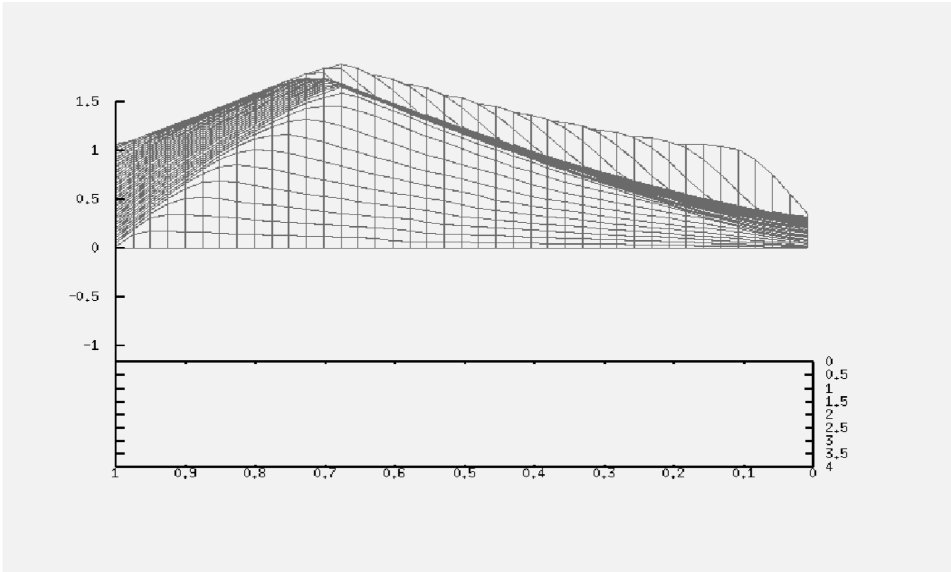

Figure 15: Rotated Value Function

a decline of the value of capital assets as the capital assets increase further. Thus, one can observe a value function with bubbles. These bubbles arise from the movements of $\phi(b/k)$ and $\theta(b/k)$, but they change their shape with changing debt.

Next, we want to explore if there are multiple regions of attraction. This can best be seen by plotting the optimal vector fields for different initial conditions. This is done in Figure 16. Figure 16 plots the vector field for the dynamics of the two state variables in the entire state space. This shows there are different regions of attraction. As is clearly visible in figure 16, for low levels of capital, the capital shrinks further and debt rises. We have already seen that if the value of assets is lower than leveraging, insolvency will arise. This is made visible here: as trajectories contracting with respect to capital assets, they can be rising in terms of debt. On the other hand, low borrowing can maintain positive capital assets. Large capital assets and borrowing will make both rise and high-level attractors for both variables appear.

Finally we show results of the case when we start with the previous case but introduce a higher bonus payment.[48]

Clearly, as we can predict from equ. (3), debt builds up; the debt rises even faster because there is less net income and debt retirement and also through the rise of the risk premium and credit spread. Yet, on the other hand, due to overoptimism and rising profit expectations, the asset value is rising too, as we can observe from Figure 17. Thus asset value rises quickly with higher leveraging, but this case can also quickly turn into insolvency or bankruptcy, since the capital assets falls quickly after the peak and the distance to default dissipates quickly.

[48]We here pre multiply the bonus payment function by a coefficient of 0.4.

