

A Boom-Bust Business Cycle Model with Search-for-Yield and Heterogeneous Expectations in the Bond Market

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Abstract

This paper analyzes how heterogeneous expectations in the credit market amplify the transmission of shocks from the financial sector to the real economy. We adapt Chiarella and di Guilmi (2011) to include a credit market in which investors switch expectations according to the mechanism proposed by Brock and Hommes (1997). During boom phases more and more investors follow a trend-trading strategy. This search for yield lowers the risk premium, making firms take on more debt to finance more investment, which validates investors' expectations. Eventually, firms are over-leveraged, a small shock forces default and the economy enters the bust phase. This model offers a clear explanation for the behavior of risk premia over the business cycle, shows how they can be mis-priced and considers the welfare implications of the mis-pricing of risk. The model is first simulated using agent-based modelling techniques and then solved with stochastic aggregation methods.

Keywords: Business cycle; Fluctuations; Leverage; Default

JEL Codes: TBA

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1 Introduction

The 2007-9 global financial crisis (GFC) has shown with force that High Street and Wall Street are inextricably linked. Firms, responsible for production of the economy's goods and services, rely on financial markets to finance their investment. Financial markets, though reliant on firms, pursue their own objectives. These may not coincide with society's overall objectives and history has revealed repeatedly that pathologies in the financial markets can bring down the rest of the economy.

This paper is motivated by two key observations. First, aggregate demand and credit growth are highly correlated (see figure 1.) In other words, the business cycle coincides with a debt cycle. Second, during large credit booms there appears to be a compression of interest rates between safe and risky bonds, implying that risk premia for relatively risky bonds appear unrealistically small. The most striking example is the yield on sovereign bonds of some of the periphery countries in the Eurozone, particularly of Greece, prior to the GFC. It is now well accepted that Greek sovereign debt was grossly underpriced. However, a similar underpricing can also be seen in corporate bonds (figure 2).

The need for linking the business cycle to the evolution of debt in the economy is self-evident from figure 1. Investment in modern industrialized countries is largely debt-financed. Hence, changes in economic activity, driven by investment cycles, necessarily alter the soundness of firms' balance sheets which in turn affect firms' willingness or ability to invest. Not modelling the interdependency between investment and the supply of credit, as is typical in the macroeconomics literature, misses a key feature of modern economies that, in our view, is responsible for generating, amplifying and propagating cycles. Our model explicitly links investment behavior to the provision of credit and keeps track of each individual firm's debt position over time.

In the corridors of central banks and other financial institutions, such underpricing of risk is often considered to be the result of a 'search for yield' (SFY) by investors. Cecchetti and Schoenholtz (2011) describe SFY as follows:

“In some circumstances, many investors underestimate the risks of owning particular assets. If the risks materialize, investors

can face painful losses. In the case of bonds, investors lacking sufficient regard for risk typically seek higher-yield bonds even if these bonds are riskier (due to longer maturities or higher default probabilities).

What can prompt such underestimation of risk? Experience suggests that some investors extrapolate from recent patterns and pay less attention to the more distant past. For example, if interest rates are currently low and stable, investors may expect this pattern to persist even if in prior years rates tended to be higher and more volatile.

Extrapolation of recent experience also can lead investors to underestimate default risk. For example, defaults by households and businesses are relatively infrequent during economic expansions. Because such booms are long while recessions are short, investors can become accustomed to low levels of default. Again, naively projecting recent experience forward leads to the underestimation of the default risks for which investors should be compensated when buying corporate bonds or securities backed by mortgages or consumer loans.”

While SFY is a widely accepted phenomenon in the finance world, it has largely eluded academic economists. There is virtually no formal modelling of this process and, consequently, its implications for the economy have hardly been studied. Our primary motivation in writing this paper is to provide a first pass at including SFY investors in a macroeconomic model and to evaluate the implications of their behavior for the real side of the economy.

Most mainstream business cycle models do not generate cyclical behavior endogenously. These models, the dominant class of which are dynamic stochastic general equilibrium (DSGE) models, are intended to analyze the amplification and propagation of exogenous shocks to an economy (see, for example Gali, 2008, Walsh, 2010). They consist of a system of equations, linearized around a non-stochastic steady-state, derived from utility and profit maximizing behavior of representative households and producers. Without an exogenous innovation, these economies rest at their steady-states; there are no intrinsic dynamics that capture the instability of economies witnessed in the data.

