A Dynamic Agent-Based Computational Economics (ACE) Model of RMBS Issuance, Credit Risk Transfer and Financial Stability

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Abstract

This paper uses a two-sector agent-based computational economics (ACE) model to assess whether a system of dynamic decision making by institutional investors and/or by issuing banks (e.g. loss aversion, decision making according to simplified rule of thumb behaviour) can lead to unsustainable increases in issuance or large scale fluctuation in prices of securitised assets. The paper also highlights policy issues associated with the design of financial market regulations and the financial market infrastructures (FMIs) such as central counterparties (CCPs) that directly participate in the pricing of underlying credit and other risks.

key discussion point - securitisation and the pricing of credit risk, externalities,

Keywords: Credit risk transfer, securitisation, systemic risk, reinforcement learning, markov decision process

1 Introduction

The case of environmental externalities in which the overuse and degradation of resources result from the underpricing of a resource or asset with no consideration of the clean-up costs is increasingly being seen as salutary for pricing credit risk and the systemic consequences of credit risk. Economic activities and financial products that transfer risk should not be valued solely on the principle of marginal costs because that will trigger the well-understood problem of the Tragedy of the Commons or, as with firm-level constraints such as under the Basel I capital adequacy requirement, result in regulatory arbitrage. Oversupply (or production) occurs at the level of the individual economic entity because there is a missing market to price the risk of negative spillovers analogous to

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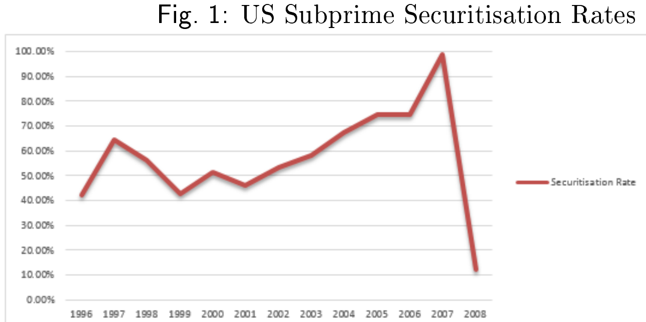
environmental externalities. The main implication is that the securitisation based financial innovation was inherently good, but the overproduction of inside money due to the critical underpricing of credit risk at the individual level resulted in an oversupply of liquidity at a macro level.

Many regard the severity of the global economic crisis (Almunia et al., 2009; Dam, 2010; Hilsenrath, et al., 2008; Shiller, 2008; Zandi, 2010) as resembling the Great Depression. The origins of the financial contagion from the subprime crisis in the US can be traced back to the development of financial products such as Residential Mortgage Backed Securities (RMBSs), Collateralized Mortgage/Debt Obligations (CMOs/CDOs), structured investment vehicles (SIVs) and Credit Default Swaps (CDSs). By moving risk weighted assets off bank balance sheets, they not only helped banks minimise regulatory capital charges, but also created a mechanism through which banks could restructure their balance sheets to attain substantial asset accumulation rates and fuel a large-scale and unsustainable growth in international borrowing (Milne, 2009). The resulting diffusion of these financial innovations, which Warren Buffet dubbed weapons of mass destruction, led to multiple levels of debt or leverage with little contribution to returns from investment in the real economy. Nevertheless, whilst these instruments had evolved from very basic mortgage bonds in the late 1970s to complex SIV structures in 1988, they were subjected to little or no regulatory scrutiny. Indeed, McCulley (2009) and Noeth and Sengupta (2011) ascribe the housing market bubble that underpinned the subprime crises to creativity in the generation of financing through the rise of a shadow banking system, which operated legally, yet almost completely outside the realm of banking regulation. Others treat the subprime crisis as a Minskey Moment, in which financial innovation ultimately worked to bring about the systemwide securitisation Ponzi scheme that collapsed and serially engulfed Wall Street, starting with Bear Sterns in March 2008 and culminating with the demise of Lehman Brothers in September 2008 (Lahart, 2007; Magnus, 2007a, 2007b, 2007c, 2008; McCulley, 2009; Vercelli, 2009; Whalen, 2008a, 2008b; Wolf, 2007, 2008).

Fig. 1: US Subprime Securitisation Rates 1996-2008



Data Source: Inside Mortgage Finance (2007) as presented by The Financial Crisis Inquiry Commission (2011).

One of the largest US mortgage lenders, Countrywide, between 2003 and

2007 directly or indirectly through mortgage sales to government-sponsored enterprises (GSE) such as Fannie Mae and Freddie Mac, had securitised over 95% of its US$2.4tn in mortgage originations. A similar picture is painted in the UK, where Milne (2009), citing the HM Treasury report that Sir James Crosby commissioned, notes that two thirds of UK banks mortgage lending in 2006 was financed by the issuance of mortgage-backed securities. Even where these securities were underscored by low-quality collateral, by issuing mortgage-backed securities under a tranche structure with multiple layers of note seniority accredited by an external ratings agency such as Moodys, banks were able to attract institutional investors. The resulting flood of liquidity and nonconventional mortgage products such as variable-rate or Adjusted Rate Mortgages (ARMs), fuelled a house and asset price bubble that set in motion positive feedback loops to keep default risk on mortgages initially low as prices rose, but led to widespread panic as foreclosure rates increased with the housing market collapse.