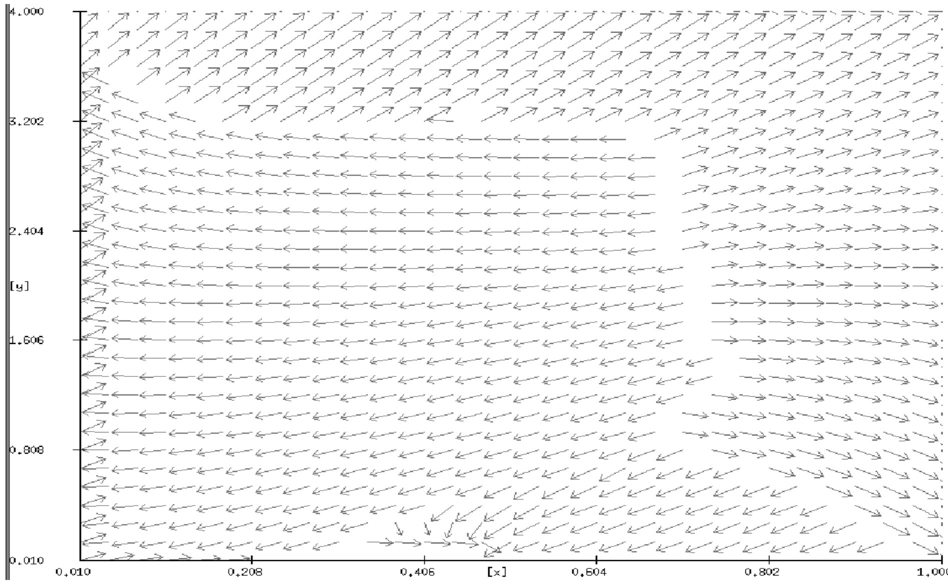

Figure 16: Vector field of the dynamics

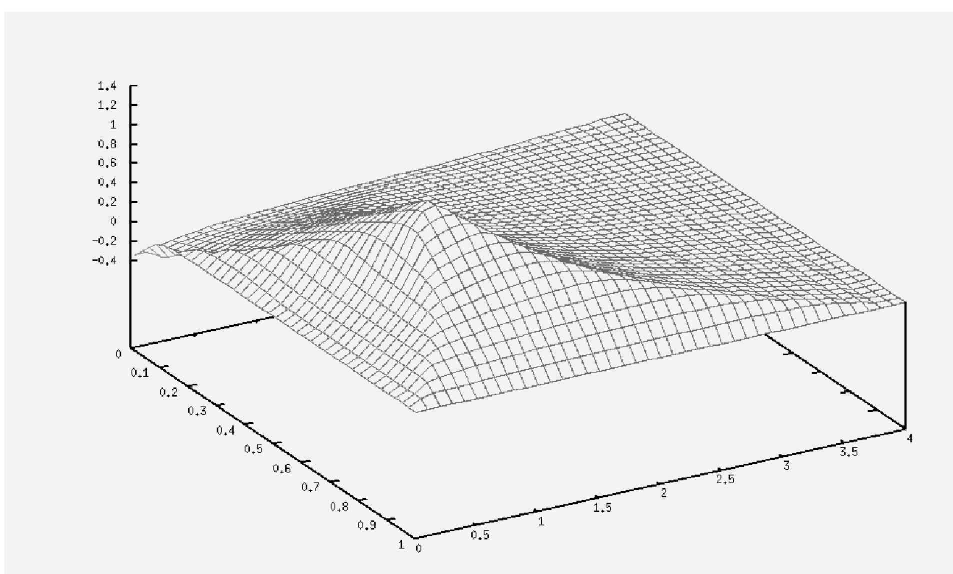

Figure 17: Value function with rising bonus payments

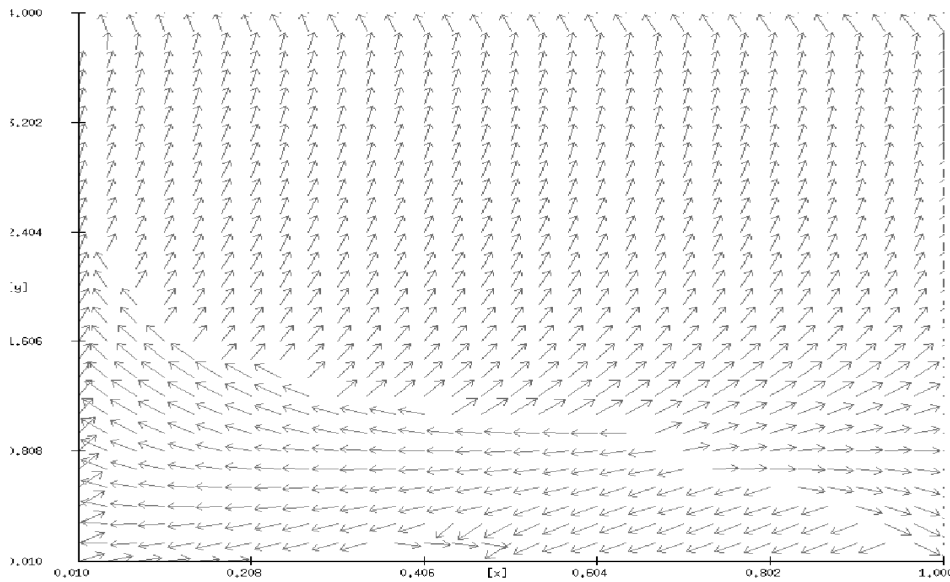

Figure 18: Vector field with bonus payments

Next we want to show the vector field of this.