We disapprove of this *deus ex machina* approach to modelling business cycles, believing that a good theory should be able to explain and gener-

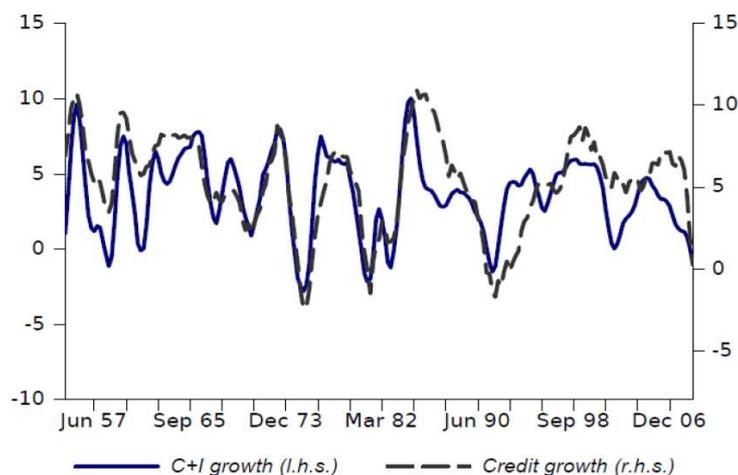
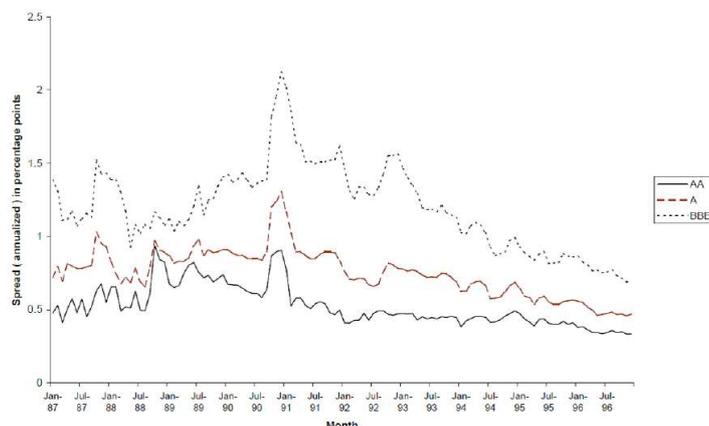


Figure 1: US demand growth and credit growth).

ate cycles endogenously, not assume them. There exist several approaches to modelling endogenous business cycles. Two stand out in particular. The first approach uses small analytical models of dynamic equations, with complex root eigenvalues, that generate nonlinear behavior. See, for example, Goodwin (1990) and Guesnerie (2001). The problem with this class of models is that they are very difficult to solve due to their nonlinearity. As a consequence they tend to be small, with minimal structure. The second approach, going by the name of agent based models (ABM) or agent based computational economics (ACE), is often described as a bottom-up approach: the modeller specifies the behavior for a large number of individual heterogeneous agents, who are often allowed to interact, and the system is then simulated numerically to arrive at the behavior of the economy in aggregate. See, as matter of example, Delli Gatti et al., (2011) and various chapters in Tesfatsion and Judd (2006). This method acknowledges the inherent complexity of an economy populated by many agents: aggregate behavior is *emergent*; it cannot easily be deduced from the observation of agents' individual behavior.

Our model is an ABM. This approach allows us to carefully model the investment behavior of individual firms while at the same time allowing for heterogeneity. Such heterogeneity is crucial to our argument—the boom-bust dynamics of the business cycle are driven by the evolving balance sheets of firms. The simulations will show the cyclical behavior of the economy and



Source: Elton et al. (2001)

Figure 2: Spreads on US industrial bonds of 6-year maturity.

we can use Monte Carlo simulations to numerically analyze the properties of the system.

2 Related Literature

Since the GFC there has been a burgeoning literature attempting to incorporate the financial sector into standard DSGE models. More prominent examples include Cúrdia and Woodford (2009) and Gilchrist and Zakrajšek (2011), who introduce two distinct interest rates to allow for variations in credit spreads, and Adrian and Boyarchenko (2012), who model intermediary leverage cycles that generate systemic solvency and liquidity risks.

A growing number of empirical papers document the tight linkages between the real side and the financial side of the economy. Using an extensive database of over 200 business and 700 financial cycles in 44 countries for the period 1960-2007, Claessens, Kose and Terrones (2011) show that the phases of business and financial cycles are highly synchronized. Another important contribution includes Biggs, Mayer and Pick (2009), who, using data from developed and emerging market countries, find that the flow of credit has a higher correlation with GDP than the stock of credit.

Numerous authors have modelled the finance-investment nexus by abandoning the DSGE framework. Recent examples include Bezemer (2011), Dosi

et al. (2010) and Godin and Kinsella (2012). Several authors were inspired by Minsky’s financial instability hypothesis, including Taylor and O’Connell (1985) and Keen (1995). A recent innovative approach is Brunnermeier and Sannikov (2012) who focus on the highly nonlinear amplification effects of financial frictions and the endogeneity of systemic risk.

The literature studying investors’ SFY is virtually non-existent. One exception is Gai and Trivedi (2009) who link the SFY notion to the global savings glut hypothesis and the recent asset price boom. Other discussions about the SFY phenomenon are usually found in discussions published by institutions such as the OECD, the BIS and various central banks.

Agent-based models no longer populate a small niche in the economics discipline but constitute a well and truly established field. Useful overviews are provided by Delli Gatti et al. (2011) and the chapters contained in the second volume of the Handbook of Computational Economics.

3 The Model

We present a simple agent-based model that borrows heavily from Chiarella and Di Guilmi (2011). The key objective is to build a link between the investment behavior of heterogeneous firms and the portfolio decisions of financial market investors who “search for yield”.