The literature is awash with explanations as to the underlying motivations of banking sector business models shifting away from traditional intermediation functions of liquidity transformation and delegated monitoring (Diamond, 1984; Diamond and Dybvig, 1983) towards the originate-to-distribute (O&D) model (Pennacchi, 1988 and Gorton and Pennacchi, 1995).[1]Amongst the list of motivations are; (1) reduction in liquidity constraints and the duration gap between assets and liabilities to improve shareholder earnings and financial reporting aesthetics (see for example Agostino and Mazzuca, 2010; Casu et al., 2009; Cebenoyan and Strahan, 2004; Dechow and Shakespeare, 2009; DeYoung and Rice, 2004; Drucker and Puri, 2006; Duffie 2008; Greenspan, 2004;Loutskina and Strahan, 2007; Martelline et al., 2003; Milton, et al., 2004; Molyneux, 2004; Parlour and Plantin, 2008; Pennacchi et al., 2013; Uzun and Webb, 2007); (2) the extent to which economic efficiencies are gained through the reallocation of credit risk associated with associated with a defined pool of receivables (see Cumming, 1987; Dahiya el al., 2003; Flannery, 1994; Greenbaum and Thackor, 1987; Pavel and Philis, 1987, Ambrose et al., 2005; Calem and LaCour, 2003; Calomiris and Mason, 2004; Gorton and Souleles, 2005; Hänsel and Krahnen, 2007; Higgins and Mason, 2004; Krahnen and Wilde, 2006; Milne, 2009; Passmore et al., 2001; Uhde and Michalak, 2010; Vermilyea et al., 2008; Vickery and Wright, 2013; Wolfe, 2000); (3) regulatroy arbitrage through which banks are able to expand their loan origination and assume riskier balance sheets whilst simultaneously reducing both regulatory and economic capital (see Allen, 1996; Allen and Gale, 2003, 2004; Arping, 2004; Ambrose et al., 2005; Agarwal et al., 2009; Berger et. al., 1995; Berger and Udell, 1993; Benmelech et al., 2009; Calomiris and Mason, 2003; Donahoo and Shaffer, 1991; Franke and Krahnen, 2005; Froot et al., 1993; Hänsel and Krahnen, 2007).

[1] The O&D model is the operational model whereby banks expand their funding sources to include bond financing, commercial paper financing, and repurchase agreement (repo) funding while simultaneously distributing loans they originate by syndicating loans, selling them in the secondary loan market, or pooling and selling the said consolidated debt as bonds, pass-through securities, or collateralised mortgage obligations (CMOs) to various investors.

Nevertheless, the long-run viability of the O&D model has also been found to be critically dependent on the ultimate location of credit risk within the financial sector and the costs of securitisation imposed by investors in the issued notes (see Allen and Carletti, 2005; Allen and Gale, 2005; Chiesa, 2004; Hellwig, 1994, 1995, 1998; Jiangli, et al., 2007; Kloman, 2003; Persuad, 2002; Gorton and Souleles, 2005; Martinez-Solano et al., 2009; Solano et al, 2006; Wagner and Marsh 2004; Morrison, 2005; Wagner, 2005a, 2005b).[2]By extending the findings of Markose et al (forthcoming), this paper contributes to the current body of literature on securitisation and CRT, more specifically, by reshaping the research from the view point of agent-based computational economics (ACE) by characterising securitisation as a flow process or complex adaptive system (CAS) consisting of autonomous decision making agents influenced by feedback loops. The focus on modelling the market microstructure of the issuance process to determine whether a system of behavioural decision making by institutional investors and/or by issuing banks (e.g. loss aversion, decision making according to simplified rule of thumb behaviour) can lead to unsustainable increases in issuance or large scale fluctuation in prices of securitised assets? Pricing these assets in terms of the cost of the underlying credit risk, this multi-agent-based ACE approach is considered advantageous because it not only provides look-through at the level of individuals that comprise the system, but also enables a more granular assimilation of the interactions between agents. In the rest of the paper, the ACE and market microstructure of securitisation are discussed, followed by the two sector model developed. The paper then breifly discusses the data before presenting the results and concluding remarks. Given this paper is tasked with presenting a two sector model of autonomus decision making agents, the sections on model specification employ a sizable number of parameters. A full listing of these parameters and their definitions are in the Appendix.

2 Securitisation as a Market Micro-Structure ACE model

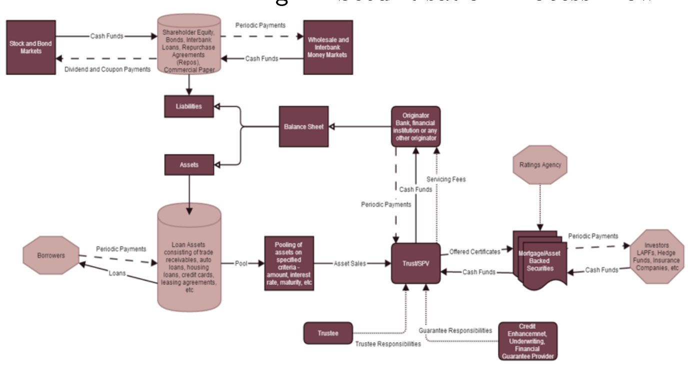
Market microstructure agent-based models are geared towards capturing the structural dynamics of CAS from not only the micro-behavioural, but also the institutional/rules perspective.[3] That is, such models assess evoluving macroscopic outcomes from the microscopic standpoint of agents' behavioural incentives, their interactions, and other determinants of transaction costs, prices, quotes, volume, and trading behavior that are inherent in institutions, rules

[2] The cost of securitization is the cost that banks or their special purpose vehicles (SPVs) pay to securitise assets successfully. It includes interest cost of the debt; issuance expenses of the debt; credit enhancement and liquidity support for the assets; structuring fees payable to bankers; legal, accounting, and tax advice fees; rating-agencies' fees; and management time (Giddy, 2000).

[3] Complex adaptive systems are complex macroscopic self-organising collections of relatively similar and partially connected and interacting micro-structures formed in order to adapt to changing environments and increase macro-structure survivability. Rather than models for predicting outcomes, CAS is a philosophical/theoretic framework for thinking about the world around us and thereby provides a variety of new options giving the researcher more choice and freedom.

and processes through which markets clear and settle on daily and intraday basis (see Helding 2009,2010; Helbing and Balietti 2011 for a full discussion on ACE models). The success of such models at capturing real world dynamics and the validation of their results is well documented in the financial markets literaure where understanding market microstructures has gained the most attention (see Barde, 2016; Chen et al. 2011, Cona, 2008; Farmer and Joshi, 2002; Gilli and Winker, 2003; Kirman, 2013; Kukacka and Barunik, 2016; LeBaron, 2005; Platt and Gebbie, 2016a &b, Arthur et al., 1996; Gode and Sunder, 1993; Kirman and Vriend, 2001; LeBaron, 2002;).