As to the vector field, if one compares the Figure 18 with Figure 10, where there is no new borrowing and no effect on profit expectations, in Figure 18 there is only a small region of stability. Trajectories to the right of the bifurcation line move quickly up to high debt, and we quickly will have the situation of $V < b$, the bankruptcy scenario.

We can summarize our results in several points:

- Higher debt to capital asset ratio usually entails risk premia and credit spreads, this can produce fluctuations in asset value and higher bankruptcy risk (two regions of attraction arise, one sustainable, and another one unsustainable)
- Taking into account the linkage of leveraging and profit expectations, the asset value of capital is likely to rise– thought there can sometimes be excessive optimism with respect to leveraging or low profit expectations with regard to the leveraged investments (thus borrowing is sometimes over-covered by expected collateral value and sometimes under-covered)[49]
- If there are two regions of attractions arising, which are likely to occur with further nonlinearities - nonlinearities over and above the one creating the risk premium – then again one region represents usually sustainable debt, the other region: bankruptcies — bankruptcies occurring whenever V<b

[49]Since there is the future-thinking involved in calculating asset prices, the collateral values as constraints are mostly speculative. One could thus speak of a "speculative" constraints for borrowing.

- If the three dimensional value function representation is reduced to a two dim representation by slicing the value function along the debt dimension, one can observe the changing value functions for different levels of debt

- With bonus payments (and other factors), causing the rise of the debt to capital ratio, the debt is rising faster but if the euphoric boom and over-optimism in profit expectations is accompanying the rise of debt, the asset value also rises quickly but also falls quickly, entailing financial fragility, disruptions and busts.

As we have discussed in Section 2, the risk transfer by financial firms using complex securities have amplified the risk taking but decreased the risk screening of borrowers. These magnifying forces are particularly relevant in explaining the most recent boom-bust cycle. It also gave rise to the housing boom experienced by individuals who are not, in general, equity players. Yet, instead of looking there for explanation, we believe that it was the growth of the CDO industry, specifically MBS products, that suddenly released excessive risk taking and a vast amount of capital to risky investments.

Taking into account the dynamics that complex securities might add to the complexity of intermediation, and to higher leveraging and asset pricing, one should mention further important factors, contributing to the high asset value of complex securities. For example, were the expectations based on low delinquency rates, low default correlations, or high pay offs? Higher leveraging than was justified by asset values, apparently, created slight changes in delinquency rates in the housing sector, triggering insolvencies and default correlations making leveraging shrink. Lower leveraging caused asset prices to fall and the vicious cycle downward continued.

The existence of multiple attractors might explain the characteristic overshooting phenomena seen in the Case-Schiller index with the sudden decline. Investors above/below this point continue to make investment decisions that increase/decrease the size of their assets. At first, this is realized as increased market value. However, as they continue to increase assets, they may overshoot to investment levels that are unsustainable. If the investors are able to sustain investment of sufficient size to get beyond some critical level, but with further leveraging, as we showed, asset value will eventually fall. Yet there was the sudden drop of asset prices, as well as leveraging — this might have come, as argued above, from the sensitivity of the pricing of complex securities with respect to small changes in delinquency rates, default correlations and so on, and this might also explain the collapse of the Case-Shiller index.

Many had expected real estate prices to level off around 2001 - the end of the dot-com era. Instead, we see real estate prices breaking through the barriers to new levels from 2000 to 2007. Also, as we can see from the single-family home sales, volume follows a similar pattern. We believe that it was the growth of the complex securities, specifically MBS and CDO products, and their expected rising prices that suddenly released vast amounts of capital to risky investments and magnified the usual boom-bust cycle.

4 Conclusions

It appears that many boom-bust cycles are driven by linkages between leveraging and and asset prices, yet leveraging could be over-covered or under-covered by collateral value. As we show, collateral value appears a rather fuzzy concept based on speculative elements. The mechanism observable in boom-bust cycles is rather general: the boom period triggers over-confidence, overvaluation of assets, over-leveraging, underestimation of risk, and over-issuing of unsecured loans; then follows a triggering event and the market mood turns pessimistic; finally, undervaluation of asset prices and deleveraging takes place. Most of the historically experienced boom-bust cycles exhibited such features. Yet, recently, beside credit, bonds and stocks, new financial tools have been developed, such as MBS and CDOs, that has acted as instruments of financial risk transfers. [50] We have demonstrate the magnifying effects arising from the risk transfer and pricing of the new financial market instruments. If some fraction of total asset accumulation is funded by the recently developed and implemented complex securities, debt is presumably built u faster and this the new instruments of financial risk transfer, is, as we showed, likely to magnify the usual mechanism of booms and collapses.