3.1 Firms

Variables are written with the subscript i when they refer to a generic firm. Aggregate variables are without any subscript. The economy is populated by 1000 firms, indexed by i . Firms are *ex ante* heterogeneous, as each firm starts with a different endowment of capital in period $t = 0$, but identical in every other respect.

Each firm produces a differentiated good that is either consumed or invested, using a Leontief production technology with labor and capital as inputs,

$$X_{it} = \min[aK, (1/b)L], \tag{1}$$

with $a, b > 0$. As usual, K and L represent, respectively, physical capital and labour and X_{it} the quantity of the good produced.

For simplicity we assume that labor supply is infinitely elastic at some exogenous (nominal) wage w . Given that the labour/output ratio b is con-

stant, it is therefore possible to define the production function merely as a function of capital so that

$$X_{it} = a K_{it} \quad (2)$$

where the output/capital ratio a is a constant parameter.

The price of the final good is obtained by applying a mark-up μ on the direct production costs according to¹

$$P = (1 + \mu)wb. \quad (3)$$

Since w, μ and b are all constant, price is also constant.

We assume that product demand is distributed among firms according to firm size but consumer preference shocks render each individual firm's demand stochastic. Firm i 's expected market share is given by

$$\mathbb{E}[X_{it}^d] = X_t^d \frac{K_{it}}{K_t}, \quad (4)$$

where K_t is the economy-wide capital stock, X_{it}^d firm i 's demand for its product, and X_t^d aggregate demand. A firm's market share is hit by an additive stochastic disturbance \tilde{s} . Assuming that it is uniformly distributed with $E[\tilde{s}] = 0$ we can write²

$$s_{it} = \tilde{s}_{it} \left(1 - \frac{\mathbb{E}[X_{it}^d]}{X_t^d} \right), \quad (5)$$

with $\tilde{s} \in [-0.2, 0.2]$. Accordingly, actual demand for firm i 's product is equal to

$$X_{it}^d = \mathbb{E}[X_{it}^d](1 + s_{it}). \quad (6)$$

Assuming that all wage income is consumed, aggregate demand X^d is equal to

$$X_t^d = wL_t + I_t. \quad (7)$$

Total demand for labour is equal to

$$L_t = bX_t^d. \quad (8)$$

¹Such mark-up pricing arises naturally when firms are monopolistically competitive. See standard references on New Keynesian models such as Galí (2008) and Walsh (2010).

²This correction on the shock makes sure that $X^d = \sum X_i^d$.

Equations (7) and (8) are simultaneously determined so that total demand can be also expressed as

$$X_t^d = \frac{I_t}{1 - wb}, \quad (9)$$

with $wb < 1$.

Firm i 's investment depends negatively on the interest rate which it must pay on the debt,

$$I_{it} = \frac{\alpha}{\varrho_{it-1}} + \phi K_{it-1}, \quad (10)$$

where α and ϕ are positive parameters and ϱ is the interest rate on debt defined below. Firm i 's capital stock thus evolves as follows:

$$K_{it} = K_{it-1} + I_{it}. \quad (11)$$

Labor demand is residually determined once the optimal level of investment, and hence of capital, is determined.

Firms finance investment by issuing one-period bonds. Current period profits are used to retire the previous period's debt plus interest. Surplus profits are fully paid out as dividends. When profits are insufficient to retire entire stock of debt, the remaining debt will be rolled over. The amount of outstanding debt, D_{it} , is equal to

$$D_{it} = D_{it-1} - \pi_{it-1} + I_{it}. \quad (12)$$

Profits are given by

$$\pi_{it} = (P - wb) X_{it}^d - \varrho_{it} D_{it}. \quad (13)$$

A firm fails if its stock of debt exceeds a multiple of its capital stock, that is if

$$D_{it} > cK_{it},$$

with $c > 1$. The probability for a bankrupted firm to be replaced is proportional to the performance of the economy. Therefore, in period of strong growth of aggregate production every ceased firm is likely to be immediately replaced while during a recession this replacement process can take many periods. New firms are endowed with a random amount of capital as at the beginning of simulations.

3.2 Financial Sector

The financial sector provides all the credit that firms demand, viz. there is no credit rationing.³ The interest rate on debt is equal to a constant risk free rate plus a risk premium that depends on the borrowing firm's leverage ratio. In particular, we assume that the risk premium ρ is equal to

$$\rho_{it} = \begin{cases} \frac{D_{it}}{K_{it}}\omega & \text{if } \frac{D_{it}}{K_{it}} \geq \bar{v} \\ 0 & \text{if } \frac{D_{it}}{K_{it}} < \bar{v} \end{cases} \quad (14)$$

where $\omega \in (0, 1)$ and $\bar{v} \in [0, c)$ are constant parameters. Using the language of [23], we can classify firms as *hedge* if $D_{it}/K_{it} < \bar{v}$ or *speculative* if $D_{it}/K_{it} \geq \bar{v}$. Let z be an indicator variable that takes on the value 1 when identifying a hedge firm and 2 when identifying a speculative firm.