Fig. 2: Securitisation Process Flow



Notes: (1) The direction of arrows signify the direction of cash flows, claims, ownership, responsibilities. (2) ← is used to signify a composition. (3) ← is used to signify definite transfer of cash funds, payments, rights and claims. (4) ← – – is used to signify credit contingent claims and payments. (5) ←⋯ is used to signify fees and other ongoing responsibilities. (6) While credit enhancements are depicted as externally provided the Mortgage/Asset backed securities may be issued with internal enhancements through layers of subordination. (7) SPV means special purpose vehicle. (8) LAPFs means Life Assurance and Pension Funds

As illustrated in Figure 2 the structural framework of a typical securitisation consists of a number of feedback loops be these, on the securitisation pool origination side or the securitised note issuance side. Consequently, one can asset the market microstructure of securitisation as a CAS. Securitisations at the pool and issuance level is a system consisting of a sufficiently large number of interacting and adapting agents (these include the underlying borrowers, the issuing banks, and investors aquiring the securities). Each of these agents, as as partcipants in other markets with specific structres and processes (e.g. housing market, labour market, cash managment, global risk managment, etc), are themselves complex systems that continously adapt to the multiplcity of environments they operate in. Thus the market for securitised note issuances is a system of interacting microscopic systems which can create outcomes at the macroscopic level that are influeced by interactions elsewhere. Secondly, through these intaractions between component agents, unplanned and unpredictable system level regularities emerge which further feed back unto the market for securitised note issuances and inform the interactions between the agents.

These feedback-loops associated with the process of securitisation are reflected in the agents' objective functions which they optimise by choosing the most appropriate action profile given all possible states. Moreover, as a system of computational agents, the ability of participants in each stage of the process flow to accurately predict outcomes must be consistent with theory of computation.[4] That is, the computational problem agents face when determining their optimal action must necessarily fall under one or more of the many complexity classes and the associated algorithmic solutions given the bounds of computational time and space. In essensence, agents are boundedly rational to the extent to which they can optimise desicion making using update rules in a reasonable amount of time and space. Under the context of ACE, such update rules can take the form of arbitrary rules of thumb, or evolutionary computation and machine learning techniques such as Reinforcement Learning, Belief Learning, Genetic Programming, Neural Networks, and Cellular Automata. The choice of update rule is problem and research objective dependent. It is important to note that unlike traditional economic models with rational agents who price perfectly, under an ACE construct, systems are necessarily endogenously dynamic and evolving. Therefore expected rewards upon which agents base their actions are typically not identical to the realised rewards; the latter being derived jointly from the actual collective actions of all particpants and actual observations of stochastic variables such as asset returns. In the context of the securitisation flow process, these realised rewards then feed back into for banks for example the cost of issuing securitised notes or for investors, the portfolio allocation decision making process.

3 Methodology

3.1 The Banking Sector Model

The banking sector model is an inter-temporal modification of the well-known Monti-Klein model (Klein, 1971; Monti, 1972) in which banks are monopolistic in that they are assumed to set both loan and deposit rates. The modifications made are geared towards the objectives of this analysis. The assumptions of the model are as follows, (a) there is no distinction between asset classes on the banks balance sheets; therefore, all assets earn the same rate of return; (b) assets consist entirely of loans and cash proceeds from securitisation, which are ploughed back to issue more loans at the end of each time interval; (c) similarly, no distinction is made between classes of liabilities, defined as insured cash deposits, on banks balance sheets. A consequence of this assumption is that no account is taken of interbank lending, acquisition of government debt, stock and debt issuance or participation in wholesale or repo markets; (d) the default probability associated with the credit risk faced in the lending function

[4] The theory of computation is a field of mathematical logic and computer science consisting of, computatiliby theory, complexity theory, and Cantor-Gödel-Church-Turing quantum states, that addresses the questions of what can be truely computed mechanically, using for example mathematical algorithms, and their catergorisation or classification according to the amount of time and space required to compute (see Thomas Breuer 2011, A Gödel-Turing Perspective on Quantum States Indistinguishable from Inside, and K. Vela Velupillai and Stefano Zambelli 2012, Computability and Algorithmic Complexity in Economics).

of banks is captured by introducing an exogenous survival rate on assets; (e) in addition to this, regulatory capital constraints on lending are incorporated into the model using an exogenous capital adequacy ratio.[5] This capital requirement is also assumed to be binding and represents the cost of doing the business of traditional intermediation. Monitoring and other loan origination costs are not factored in; (f) banks are also permitted to securitise their assets at an endogenously determined securitisation rate.
Accordingly, banks are subject to the following solvency condition:

$$if \begin{cases} A_t \geq L_t \; and \; E_t \geq \alpha A_t & solvent \\ A_t \geq L_t \; and \; E_t < \alpha A_t & requires\, capital\, injection \\ A_t < L_t \; and \; E_t < \alpha A_t & bankrupt \end{cases} \tag{1}$$

From this, the time t level of the minimum amount of capital injection required to maintain solvency is derived such that

$$\begin{aligned} M_t &= \varepsilon\left(1-\alpha\right)A_t - \left(A_t - L_t\right) \\ &= \varepsilon\left(1-\alpha\right)A_t - E_t \end{aligned} \tag{2}$$

The banks asset accumulation process is accordingly specified as

$$A_{t+1} = \gamma\left(1-\alpha\right)A_t + \alpha A_t + r^A\gamma A_t - M_t - C\left(\alpha\right)A_t \tag{3}$$

where

$$C\left(\alpha\right) = \begin{cases} \alpha\beta & linear \\ \left(\alpha+\alpha^2\right)\left(\theta+\mu_{\gamma,t}\right) & non-linear \end{cases} \tag{4}$$

represents the securitisation cost subtracted from the total benefits accrued from the securitising of assets. Since M_t is a measure of a banks solvency, $-M_t$ can be regarded as a proxy to the banks profit and $^{-M_t}/_E$ as an approximation of return on equity (ROE).