The role of the new complex securities for the mechanism of the crash is studied in other interesting works on the recent financial market crash; see Adrian and Shin (2009), Brunnermeier and Sannikov (2010) and Geanakoplos (2010). Yet, they stress the impact of the new complex securities on the excessive leveraging and its impact on the crash. In contrast to their work we refer also to the asset pricing mechanism that seems to have magnified the boom bust cycle and accelerated the crash. As we have shown, these new types of complex assets can lead to a rapid rise and then decline in asset valuations. This seems to originate in an intrinsic non-robustness in profit expectations and asset pricing of the new financial instruments in connection with leveraged financing. We have shown, using a pricing model for the complex securities, the non-robust character of these new financial instruments of intermediation: change of interest rates, delinquency rates, recovery rates, sudden rise of default risk and default correlations may make prices of those new complex securities very volatile, magnifying sharp rises or collapses of asset pricing, credit, and economic activity. Some of those phenomena were attempted to be captured in a simple dynamic model of asset pricing and leveraging.

[50] Also, see the recent book by Kaufman (2009) on this matter.

5 Technical Appendices

5.1 Cholesky Algorithm Used for Pricing Complex Securities

VB code for computing the Cholesky Decomposition:

```
Function Cholesky(Mat As Range)
    Dim A, L() As Double, s As Double
    A = Mat
    n = Mat.Rows.Count
    M = Mat.Columns.Count
    If n <> M Then
        Cholesky = "?"
        Exit Function
End If
ReDim L(1 To n, 1 To n)
For j = 1 To n
        s = 0
        For k = 1 To j - 1
            s = s + L(j, k)^2
            Next k
        L(j, j) = A(j, j) - s
        If L(j, j) <= 0 Then Exit For
        L(j, j) = Sqr(L(j, j))
        For i = j + 1 To n
```

```
            s = 0
            For k = 1 To j - 1
                s = s + L(i, k) * L(j, k)
                Next k
        L(i, j) = (A(i, j) - s) / L(j, j)
            Next i
Next j
Cholesky = L
End Function
```

5.2 Solution Method

We here briefly describe the dynamic programming algorithm as applied in Gruene and Semmler (2004) that enables us to numerically solve our dynamic model variants. The feature of the dynamic programming algorithm is an adaptive discretization of the state space which leads to high numerical accuracy with moderate use of memory.

Such algorithm is applied to discounted infinite horizon optimal control problems of the type introduced for the study of the global dynamics. In our model variants we have to numerically compute $V(x)$ for

$$V(x) = \max_{u} \int_{0}^{\infty} e^{-\theta t} f(x,u) dt$$

$$\text{s.t. } \dot{x} = g(x,u)$$

where u represents a vector of control variables and x a vector of state variables; this represents, in our case, the stock of wealth and debt.

In the first step, the continuous time optimal control problem has to be replaced by a first order discrete time approximation given by

$$V_h(x) = \max_{j} J_h(x,u), \quad J_h(x,u) = h \sum_{i=0}^{\infty} (1-\theta h)\hat{\imath} f(x_h(i), u_i)$$

where x_u is defined by the discrete dynamics

$$x_h(0) = x, \; x_h(i+1) = x_h(i) + hg(x_i, u_i) \tag{A2}$$

and $h > 0$ is the discretization time step. Note that $j = (j_i)_{i \in \mathbb{N}_0}$ here denotes a discrete control sequence.