Financial institutions follow heterogeneous behavioural rules in allocating their portfolio. In particular, we classify investors into two groups: fundamentalists, who invest only in safe bonds issued by hedge firms, and chartists, who invest in risky, high-return bonds. A firm's bond fundamental yield is equal to $r + \rho_{i,t}$, where r is the equilibrium return for a safe (zero risk) bond, assumed to be constant. Investors switch between the two different categories according to the mechanism proposed in Brock and Hommes (1997) such that the share of fundamentalists n_f is given by

$$n_{ft+1} = \frac{\exp(\beta\gamma_{f,t})}{\exp(\beta\gamma_{ft}) + \exp(\beta\gamma_{ct})}, \quad (15)$$

and the share of chartists n_c by

$$n_{ct+1} = \frac{\exp(\beta\gamma_{c,t})}{\exp(\beta\gamma_{ft}) + \exp(\beta\gamma_{ct})}. \quad (16)$$

The parameter β captures the intensity of switching. The symbols γ_f and γ_c indicate the fitness functions for the fundamentalist and chartist strategies, respectively. They are defined as

$$\begin{aligned} \gamma_{ft} &= \pi_{ft} + \eta\pi_{ft-1}, \\ \gamma_{ct} &= \pi_{ct} + \eta\pi_{ct-1}. \end{aligned} \quad (17)$$

where $\eta \in [0, 1]$ is a memory parameter.

³This assumption will be relaxed at a later stage.

For the sake of simplicity we assume zero costs for investors. The profits associated with each strategy are given by

$$\pi_f = \sum_i^{N_1} \varrho_{izt} D_{izt} \text{ for } z = 1, \quad (18)$$

$$\pi_c = \sum_i^{N_2} \varrho_{izt} D_{izt} \text{ for } z = 2. \quad (19)$$

Note that N_2 only contains surviving (solvent) firms.

3.3 The Bond Market

We assume there exist only two classes of bonds: risky, issued by speculative firms, and risk free, issued by hedge firms. Investors do not distinguish among bonds issued by hedge firm, hence, economy-wide there is only one price for safe bonds. The price of bonds issued by speculative firms differ among firms as specified below.

At the beginning of each period firms issue bonds whose expected return is given by the riskless interest rate plus the correct risk premium. Normalising the price to 1, the face value (or fundamental value) of the bond issued by firm i , belonging to group z , can be quantified as

$$P_{izt}^{Bf} = 1 + r + \rho_{izt}. \quad (20)$$

Since for all hedge firms $\rho_{i1t} = 0$, we have that $P_{i1t}^{Bf} = P_{1t}^{Bf} = 1 + r$.

Once the bonds are placed on the market, their price can vary depending on investors' preferences. To capture the "search for yield" process, in which demand for higher yielding (but riskier) assets increases as the yield on safe assets falls, we assume the two types of bonds P_{B1} and P_{B2} are priced as follows:

$$P_{i1t}^B = P_{1t}^B = 1 + r n_t^f \quad (21)$$

$$P_{i2t}^B = 1 + (r + \rho_{it}) n_t^c. \quad (22)$$

Therefore the actual interest rate that any hedge firm pays on the debt is

$$\varrho_{1t} = P_{1t}^{Bf} - P_{1t}^B = r(1 - n_t^f), \quad (23)$$

while the interest rate for speculative firms, which varies according to the firms' fundamental risk, is

$$\varrho_{i2t} = P_{2t}^{Bf} - P_{2t}^B = (r + \rho_{it})(1 - n_t^c) \quad (24)$$

Since n_t^f and n_t^c are between zero and one, the actual interest rate ϱ_i facing firms may be less than the correct (fundamental) interest rate $r + \rho_i$, implying a mis-pricing of risk.

4 Results

The above model was coded in Matlab and simulated for 1450 periods with the following parameter values:

Parameter	Value	Parameter	Value
α	1.65	ϕ	0.01
b	1	a	0.575
μ	0.01	η	0.25
β	0.0001	ω	0.05
Ψ	1	c	2.5
\bar{v}	1.2	r	0.03
w	0.95		

4.1 Baseline Simulations

The chart reported in figure 3 of a representative run gives displays the dynamic properties of this model economy.

The economy clearly exhibits quite regular cycles. These are endogenous, not imposed on the system. The story behind this cyclical pattern is straightforward. At the beginning of an expansion firms' debt-capital ratios are low and only few firms are defaulting. Firms invest and their debt-capital ratios rise. Consequently, some firms switch from being safe (hedge) firms with zero risk to risky (speculative) firms with positive risk. At the same time, while default rates are still low, financial investors, in their attempt to 'search for yield', increasingly invest in risky bonds; that is, the share of chartists rises. This larger share of chartists pushes down the yield of risky bonds, making credit more affordable for speculative firms who respond by taking on more debt to finance further investment.