Substituting for $-M_t$ (from equation 2) in equation 3, yields:

$$\begin{aligned} A_{t+1} &= \gamma\left(1-\alpha\right)A_t + \alpha A_t + r^A\gamma A_t - \varepsilon\left(1-\alpha\right)A_t - \left(A_t - L_t\right) - C\left(\alpha\right)A_t \\ &= \left[\left(\gamma-\varepsilon\right)\left(1-\alpha\right) + \alpha + r^A - C\left(\alpha\right)\right]A_t + E_t \\ &= qA_t + E_t \end{aligned} \tag{5}$$

where the asset accumulator

$$\begin{aligned} q &= \left[\left(\gamma-\varepsilon\right)\left(1-\alpha\right) + \alpha + \gamma r^A - C\left(\alpha\right)\right] \\ &= \left[\Omega_1 + \alpha\Omega_2 - C\left(\alpha\right)\right] \end{aligned} \tag{6}$$

and

[5] Bernanke and Lown (1992) were amongst the first to show how capital requirements influenced loan portfolio growth. The analysis in this chapter will assess this relationship.

$$\Omega_1 = \left[(\gamma - \varepsilon) + \gamma r^A\right]$$

$$\Omega_2 = [1 - (\gamma - \varepsilon)]$$

where$\Omega_1 > 0$ and $\Omega_2 > 0$ imply that q is a positive function of α and declining in ε. Substituting back into (2) gives the bank's objective function which it maximises by selecting the appropriate α

$$-M_t = E_t - \varepsilon (1 - \alpha) (qA_t + E_t) \tag{7}$$

Moreover, since equations 5 and 7 are recursion relationships, one can solve backwards for time $t = 0$ by repetitive substitution. Therefore, since $A_t = L_t + E_t$, the asset accumulation process is given by

$$A_T = (1 + q)^T A_0 - \sum_{t=1}^{T} (1 + q)^{t-1} L_{T-t} \tag{8}$$

3.1.1 Securitization of Non-Conventional and Subprime Assets with Loan Quality Deterioration

To account for dynamics of ARM loans, the model is extended to a multi-period setting where mortgage contract rates and survival probabilities change as time progresses. This is done by reformulating equation 5 as

$$\begin{aligned} \widetilde{A}_{t+1} = \gamma_t^{ARM} (1 - \alpha) \widetilde{A}_t + \alpha \widetilde{A}_t + r_t^{ARM} \gamma_t^{ARM} \widetilde{A}_t \\ -\varepsilon (1 - \alpha) \widetilde{A}_t - \left(\widetilde{A}_t - \widetilde{L}_t\right) - C(\alpha) \widetilde{A}_t \end{aligned} \tag{9}$$

where

$$\widetilde{L}_t = L_0 \prod_{t=0}^{T-1} \left(1 - r_t^L\right) \tag{10}$$

Therefore, solving backwards for time in a similar fashion as used to derive equation 8, equation 9 may be specified as

$$\widetilde{A}_t = A_0 \prod_{t=0}^{T} X_t - L_0 \prod_{t=1}^{T} X_t - \widetilde{L}_1 \prod_{t=2}^{T} X_t \ldots - \widetilde{L}_{T-1} \prod_{t=T}^{T} X_t - \widetilde{L}_T \tag{11}$$

where

$$X_t = \left[1 + \left(\gamma_t^{ARM} - \varepsilon\right)(1 - \alpha) + \alpha + \gamma_t^{ARM} r_t^{ARM} - C(\alpha)\right] \tag{12}$$

Consequently, the optimal securitisation rate is obtained by maximizing the capital accumulation function over a T-periods forward horizon. That is to say, maximise

$$-\widetilde{M}_t = [1 - \varepsilon (1 - \alpha)] \widetilde{A}_T - \widetilde{L}_T \tag{13}$$

Note that since the only modification to the original asset accumulation process is in allowing multiple asset survival rates and asset returns, if these rates were kept constant over the T-period horizon, one would expect the optimisation of equation 13 to yield approximately the same value as optimising equation 7. The following section describing the optimisation algorithm will refer to the optimisation of $-M_T$. Nevertheless, the approach described will apply equally to the optimisation of $-\widetilde{M}_T$.

3.1.2 Securitization of Non-Conventional and Subprime Assets with Loan Quality Deterioration

The Roth -Erev RL optimisation assumes banks seek to maximise their 5-period look ahead capital accumulation, $-M_T$, where $T = 5$, by choosing an appropriate securitisation rate. Equations 7 and 13, depending on the securitisation model used, in this instance become the banks reward functions. As before, the key factors constraining bank decisions are the regulatory capital requirements and securitisation cost. For the set of securitisation rate choice actions,$\mathbb{A}^{BANK}$ which has a cardinality of N,the Roth-Erev RL algorithm assigns propensity values to all possible actions in the domain. These propensities are then translated into a probability distribution that governs successive choices of actions. The specific implementation used here is based on the Nicolaisen et al. (2001) variant of the Roth-Erev algorithm and utilises the Gibb-Boltzmann distribution.[6]Moreover, since $-M_T$ may assume positive, zero or negative values, this particular implementation is deemed appropriate and more robust than the standard Roth-Erev algorithm. With this implementation, action propensities $(\widehat{q}_i(t))$, the experience function $(\hat{E}_i(\varrho, i, j, t))$, and action probabilities $(p_i(t))$ are respectively specified as

$$\widehat{q}_i(t+1) = [1 - \phi]\, \widehat{q}_i(t) + \hat{E}_i(\varrho, i, j, t) \tag{14}$$

$$\hat{E}_i(\varrho, i, j, t) = \begin{cases} r_j(t)\,[1 - \varrho] & if\ i = j \\ \widehat{q}_i(t) \frac{\varrho}{N-1} & if\ i \neq j \end{cases} \tag{15}$$

$$p_i(t) = \frac{\varrho^{\widehat{q}_i(t)/\tau}}{\sum\limits_{j=1}^{N} \varrho^{\widehat{q}_i(t)/\tau}} \tag{16}$$

Note that in equations 14 to 16, the parameters ϱ and ϕ refer respectively to the exploration/experimentation rate and the recency or forgetting rate banks

[6] The Java implementation is an adaptation of the RothErevLearner in the Java Reinforcement Learning Module (JReLM), which is itself an adaptation of the RothErevLearner in the Java Agent-Based Modelling toolkit (JASA) by Steve Phelps at the Centre for Computational Finance & Economic Agents (CCFEA) University of Essex.

apply in their decision making. The exploration rate, can be thought of as each banks willingness to the action/search space to find more profitable locations or actions. It is thus a proxy of the banks profit seeking or risk taking. Increasing the exploration rate can result in better accuracy in action choices but, may also lead to more random behaviour. By contrast, the recency parameter captures the tendency of banks to ignore past actions and to prioritise more recent experience. The lower the value of the recency parameter, the more influence past actions will have on the current choice of action than the potential for future gains by changing actions. This may result in less accuracy but give rise to more predictable behaviour.