The optimal value function is the unique solution of a discrete Hamilton-Jacobi-Bellman equation such as

$$V_h(x) = \max_{j} \{hf(x,u_o) + (1-\theta h) V_h(x_h(1))\}$$

where $x_h(1)$ denotes the discrete solution corresponding to the control and initial value x after one time step h. Abbreviating

$$T_h(V_h)(x) = \max_{j} \{hf(x,u_o) + (1-\theta h) V_h(x_h(1))\}$$

the second step of the algorithm now approximates the solution on a grid Γ covering a compact subset of the state space, i.e. a compact interval $[0, K]$ in our setup. Denoting the nodes of Γ by $x^i, i = 1, ..., P$, we are now looking for an approximation V_h^Γ satisfying

$$V_h^\Gamma(x^i) = T_h(V_h^\Gamma)(x^i) \tag{A5}$$

for each node x^i of the grid, where the value of V_h^Γ for points x which are not grid points (these are needed for the evaluation of T_h) is determined by linear interpolation. We refer to the paper cited above for the description of iterative methods for the solution of (A5). Note that an approximately optimal control law (in feedback form for the discrete dynamics) can be obtained from this approximation by taking the value $j^*(x) = j$ for j realizing the maximum in (A3), where V_h is replaced by V_h^Γ. This procedure in particular allows the numerical computation of approximately optimal trajectories.

In order the distribute the nodes of the grid efficiently, we make use of a posteriori error estimation. For each cell C_l of the grid Γ we compute

$$\eta_l := \max_{k \in c_l} \mid T_h(V_h^\Gamma)(k) - V_h^\Gamma(k) \mid$$

More precisely we approximate this value by evaluating the right hand side in a number of test points. It can be shown that the error estimators η_l give upper and lower bounds for the real error (i.e., the difference between V_j and V_h^Γ) and hence serve as an indicator for a possible local refinement of the grid Γ. It should be noted that this adaptive refinement of the grid is very effective for computing steep value functions and models with non-differential value functions and multiple equilibria, see Gruene and Semmler (2004).

5.3 Alternative Formulations: Default Premia and Wealth Accumulation

As compared to the formulation of default premia and wealth accumulation in section 3, one could use alternative modeling procedures. Default premia could also be empirically estimated.

Estimated Default Premia

In Gruene, Ohrlein, and Semmler (2009), a periodic behavior of default premia is modeled through a Discrete Fourier Transform (DFT). A harmonic regression is applied to historical data of bond returns in order to extract frequency movements of returns, their booms and busts, from actual time series. We can use this idea to study default premia. Following

Gruene et al. (2009), Hsiao and Semmler (2009), and using DFT, one can estimate the frequency components of the bubble part of the bond data, namely θ, from data using $r(t)$:

$$r(t) = \sum_{i=1}^{2} \Big(a_i \sin(t) + b_i \cos(t) \Big) . \tag{11}$$

In general, the movement of such bubble term, capturing synchronized behavior of agents, can be modeled by a set of sine-cosine functions, representing oscillations with different frequency and amplitude depending on time. Such a model can exhibit sharp peaks and troughs. Note that movements of $r(t)$ do not necessarily need to be smooth. Using DFT, as in our above formulation of the problem there can be sharp peaks and collapses, as in the saw tooth function, in the DFT composed of a set of sine-cosine functions of different frequency and amplitude. This will occur less so in our formulation above. This could replace our 2 dimensional formulation $r(b/k)$ if it is too cumbersome. We can use the above harmonic regression which gives very similar results.

Wealth Accumulation with Preferences

Since, in the model of section 3, the state variable k could represent wealth, our simple version, with constant interest rate, r, can be turned into a commonly used dynamic portfolio model with portfolio decisions and wealth accumulation based on preferences. If we replace under the integral the term $f\left(k(t), j(t)\right)$ by $d(t)$ we then can write a version of a wealth accumulation model:

$$V = Max \int_0^{\infty} e^{-rt} \ln d(t) \; dt$$

$$\dot{W}(t) = (r_W - \delta_W)W(t) - d(t), \quad W(0) = W_0.$$

.

Herein, $d(t)$ is the dividend payment which could be consumed. For the holder of the asset, the discounted dividend payment provides the value of the asset. With preferences $u(d(t)) = lnd(t)$, it can be shown that the valuation of the assets has a simple solution: namely the value of assets is proportional to consumption, $d(t)$, see Cochrane, (2001, ch. 9). The dynamic process of wealth accumulation is represented by the last equation above. Note that we have assumed that the investor is investing only in assets with fixed returns. This allows us to draw on the similarity of the capital accumulation model of equs. (1)- (4) and the wealth accumulation model here with portfolio decisions. An actual portfolio decision model would arise if we allow for an investment into two assets (maybe risky and risk-free assets). Then we would have:

$$\dot{W}(t) = \alpha(r_W - \delta_W)W + (1-\alpha)r_f W - d(t)$$

Hereby r_f is the risk free interest rate, for details see Hsiao and Semmler (2009). Wealth is increasing through a return r_W and reduced by fixed retirement of wealth, δ_W. We can think of $ak^\alpha = y$, with y total income; then, the marginal product of capital is $r_k = \alpha k^{(1-\alpha)} = r_W$, which has been used as the return above (it could have originated in real capital, housing stock, or other activities). Yet the above set-up, by excluding the effects arising from the leveraging and profit expectation terms, as included in the model of section 3, would not generate the booms bust scenarios as are studied in section 3.