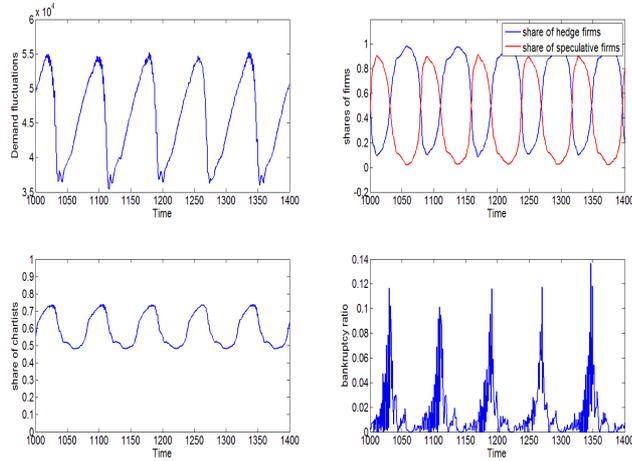


Figure 3: Representative run.

At some point the leverage of speculative firms reaches a critical threshold, leading to a sharp increase in bankruptcies, which cause painful losses for the investors who were primarily invested in risky firms. Investors therefore switch out of risky bonds, into safe bonds, which in turn increases the cost of financing investment for the remaining speculative firms. This increase in the interest rate makes it more likely that a speculative firm defaults, causing further losses for investors. This process continues until nearly all speculative firms are purged, the nadir of the cycle is reached, and a new investment cycle can take shape.

The chart reported in figure 4 clearly capture this story. At the peak of the cycle the share of speculative firms is nearly one and the share of chartists also reaches its maximum at approx. 0.75. The bankruptcy ratio peaks at the same point, reaching a value of around 0.12. The share of speculative firms then drops dramatically, as does the bankruptcy ratio, while the share of investors investing in risky bonds steadily falls. At the trough of the business cycle, most of the remaining firms are safe hedge firms and the bankruptcy ratio hovers barely above zero. The average risk premium broadly follows this pattern (it rises during an expansion and falls during a contraction) although its behavior is more jagged.

This pattern is caused by a virtuous/vicious cycle in which the behavior of investors reinforces the behavior of firms and vice versa, a feature that is

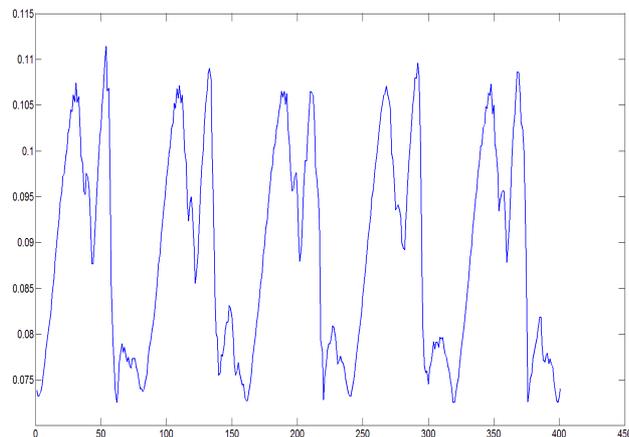


Figure 4: Average risk premium.

largely absent in the business cycle literature.

The business cycle that emerges in these simulations is intrinsic to the real side of the economy. Firms have an incentive to invest and grow their capital stock. This raises firms' leverage, as investment is financed through debt, making their balance sheets increasingly fragile. Ultimately, even a small negative demand shock will suffice to force a high-leverage firm into default. This basic mechanism does not rely on the mis-pricing of risk that is taking place in financial markets. The presence of investors who 'search for yield' (SFY) reduces the yield on risky bonds, which in turn reduces the cost of investment for speculative firms. Consequently, firms incur more debt, exacerbating the debt-investment cycle. This can be seen by comparing the average duration of the business cycle (peak to peak) with SFY investors to the average duration without SFY investors (computed by assuming $P_{i1t}^B = P_{i2t}^B$):

	With SFY Investors	Without SFY Investors
Duration of business cycle	~ 80 periods	~ 36 periods

4.2 Monte Carlo Simulations

A better understanding of the model's features can be gleaned from performing Monte Carlo simulations that test the sensitivity to different values of the key parameters. We do this for $\alpha, \beta, c, \bar{v}$ and η , with 200 replications for each parameter. The following charts show how each parameter affects average output (\bar{X} in the charts), the variance of output ($Var(X)$), the market interest rate (ϱ), the average risk premium (ρ), the bankruptcy ratio (BKR ratio), the correlation between the share of chartist investors and the market interest rate ($corr(nc, \varrho)$), the correlation between the share of chartist investors and total output ($corr(nc, xd)$), and the correlation between the average risk premium and total output ($corr(\rho, xd)$).