3.2 The Life Assurance and Pension Fund (LAPF) Sector Model

The economic problem facing LAPFs are threefold.[7] Firstly LAPFs must determine how to value their assets and liabilities when the assets are liquid and subject to market movements while liabilities are not (or more strictly are less liquid and potentially less volatile). Secondly, they must be able to ensure that there is always sufficient cash flow from the assets to meet liability payments when they fall due. Finally, LAPFs should be capable of delivering these pensions at the lowest economic cost to the sponsor. In addition to these objectives, it is further assumed that (a) LAPFs are risk averse and hold particular sentiments towards the general direction of activity in the housing market, (b) funds independently make forward-looking investment decisions based on information available about asset returns and the current state of their portfolios, (c) LAPFs decisions are updated based on returns received in each successive period, (d) the returns on each asset held by LAPFs are assumed to be independent of returns on other assets held, (e) asset returns can fall into one of three possible states {positive, zero, negative} at the end of each investment cycle, and (f) the demand for RMBS by LAPF forms the basis of securitisation costs faced by banks in each successive period.

The asset-liability management problem facing LAPFs is modelled as a discrete time liability driven model similar to Wise (1984a, 1984b, 1987a, 1987b), Wilkie (1985) and Sherris (2003). An implicit assumption is that asset allocation decisions and solvency tests are undertaken at discrete intervals which coincide with actuarial or regulatory valuations. It is also assumed that claimants of insolvent funds receive an amount equal to the difference between fund liabilities and the deficit. Moreover, as a liability driven process, assets are held specifically to meet the value of the expected liabilities which is exogenously determined. The objective of the fund is to find the optimal strategic asset allocation in each time step that maintains its solvency.

[7] It should be noted that when referring to pension funds in this model, only the defined benefit (DB) or final salary schemes are considered and not defined contribution (DC) or market value schemes. This is because only DB schemes provide any guarantees as to the market value of the annuity to be purchased upon retirement. That is DB schemes guarantee a minimum value of the annuity at retirement linked to salary at the retirement date.

3.2.1 LAPF Solvency Analysis

Where funds are given an initial endowment of assets to meet liabilities at the beginning of each time period it follows that

$$A^{LAPF} \equiv C + K. \tag{17}$$

Moreover, because is the funds risk capital, identity 17 can be re-written in the form of a solvency margin multiplied by the fixed component of assets required to fund the net present value of future liabilities; therefore,

$$A^{LAPF} \equiv (1+\rho)\, C \tag{18}$$

where $\rho = K/C$.
Furthermore, if the actual value of assets is greater than A^{LAPF}, the fund has an initial surplus. Otherwise, the fund is insolvent and its assets are distributed amongst the scheme members or policy holders. The objective of the fund is therefore to allocate A^{LAPF}across all asset classes at the beginning of the investment period in order to meet liabilities at the end of that investment period at the lowest economic cost to the sponsor. Thus, the expected end-of-period surplus is given by

$$S_t = A^{LAPF}\left(E\left[\sum_{k=0}^{n}\left(\left(1 + r_{k,t+1}\hat{\Omega}_{k,t+1}\right) - f\left(w_k\right)\Phi\right)^{\lambda}\right]\right) - L_t \tag{19}$$

or

$$S_t = \Psi_t\,(1+\rho)\, C \tag{20}$$

where

$$\Psi_t = E\left[\left(\sum_{k=0}^{n}\left(\left(1 + r_{k,t+1}\hat{\Omega}_{k,t+1}\right) - f\left(w_k\right)\Phi\right) - \left(1/\left(1+\rho\right)\right)\eta_t\right)^{\lambda}\right] \tag{21}$$

$r_{k,t+1}$ is the return on asset k realised at time $t+1$ and where $\lambda^t$is the discount factor applied to returns received on asset k at time t. Using the variable

$$\hat{\Omega}_{k,t+1} = 1 + log\left(\frac{\gamma_{t+1}^{k}}{\gamma_t^{k}}\right), \tag{22}$$

to represent the risk adjustment in asset k, LAPFs are allow to hold a view of future movements in asset returns not captured in fluctuations in asset returns. If $\hat{\Omega}_{k,t+1} > 1$, the LAPF is optimistic about the future direction of asset k. If $\hat{\Omega}_{k,t+1} < 1$, the LAPF believes the issuer of asset k is likely experience some future economic hardship, which translates into a credit quality downgrade or decline in the value of asset k. On the other hand, $\hat{\Omega}_{k,t+1} = 1$ implies that the LAPF does not expect sudden changes in the value of asset k during the investment horizon.

Defining the Stochastic Model Note that since each asset in the portfolio may assume differnt states at the end of each investment cycle, it is possible to define state transition probability matrices for each of the assets.[8] Thus, for each of the n risky assets $k \in \{0, 1, 2, .., n\}$, there is an end of cylce state $x \in \mathbb{X}$ indexed by $e_{k,t}(x) \in \mathbb{E}_k$ such that the asset transitions between end of cycle states $e_{k,t}(x)$ and $e_{k,t}(x')$ with a probability $P(e_{k,t}(x), e_{k,t+1}(x'))$.[9] The state transition matrix is therefore given by

$$\begin{bmatrix} P(e_k(0), e_k(0)), & P(e_k(0), e_k(1)), & \cdots & P(e_k(x'), e_k(x)) \\ P(e_k(1), e_k(0)), & P(e_k(1), e_k(1)), & \cdots & P(e_k(x'), e_k(x)) \\ \vdots & \vdots & \ddots & \vdots \\ P(e_k(x'), e_k(0)), & P(e_k(x'), e_k(1)), & \cdots & P(e_k(x'), e_k(x)) \end{bmatrix} \tag{23}$$

If for simplicity, it is assumed that the LAPF portfolio consists of three assets, a risk free bond with constant returns and two risk assets, an equity fund and a composit of RMBS notes, with independent returns, then the portfolio states is stochastic with joint transition probabilities computed as,

$$P\left(\{e_k(z), e_l(y)\}, \{e_k(\widetilde{z}), e_l(\widetilde{y})\}\right) = P\left(\{e_k(z), e_k(\widetilde{z})\}\right) * P\left(\{e_l(y), e_l(\widetilde{y})\}\right). \tag{24}$$

The term $P\left(\{e_k(z), e_l(y)\}, \{e_k(\widetilde{z}), e_l(\widetilde{y})\}\right)$ denotes the joint probability of asset k transitioning from state z to the state $\widetilde{z}$ and asset l evolving to state $\widetilde{y}$ from state y. In a two risky-asset model where each asset has three possible states the joint transition probability matrix will consist of eighty-one elements before accounting for the set of vectors specifying the portfolio weights; which translate to the set of actions.