References

[1] Adams, K., Marcet, A., 2010. Booms and Busts in Asset Prices. Institute For Monetary And Economic Studies Discussion Paper Series, http://www.imes.boj.or.jp/research/papers/english/10-E-02.pdf

[2] Adrian, T., Shin, H., 2009. Money, Liquidity, and Monetary Policy. American Economic Review, American Economic Association, vol. 99(2), 600-605, May.

[3] Aghion, P., Baccehetta, P., Banerjee, A., 2000. Currency Crisis and Monetary Policy in an Economy with Credit Constraints. Center for Economic and Policy Research Discussion Paper No. 2529.

[4] Akkeren, M., Hansen, H., 2004. On Mortgage Prepayment and Default: A Historical Distribution Analysis Approach. AFIR Colloquium, Boston, United States of America, 8-10 November.

[5] Beaudry, P., Portier, F., 2004. When Can Changes in Expectations Cause Business Cycle Fluctuations in Neo-Classical Settings?. Center for Economic and Policy Research Discussion Paper No. 4628.

[6] Beja, A., Goldman, M., 1980. On the Dynamic Behaviour of Prices in Disequilibrium. Journal of Finance, 34, 235-247.

[7] Bernanke, B., 1983. Non-Monetary Effects of the Financial Crisis in the Propagation of the Great Depression. American Economic Review, 73, June: 257-276.

[8] Bernanke, B., Blinder, A., 1998. Credit, Money, and Aggregate Demand. American Economic Review, Papers and Proceedings, 78: 435-439.

[9] Bernanke, B., Gertler, M. 1994. The Financial Accelerator and the Flight to Quality. Review of Economics and Statistics, vol. 78, no. 1: 1-15.

[10] Bernanke, B., Gertler, M. and S. Gilchrist, S., 1998. The Financial Accelerator in a Quantitative Business Cycle Framework. National Bureau of Economic Research Working Paper No. 6455, In: Taylor, J. and Woodford, M. (Eds.). Handbook of Macroeconomics, Amsterdam: North-Holland.

[11] Blundell-Wignall, A., Atkinson, P., 2008. The sub-prime crisis: Causal distortions and regulatory reform. In P. Bloxham, P., Kent, C. (Eds.). Lessons from the financial turmoil of 2007 and 2008, Reserve Bank of Australia.

[12] Brunnermeier, M., 2009. Deciphering the Liquidity and Credit Crunch 2007-2008. Journal of Economic Perspectives., Volume 23, No. 1, Winter, pp 77–100.

[13] Brunnermeier, M., Sannikov, Y., 2010. A Macroeconomic Model with a Financial Sector. Working paper: Princeton University.

[14] Burnside, C., Eichenbaum, M., Rebelo, S., 1999. Hedging and Financial Fragility in Fixed Exchange Rate Regimes. European Economic Review, 45: 1151-1193.

[15] Cappuzzo-Dolcetta, I., 1983. On a discrete approximation of the Hamilton-Jacobi

[16] Chacko, G., Sjöman, A., Motohashi, H., Dessain, V., 2006. Credit Derivatives: A Primer on Credit Risk, Modeling, and Instruments. Upper Saddle River, New Jersey: Wharton School Publishing.

[17] Chiarella, C., Flaschel, P., Franke, R., Semmler, W., 2009. Financial Markets and the Macroeconomy: A Keynesian Perspective. New York, NY: Routledge International Studies in Money and Banking, Routledge Publishing.

[18] Christiano, L., Motto, R., Rostagno, M., 2006. Monetary Policy and Stock Market Boom-Bust Cycles. Working paper.

[19] Christiano, L., Motto, R., Rostagno, M., 2007. Two Reasons Why Money and Credit May Be Useful in Monetary Policy. Working paper.

[20] Cochrane, J., 2001. Asset Pricing. Princeton, NJ: Princeton University Press.