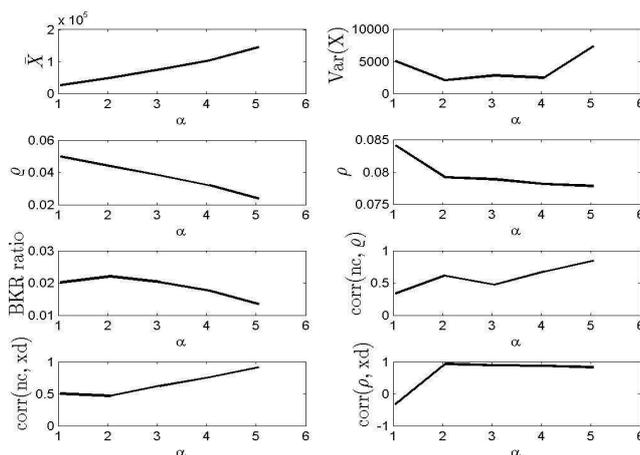


Figure 5: Monte Carlo simulation for α .

The parameter α (figure 5) captures the sensitivity of firms' investment with respect to the market interest rate. Hence, for any given interest rate an increase in α leads to more investment and therefore to more output. This coincides with a reduction in the risk premium and the market interest rate as increased investment makes it more attractive for SFY investors to switch into risky bonds, thus lowering their yields. The non-monotonic behavior of the variance of output is difficult to interpret as are some of the correlations.

The MC simulations for β (figure 6), the switching intensity of financial market investors, are very difficult to interpret, a feature well-known in the

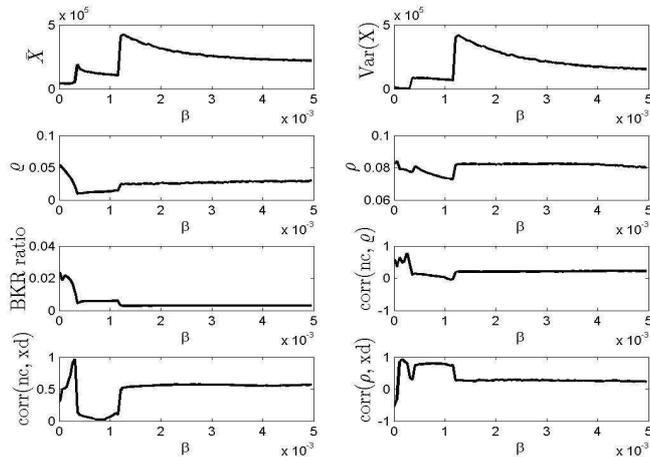


Figure 6: Monte Carlo simulation for β .

literature that adopts the Brock and Hommes (1997) approach. The system is very sensitive to values of β within the approximate range $[0, 0.0001]$, displaying highly non-monotonic behavior. For values of $\beta > 0.0002$, the system settles down with very little further sensitivity to β .

As expected, an increase in the maximum leverage ratio for firms, c , raises investment, total average demand and its variance as shown by figure 7. These results are consistent with the ones obtained by Chiarella and Di Guilmi (2011). An increase in c also raises the risk premium (ρ) but higher investment makes SFY investors purchase bonds of speculative firms, pushing down their yields so that the net effect is a reduction in the market interest rate (ϱ) in spite of the increase in the risk premium. This is an intriguing feature of the model: while the true risk premium increases, the actual interest paid by firms decreases. A looser limit to debt accumulation therefore seems to conceal the risk. Unsurprisingly, the bankruptcy ratio also falls as c rises, which simply captures the idea that the debt-capital ratio becomes less and less binding.

Values of \bar{v} (figure 8), the parameter that marks the distinction between speculative, e.g. risky, firms and hedge, e.g. safe, firms, below one have no real consequence for the economy. As \bar{v} rises above one, the risk premium and the market interest rate increase. This is because for any given debt-capital ratio a higher \bar{v} implies a higher probability that there will be a zero

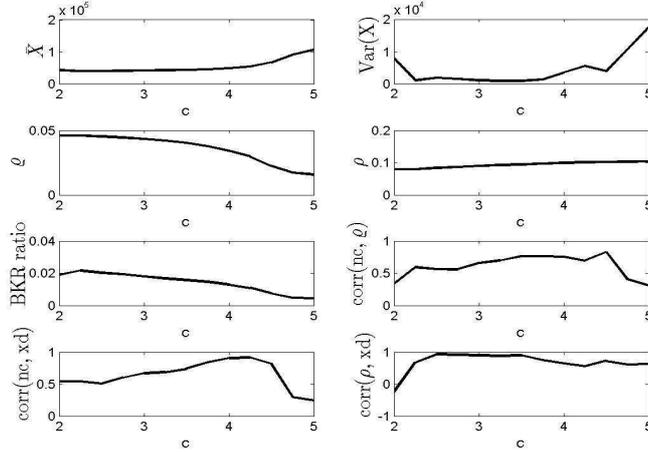


Figure 7: Monte Carlo simulation for c .

risk premium (see equation 14). Since the risk premium is rising with the debt-capital ratio and, when \bar{v} is large, only firms with high debt-capital ratios carry a non-zero risk premium, the *average* risk premium necessarily rises. This is then also reflected in a higher *average* market interest rate. The reduction in bankruptcies is clearly visible in the fifth panel as is the increase in average output in the first panel.