By construction, therefore, the LAPF surplus optimisation problem is reduced to a Markov decision process (MDP) with the basic mathematical form

$$\left\{\mathbb{S}, \mathbb{A}^{LAPF}, \mathbb{T}_{a \in \mathbb{A}^{LAPF}}(s, s'), R_a(s, s'), v(s)\right\} \tag{25}$$

whereby,

1. at each discrete time step t, the LAPF with a portfolio in state $s \in \mathbb{S}$ applies an investment or asset allocation strategy $a \in \mathbb{A}^{LAPF}$, available to it at state s.

2. the system then transitions to state $s' \in \mathbb{S}$ according to a transition kernel $\mathbb{T}_{a \in \mathbb{A}^{LAPF}}(s, s')$, and the LAPF receives the portfolio return $R_a(s, s')$, given the initial state s and action a but not any other state $s^{\neg}$ or action $a^{\check{n}}$ that may have preceded state s and action a.

[8] The transition model may be derived through any number of means: Monte Carlos simulation of the asset price generation process, historically observed data or some probability distribution such as a generalized Bernoulli distribution where a random event can take on one of possible outcomes and the probability of each outcome separately specified (Bishop, 2007; Fanga et al., 2014).

[9] Except where necessary, the time stamping of states will be dropped going forward to ease notation.

Accordingly, the state of a given LAPFs portfolio will comprise of the states each the individual assets are in and the portfolio weights assigned to those assets

$$s_t = (e_{0,t}, e_{1,t}, e_{2,t}, \cdots, e_{n-1,t}, e_{n,t}) \mid (w_{0,t}, w_{1,t}, w_{2,t}, \cdots, w_{n-1,t}, w_{n,t}), \quad (26)$$

Thus, the portfolio or MDP state space, $\mathbb{S}$, has a cardinality of $n^{\mathbb{X}W}$ with the portfolio following a stochastic process defined by the joint state transition probabilities across all of its constituents.
Moreover, by specifying a sub-domain of actions, $a \in D \subseteq \mathbb{A}^{LAPF}$ to be permissible at each state, the cumulative probability of transitioning from any given portfolio state s to an adjacent destination state s' must necessarily sum to 1 (i.e. $\sum P_{a\in D}(s, s') = 1$). Conversely, for all non-permissible actions $\breve{a} \notin D \subseteq \mathbb{A}^{LAPF}$, the cumulative state transitions probability is $\sum P_{\breve{a}\in D}(s, s') = 0$. Permitted actions a are defined as vectors of n portfolio weights where a limit of $\pm\delta$ is set as the maximum permissible overall weight change from the starting vector of weights at the time decision making occurs.[10] LAPFs, therefore, maximise the expected value of future funding surpluses by selecting, for all possible states, the optimal investment policy $\pi^*(\mathbb{S}) = \left\{a_t^*, a_{t+1}^*, a_{t+2}^*, \cdots, a_T^*\right\}$.

Risk Aversion and the Value Function As risk averse agents, LAPFs are assigned logarithmic state dependent utility functions[11] $U(s) = log(s)$ with $dom\, U = (0, \infty)$, and they solve the one-period utility optimisation problem

$$u_t := sup_{a\in\mathbb{A}_{\approx}} E\left[log\left(\Psi_t\left(a\right)\right)\right]. \quad (27)$$

Permitting investment in a risk-free bond, the value function at each state is

$$V_t\left(s\right) = max_{a\in\mathbb{A}} E\left[log\left(s_{t+1}\right) + \left(\lambda \sum_{j=t}^{T-1} \lambda^j log\left(1 + w_{rf} r_{rf,j+1}\right) + u_j\right)\right] \quad (28)$$

This can be written as a simple backup operation combining the policy improvement and truncated policy evaluation steps for all $s \in \mathbb{S}$:

$$V_t\left(s\right) \quad = \quad max_{a\in\mathbb{A}} E\left[log\left(s_{t+1}\right) + \left(\lambda \sum_{j=t}^{T-1} \lambda^j log\left(1 + w_{rf} r_{rf,j+1}\right) + u_j\right) \mid s_t = s,\ a_t = a,\ s_{t+1} = s'\right]$$

[10] The constraint of an overall change in weight of $\pm\delta$ from one vector of weights to another helps ensure that the restriction on short selling holds, as well as limiting the extent to which LAPFs can buy or sell any given asset in one time period. It is also practice that institutional investor do not make such large changes in their portfolio allocations that could effect price determination within the market.

[11] This is in keeping with empirical results indicating relative risk aversion forms a key driver of human decision making (Abdulkadri and Langemeier, 1999; Christopoulos et al., 2009; Friend and Blume, 1975; Fullenkamp et al., 2003; Van Praag and Booji, 2003).

$$= max_{a\in\mathbb{A}}\sum_{s'}P_a\left(s_t,s'\right)\left[R_a\left(s_t,s'\right)+\lambda V\left(s'\right)\right] \quad (29)$$

Equation 29 is simply the Bellman equation expressed as an update rule such that, given an arbitrary V_0, the sequence of V_t across all states converges to the optimal solution V^* given the stopping condition

$$max_s \mid V(s) - V^{'}(s) \mid < \hat{\theta} \quad (30)$$

where $\hat{\theta}$is the predefined utility improvement threshold of the reinforcement learning algorithm[12]

$$\hat{\theta} = \begin{cases} \varpi, & if\ \lambda = 1 \\ \varpi\left[\left(1-\lambda\right)/\lambda\right], & otherwise \end{cases} \quad (31)$$

ϖ, defines the required level of precision and the optimal policy is

$$\pi^*(s) = arg\, max_s \sum_{s'} P_a\left(s,s'\right)\left[R_a\left(s_t,s'\right)+\lambda V\left(s'\right)\right] \quad (32)$$