[21] Curdia, V., Woodford, M., 2009. Credit Spreads and Monetary Policy. National Bureau of Economic Research Working Paper No. 15289.

[22] Diamond, P., Dybvik, P., 1983. Bank Runs, Deposit Insurance and Liquidity. Journal of Political Economy, 91 (June): 401-19.

[23] Edwards, S., 1999. On Crisis Prevention: Lessons From Mexico and East Asia. National Bureau of Economic Research Working Paper No. 7233.

[24] Edwards, S., Savastano, M., 1999. Exchange Rates in Emerging Economies: What Do We Know?. National Bureau of Economic Research Working Paper No. 7228.

[25] Falcone, M., 1987. A numerical approach to the infinite horizon problem of deterministic control theory. Applied Mathematics and Optimization, 15:1-13, 213-214.

[26] Gallegati, M., Palestrini, A., Rosser, J.B., Jr., 2011. The period of financial distress in speculative markets: Interacting heterogeneous agents and financial constraints. Macroeconomic Dynamics 15, 60-79.

[27] Geanakoplos, J., 2009. The Leverage Cycle. In: Acemoglu, D., Rogoff, K., Woodford, M., National Bureau of Economic Research Macroeconomics Annual, vol. 24, 1-65, ed. Chicago, IL: University of Chicago Press.

[28] Geanakoplos, J., 2010. Solving the Present Crisis and Managing the Leverage Cycle. Forthcoming: Federal Reserve Bank of New York Economic Policy Review.

[29] Geanakoplos, J., Farmer, J., 2009. The Virtues and Vices of Equilibrium and the Future of Financial Economics. Complexity (Jan/Feb), 14(3):11-38, CFDP 1647, CFP 1274.

[30] Gilchrist, S., V. Yankov, V., Zakrajsek, E., 2009. Credit Market Shocks and Economic Fluctuations. Forthcoming: Journal of Monetary Economics.

[31] Goodhart, C., Hofmann, B., 2003. Deflation, Credit and Asset Prices. Working paper.

[32] Gorton, G., 2009. Information, Liquidity,and the (Ongoing) Panic of 2007. Prepared for the Federal Reserve Bank of Kansas City, Jackson Hole Conference, August.

[33] Gruene, L., 1997. An Adaptive Grid Scheme for the discrete Hamilton-Jacobi-Bellman Equation. Numerische Mathematik, 75, 319-337.

[34] Gruene, L., Semmler, W., Sieveking, M., 2005. Creditworthiness and Threshold in a Credit Market Model with Multiple Equilibria. Economic Theory, Vol. 25, No. 2: 287-315.

[35] Gruene, L., Semmler, W., 2004. Using Dynamic Programming with Adaptive Grid Scheme for Optimal Control Problems in Economics. Journal of Economic Dynamics and Control, Vol. 28: 2427-2456.

[36] Gruene, L., Semmler, W., 2005. Default Risk, Asset Pricing, and Debt Control. Journal of Financial Econometrics, 3(1):79-106.

[37] Gruene, L., Semmler, W., 2008. Asset Pricing with Loss Aversion. Journal of Economic Dynamics and Control, Vol. 32, Issue 10: 3253-3274.

[38] Gruene, L., Chen. P., Semmler, W., 2008. Boom Bust Cycles, Default Premia and Asset Pricing. Working paper: http://www.newschool.edu/nssr/cem

[39] Gruene, L., Ohrlein, C., Semmler, W. 2009. Dynamic consumption and portfolio decisions with time varying asset returns. The Journal of Wealth Management, 12, No. 2, 21-47

[40] Gruene, L., Semmler, W., Bernard, L. 2007. Firm Value, Diversified Capital Assets and Credit Risk. Journal of Credit Risk, Vol. 3, No. 4: 81-113, Winter.

[41] Hall, R., 2010. Forward-Looking Decision Making. Princeton, NJ: Princeton Universtiy Press

[42] Hall, R., 2011. The Long Slump. Forthcoming: American Economic Review.

[43] Hsiao, C., Semmler, W., 2009. Harmonic Fitting for Long Run Economic Data. Working paper: http://www.newschool.edu/nssr/cem/

[44] Hudson, N., 2006. The New Road to Serfdom. Harpers Magazine, May.

[45] Kalecki, M., 1937. The Principle of Increasing Risk. Economica, November, 441-447.