The parameter η may be interpreted as a memory parameter. The higher is η , the more weight investors give to previous period's profit, relative to current period's profit, in their fitness function. The results displayed in figure 9 may be explained intuitively as follows. A higher η means that investors do not react so strongly to firms' current performance. For example, when η is small, high profit for speculative firms in the current period will make it more likely that investors will switch to investing in speculative firms in the next period as investors consider speculative firms to be a better investment. A high η , however, implies that investors will not just consider current period's profit but also previous period's profit. Thus, very high profit in the current period may not necessarily force investors to switch investment strategies. This in turn means that there are fewer occasions for which a high profit, especially of a speculative firm, leads to investors switching into the same class of bonds, thereby bringing down the yield in that class and making it cheaper for firms of that class to borrow even more.

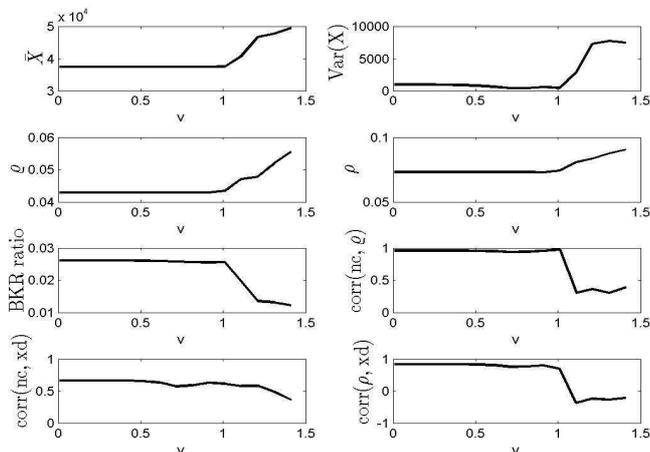


Figure 8: Monte Carlo simulation for \bar{v} .

Hence, the simulations show that a higher η is associated with a lower average risk premium (ρ) and a lower average market interest rate (ϱ). This leads to a reduction in total output as less investment is taking place but the variance of output also clearly falls (second panel) while the bankruptcy ratio rises (fifth panel).

5 Conclusion

This paper is motivated by two key observations— i) the high correlation between aggregate demand and credit growth and ii) the underpricing of risk in financial markets due to investors’ ‘search for yield’. We build an agent-based model in which firms’ investment is debt-financed and in which investors push down yields of risky bonds. The model generates endogenous cycles. At the beginning of an expansion firms’ debt-capital ratios are low and only few firms are defaulting. Firms invest and their debt-capital ratios rise. Consequently, some firms switch from being safe to being risky. Investors, in their attempt to ‘search for yield’, increasingly invest in risky bonds, pushing down their yields, thus making credit more affordable for speculative firms. High leverage of speculative firms ultimately leads to sharp increases in bankruptcies. Investors switch out of risky bonds into safe bonds, increasing the cost of financing investment for the remaining speculative firms. This process

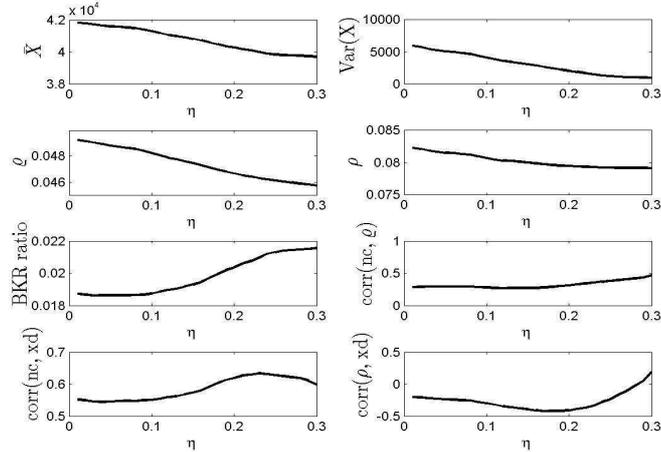


Figure 9: Monte Carlo simulation for η .

continues until a new investment cycle can begin.

While the model captures some important business cycle features and achieves much of what we set out to do, it is still lacking in some important dimensions. Here are a few:

- Certain specifications of the model, in particular firms' investment functions, are *ad hoc* and unappealing. Unfortunately, the existing literature is no good guide, as there is little agreement on how best to model investment behavior.
- Firms mechanically build up debt to unsustainable levels, ultimately leading to bankruptcy. In reality, firms alter their behavior when suffering financial distress, fighting for survival. This usually involves a process of deleveraging which, when considered for the economy as a whole, is painful and exacerbates the down-turn, a process described in detail by Koo (2009).
- There is no household sector and no modeling of the labor market which might allow for less than infinite labor supply.
- There is no credit rationing even though the evidence in its favor is strong.

- Asset price effects on firms' balance sheets are not captured. These have recently been shown to be important.
- There are no interlinkages among firms or among investors, thus precluding any systemic network effects.
- The only form of external finance is debt. Allowing firms to issue equity and to use internal finance for investment would offer a more nuanced and realistic description of the debt and business cycle.
- Finally, the model needs to be calibrated with a closer eye to the data in order to empirically validate the proposed theory.