3.2.2 Market Clearing

Conforming to the observations of Vickery and Wright (2013) in relation to subprime RMBS market conventions, a simplifying approximation of excess spreads is applied to the securitisation cost faced by banks. Specifically, the excess spread is linked to demand for RMBS by LAPFs so that lower average demand for RMBS will result in higher excess spreads and securitisation costs in the banking sector. Conversely, higher demand by LAPFs gives rise to lower excess spreads. This dynamic is captured by modifying the non-linear securitisation cost function of banks found in equation 4 to

$$C_t\left(\alpha\right) = \left(\alpha+\alpha^2\right)\left(\theta+\mu_{\gamma,t}\right) \quad (33)$$

where $\mu_{\gamma,t} = f\left(\vartheta,\left(1-\gamma\right),\bar{w}_{RMBS}\right)$is the excess spread as a function of the market average demand for RMBS, $\bar{w}_{RMBS}$. To simplify this process, credit enhancements are simulated according to obligor concentration limits,ϑ. These limits, often provided by rating agencies, are critical for setting the extent to which investors should be exposed to trade receivables transactions given the credit quality of obligors in the pool. The higher the obligors ratings, the lower the probability of loss, and the higher the obligor concentration limit. In order to dynamically assign credit enhancements on exposures based on their default risk, it is assumed that banks will retain the residual exposure against some pre-set total enhancement. Moreover, since the level of demand for RMBS reflects

[12] see Sutton and Barto (1998) for an introductory discussion of reinforcement learning (RL) and the associated evolutionary computational algorithms.

investors perceptions of risk, for a given level of demand, credit enhancements can be simulated as

$$\mu_{\gamma,t} = (1-\gamma)(1-\vartheta) \tag{34}$$

The impact of defaults on returns is captured in a downward adjustment of the stochastically generated periodic returns on RMBS. Consequently, the final market clearing return on RMBS in each period is

$$r^*_{RMBS,t} = (r_{RMBS,t} - LGD_t) \tag{35}$$

where total loss given default, LGD_t, is

$$LGD_t = \left(1-\varphi_t^C\right)(1-pf_t) \tag{36}$$

and the pool factor,pf_t,the proportion of the total initial principal of underlying mortgage loans that remain in mortgage-backed security transactionsis specified as

$$pf_t = \frac{\sum \widehat{\alpha A}}{\sum \alpha A} \tag{37}$$

noting that $\sum \widehat{\alpha A}$ is the total notional outstanding of surviving mortgage loans in the various mortgage-backed securities pools.

4 Data Description

The data set used for calibrating and evaluating the models are compiled from multiple data vendors or repositories. Mortgage contract rates are taken from the Primary Mortgage Market Survey datasets published by the Federal Home Loans Agency (FHLMC Freddie Mac). This includes contract rates on 15 to 30-year fixed rate mortgages (FRMs) and 1 to 5-year hybrid ARMs. For the purpose of modelling securitisation rates for ARM loans, the 1-year and 5-year hybrid ARM rates are indexed to yields on 1-year Constant-Maturity Treasury (CMT) securities. Historical monthly series data on CMT rates are retrieved from data releases published weekly as H.15 Selected Interest Rates by the Board of Governors of the Federal Reserve System.

Asset returns, traditional asset survival rates and transition probability matrices are derived from daily index quotes on the S&P500 equity index and the JP Morgan Mortgage-Backed Securities Fund-A (OMBAX). The motivating factors for choosing the OMBAX as a benchmark for RMBS are twofold. First, the index was in use as early as 2000; therefore, it covers the periods of interest leading up to and during the subprime crisis. Second, as an actively managed total return maximizing fund, the OMBAX represents a diversified portfolio of debt securities backed by pools of residential and/or commercial mortgages up to 10% of which are sub-prime mortgage-related securities.

Coupon rates, default rates and per tranche credit enhancement data are presented in in Table 3. Those figures listed in the second and third columns of the table are used as estimates of survival probabilities and securitisation costs, on

Tab. 1: **Simulated Joint Transition Probability Matrix for the S&P 500 and OMBAX (2000 to 2004)**

			End State								
	OMBAX		**Negative**	**Negative**	**Negative**	**Zero**	**Zero**	**Zero**	**Positive**	**Positive**	**Positive**
		S&P500	**Negative**	**Zero**	**Positive**	**Negative**	**Positive**	**Zero**	**Negative**	**Zero**	**Positive**
Start State	**Negative**	**Negative**	0.1685	0.0014	0.1844	0.0860	0.0007	0.0941	0.2211	0.0018	0.2420
	Negative	**Zero**	0.0886	0.0000	0.2657	0.0452	0.0000	0.1356	0.1162	0.0000	0.3487
	Negative	**Positive**	0.1942	0.0015	0.1586	0.0991	0.0007	0.0809	0.2549	0.0019	0.2081
	Zero	**Negative**	0.1478	0.0012	0.1618	0.0932	0.0008	0.1020	0.2346	0.0019	0.2567
	Zero	**Zero**	0.0777	0.0000	0.2331	0.0490	0.0000	0.1470	0.1233	0.0000	0.3699
	Zero	**Positive**	0.1704	0.0013	0.1391	0.1074	0.0008	0.0877	0.2704	0.0020	0.2208
	Positive	**Negative**	0.1641	0.0013	0.1795	0.0903	0.0007	0.0988	0.2213	0.0018	0.2421
	Positive	**Zero**	0.0862	0.0000	0.2587	0.0475	0.0000	0.1424	0.1163	0.0000	0.3489
	Positive	**Positive**	0.1685	0.0014	0.1844	0.0860	0.0007	0.0941	0.2211	0.0018	0.2420

Notes: From left to right each row assigns a joint transition probability of moving from a joint start state (the row entries) to a joint end state (the column entries) for both indices. For example, there is a joint transition probability of 20.81% that the system will move from a starting state where returns on the OMBAX are negative and returns on the S&P500 are positive (i.e. row three Negative/Positive) to an end state in which returns on both the OMBAX and S&P500 are positive (i.e. the final column).