[46] Kato, M., Proano, C., Semmler, W., 2009. Capital Flight, Nominal Exchange Rate Volatility and Optimal International Reserves Management. Working paper.

[47] Kaufman, H., 2009. The Road to Financial Reformation: Warnings, Consequences, Reforms. New York, NY: Wiley.

[48] Kindleberger, C., Aliber, R., 2005. Manias, Panics, and Crashes: A History of Financial Crises (5th Ed.). New York, NY: Wiley.

[49] Krugman, P., 1999a. Balance Sheets,the Transfer Problem and Financial Crises. MIT, mimeo.

[50] Krugman, P., 1999b. Comments on the Transfer Problem. Massachusetts Institute of Technology, Mimeo.

[51] Lansing, K., 2008. Speculative Growth and Overreaction to Technology Shocks. Federal Reserve Bank of San Francisco Working Paper. Paper 2008-08.

[52] MacAvoy, P., Millstein, I., 2004. The Recurrent Crisis in Corporate Governance. Palgrave-Macmillan.

[53] Mankiw, G., Weil, D., 1989. The BabyBoom, the Baby Bust and the Housing Market. Regional Science and Urban Economics, Vol. 19, 235-258

[54] Maurer, H., Semmler, W., 2010. An optimal control model of oil discovery and extraction", Applied Mathematics and Computation, 217, No. 3, 1163-1169.

[55] Merton, R., 1974. On the Pricing of Corporate Debt: The Risk Structure of the Interest Rate. Journal of Finance, 2: 449-470.

[56] Miller, M., Stiglitz, J., 1999. Bankruptcy Protection against Macroeconomic Shocks. The World Bank, Mimeo.

[57] Miller, M., Stiglitz, J., 2010. Leverage and Asset Bubbles: Averting Armageddon with Chapter 11?. Economic Journal, 120(544), 500-518

[58] Minsky, H., 1975. John Maynard Keynes. New York, NY: Columbia University Press.

[59] Minsky, H., 1982. Can it Happen again?. Armonk: ME Sharpe.

[60] Minsky, H., 1986. Stabilizing an Unstable Economy. New Haven, CT: Yale University Press.

[61] Mishkin, F., 1998. International Capital Movement, Financial Volatility and Financial Instability. National Bureau of Economic Research Working Paper No. 6390.

[62] Mittnik, S., Semmler, W., 2010. Regime Dependence of the Fiscal Multiplier. Schwartz Center for Economic Policy Analysis Working Paper.

[63] Piazzesi, M., Schneider, M., 2008. Inflation and the Price of Real Assets. Working paper.

[64] Piazzesi, M., Schneider, M., 2008. Inflation Illusion, Credit, and Asset Pricing. In: Campbell, J. (Ed.). Asset Prices and Monetary Policy. Chicago, IL: University of Chicago Press.

[65] Roethig, A., Semmler, W., Flaschel, P., 2007. Hedging, Speculation, and Investment in Balance-Sheet Triggered Currency Crises. Australian Economic Papers, Blackwell Publishing, Vol. 46(3), 224-233, 09.

[66] Piazzesi, M., Schneider, M., Tuzel, S., 2007. Housing, Consumption and Asset Pricing. Journal of Financial Economics, 83(3), 531-569.

[67] Semmler, W., Sieveking, M., 2000. Critical Debt and Debt Dynamics. Journal of Economic Dynamics and Control, vol 24, No 5-7, 1-24.

[68] Semmler, W., 2006. Asset Prices, Booms and Recessions: Financial Economics from a Dynamic Perspective (2nd Ed.). Berlin-New York, NY: Springer Publishing House.

[69] Semmler, W., Bernard, L. (Eds.), 2007. The Foundations of Credit Risk Analysis. Cheltenham, UK: Edward Elgar Publishing.

[70] Shiller, R., 1991. Market Volatility. Cambridge, MA: Massachusetts Institute of Technology Press.

[71] Shiller, R., 2001. Irrational Exuberance. New York, NY: Random House.

[72] Shiller, R., 2006. Long-Term Perspectives on the Current Boom in Home Prices. Economists' Voice, Vol. 3, Issue 4.

[73] Shiller, R., 2007. Low Interest Rates and High Asset Prices: An Interpretation in Terms of Changing Popular Models. Working paper.

[74] Tobin, J., 1980. Asset Accumulation and Economic Activity. Oxford: Basic Blackwell.