We will take up some of these points in later versions of this paper as well as in other future work.

References

- [1] Adrian, Tobias, and Nina Boyarchenko (2012). "Intermediary Leverage Cycles and Financial Stability," *mimeo*, Federal Reserve Bank of New York, August.
- [2] Bezemer, Dirk J. (2011). "Causes of Financial Instability: Don't Forget Finance," Levy Economics Institute of Bard College Working Paper No. 665, April.
- [3] Biggs, Michael, Thomas Mayer, and Andreas Pick (2009). "Credit and economic recovery," DNB Working Paper No. 218, De Nederlandsche Bank, July.
- [4] Brock, William A., and Cars H. Hommes (1997). "A Rational Route to Randomness," *Econometrica* 65(5), 1059-1096.
- [5] Brunnermeier, Markus K., and Yuliy Sannikov (2012). "A Macroeconomic Model with a Financial Sector," *mimeo*, Princeton University, April.
- [6] Cecchetti, Stephen G., and Kermit L. Schoenholtz (2011). *Money, Banking, and Financial Markets, 3rd Edition*. New York: McGraw Hill.

- [7] Chiarella, Carl, and Corrado Di Guilmi (2011). “The Financial Instability Hypothesis: A Stochastic Microfoundation Framework,” *Journal of Economic Dynamics and Control* 35(8), 1151-1171.
- [8] Claessens, Stijn, M. Ayhan Kose, and Marco E. Terrones (2011). “How Do Business and Financial Cycles Interact?” IMF Working Paper WP/11/88, April.
- [9] Cúrdia, Vasco, and Michael Woodford (2009). “Credit Spreads and Monetary Policy,” NBER Working Paper No. 15289, August.
- [10] Delli Gatti, Domenico, Saul Desiderio, Edoardo Gaffeo, Pasquale Cirillo, and Mauro Gallegati (2011). *Macroeconomics from the Bottom-up (New Economic Windows)*. New York: Springer.
- [11] Dosi, Giovanni, Giorgio Fagiolo, and Andrea Roventini (2010). “Schumpeter meeting Keynes: A policy-friendly model of endogenous growth and business cycles,” *Journal of Economic Dynamics and Control* 34, 1748-1767.
- [12] Gai, Prasanna, and Kamakshya Trivedi (2009). “Funding Externalities, Asset Prices and Investors’ ‘Search for Yield’,” *Bulletin of Economic Research* 61(1), 73-82.
- [13] Galí, Jordi (2008). *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework*. Princeton: Princeton University Press.
- [14] Gilchrist, Simon, and Egon Zakrajšek (2011). “Credit Spreads and Business Cycle Fluctuations,” NBER Working Paper No. 17021, May.
- [15] Godin, Antoine, and Stephen Kinsella (2012). “Leverage, Liquidity and Crisis: A Simulations Study,” ASSRU Discussion Paper No. 5-2012, January.
- [16] Goodwin, Richard M. (1990). *Chaotic Economic Dynamics*. Oxford: Oxford University Press.
- [17] Gourio, François (2011). “Credit Risk and Disaster Risk,” NBER Working Paper No. 17026, May.

- [18] Guesnerie, Roger (2001). *Assessing Rational Expectations: Sunspot Multiplicity and Economic Fluctuations*. Cambridge: MIT Press.
- [19] Keen, Steve (1995). "Finance and economic breakdown: modeling Minsky's 'financial instability hypothesis'," *Journal of Post Keynesian Economics* 17(4), 607-635.
- [20] Koo, Richard C. (2009). *The Holy Grail of Macroeconomics: Lessons from Japan's Great Recession*. Hoboken: John Wiley and Sons.
- [21] Madsen, Jakob B., and Sarah J. Carrington (2012). "Credit cycles and corporate investment: Direct tests using survey data on banks' lending practices," *Journal of Macroeconomics* 34, 429-440.
- [22] Minsky, Hyman P. (2008). *John Maynard Keynes*. New York: McGraw Hill.
- [23] Minsky, Hyman P. (1982) *Inflation, recession and economic policy*, ME Sharpe: New York.
- [24] Philippon, Thomas (2009). "The Bond Market's q ," *Quarterly Journal of Economics*, 1011-1056.
- [25] Scheffknecht, Lukas, and Felix Geiger (2011). "A Behavioral Macroeconomic Model with Endogenous Boom-Bust Cycles and Leverage Dynamics," FZID Discussion Paper 37-2011, Uni Hohenheim, November.
- [26] Taylor, Lance, and Stephen A. O'Connell (1985). "A Minsky Crisis," *Quarterly Journal of Economics* 100(Supplement), 871-885.
- [27] Tesfatsion, Leigh, and Kenneth L. Judd (eds.) (2006). *Handbook of Computational Economics, Volume 2: Agent-Based Computational Economics*. Rotterdam: North-Holland.
- [28] Walsh, Carl E. (2010). *Monetary Theory and Policy*, 3rd edition. Princeton: Princeton University Press.