Tab. 2: **Simulated Joint Transition Probability Matrix for the S&P 500 and OMBAX (2005 to 2009)**

			End State								
	OMBAX		**Negative**	**Negative**	**Negative**	**Zero**	**Zero**	**Zero**	**Positive**	**Positive**	**Positive**
		S&P500	**Negative**	**Zero**	**Positive**	**Negative**	**Positive**	**Zero**	**Negative**	**Zero**	**Positive**
Start State	**Negative**	**Negative**	0.1422	0.0018	0.2154	0.0845	0.0011	0.1280	0.1690	0.0022	0.2559
	Negative	**Zero**	0.1382	0.0000	0.2212	0.0821	0.0000	0.1314	0.1643	0.0000	0.2628
	Negative	**Positive**	0.1774	0.0034	0.1786	0.1054	0.0020	0.1061	0.2109	0.0040	0.2122
	Zero	**Negative**	0.1461	0.0019	0.2212	0.1002	0.0013	0.1517	0.1494	0.0019	0.2263
	Zero	**Zero**	0.1420	0.0000	0.2271	0.0974	0.0000	0.1558	0.1453	0.0000	0.2324
	Zero	**Positive**	0.1822	0.0035	0.1834	0.1250	0.0024	0.1258	0.1865	0.0035	0.1877
	Positive	**Negative**	0.1628	0.0021	0.2465	0.0926	0.0012	0.1402	0.1404	0.0018	0.2126
	Positive	**Zero**	0.1582	0.0000	0.2531	0.0900	0.0000	0.1440	0.1364	0.0000	0.2183
	Positive	**Positive**	0.2031	0.0039	0.2044	0.1155	0.0022	0.1162	0.1752	0.0033	0.1763

Notes: From left to right each row assigns a joint transition probability of moving from a joint start state (the row entries) to a joint end state (the column entries) for both indices. For example, there is a joint transition probability of 17.74% that the system will move from a starting state where returns on the OMBAX are negative and returns on the S&P500 are positive (i.e. row three Negative/Positive) to an end state in which returns on both the OMBAX and S&P500 are negative (i.e. the final column).

Tab. 3: Simulated RMBS Default Rates, Coupon Payments and Credit Enhancements by Exposure Ratings

Credit Rating	**Simulated Default Rate** $(1-\gamma)$#	**Simulated Coupon Rate on RMBS 2001-2007***	**Simulated Coupon Rate on RMBS 2001-2004***	**Obligor Concentration Limits as a Percentage of Total Enhancement AA/R-1 (middle) Rating**	**Required Issuer Support** $(1-\vartheta)$	**Simulated Credit Enhancement** $(\mu_{\gamma,t})$**
CCC-	0.33	0.16	0.16	25%	75%	0.12
CCC	0.16	0.16	0.16	25%	75%	0.12
BB-	015	0.15	0.15	25%	75%	0.11
	0.16	0.14	0.14	25%	75%	0.11
	0.13	0.13	0.13	25%	75%	0.10
	0.12	0.12	0.12	25%	75%	0.09
	0.11	0.11	0.11	25%	75%	0.08
BB	0.1	0.1	0.0987	25%	75%	0.08
BBB-	0.07	0.07		25%	75%	0.05
BBB	0.05	0.06	0.0642	33.3%	66.7%	0.04
A	0.05	0.06	0.0517	50%	50%	0.03
AA	0.001	0.04	0.0503	100%	0%	0.00
AAA	0	0.03	0.044	100%	0%	0.00

 # Simulated Default Rates are per tranche arithmetic averages of 5 and 10 year cumulative default rates.
** The simulated coupon rates are the arithmetic average of coupon rates by issuance credit ratings from a sample 500 securities issued between 2001 and 2007.*
*** The simulated credit enhancement assumes a total enhancement equal to the coupon rate on tranche being evaluated. The total enhancement coupon rate is then multiplied by the Issuer Exposure to arrive at the final per tranche Simulated Credit Enhancement. Data Sources: (1) Coupon Rates: DataStream and JP Morgan ABS CDO Weekly Snapshot (2003-2005). (2) Default Rates: DBRS (2007-2012), Fitch (2006 and 2008), Moodys (2009, 2010), Standard and Poors (2008-2012). (3) Obligor Concentration Limits: DRBS (2004).*

the basis of the underlying credit quality of notes issued. Data on coupon rates is was collated from a sample of 500 mortgage-backed securities deals issued between 2001 and 2007 available on DataStream and JP Morgan ABS-CDO Weekly Snapshot reports between November 2003 and December 2005. Default probability data is collated as the average 5 to 10 year cumulative default rates as reported by the four major ratings agencies DBRS, Fitch, Moodys and Standard and Poors in their various rating transition and default studies released between 2006 and 2012. To proxy the dynamics of an excess spread obligor concentration limits published in DBRS (2004) are transformed into the stylised credit enhancement process specified in equation 36.

Banks are initialised using data published by Inside Mortgage Finance (2007) as presented in Ashcraft and Schuermann (2007), Sadry and Schopflocher (2007) and The Financial Crisis Inquiry Commission (2011). Specifically, the total principle balance of subprime loan originations as of 2002 is allocated across all banks using their 2006 market share. Liabilities are set from the subprime origination data to ensure that each bank is solvent on initiation. The 2005 and 2006 market share data is summarised in Table 2. This is done because the bank level market share data for 2002 was not readily available.

Simulated life assurance and pension funds are constructed using data gathered from the annual Global Pension Assets Study releases published by the actuarial firm Towers Watson (formerly Watson Wyatt). This is further supplemented with asset and liability data found in the October 2012 press release FTSE350 Pensions 2002-2012: 175bn of Contributions Fails to Reduce Pension Scheme Deficits by the global consulting firm Mercer.

5 Results

5.1 Model Callibration

Both banking sector and LAPF sector models are callibrated through repeated experimentation to asscertain appropriate parameter settings. The calibration of the banking sector model with regards to selecting the Roth-Erev RL models experimentation (ϱ), recency/exploitation (ϕ), and Gibbs-Boltzmann
Cooling (τ) parameters did not yield conclusive convergence on a single set of values. The consequence was therefore to make the assumption that banks are both profit seeking and opportunistic when making decisions. Thus, while banks will look to explore the search space for potentially more profitable actions then their last action, they will also place some weight on their previous choices to mitigate potential losses. As such a suitable range for these parameters was considered to be $0.75 \leq \varrho \leq 0.90$, $0.50 \leq \phi \leq 0.75$, and $\tau = 1$. Within this range, banks will explore the search space in an attempt to attain more profitable outcomes but place a sufficiently large amount of weight on past actions so as not to disregard the risk of loss.[13]

[13] It is worth noting that whilst the final parameter values are specified according to the abovementioned analysis, further research is required similar to comparative studies aimed at

Tab. 4: Banking Sector Model Parameters Settings

Banking Sector	
Parameter Description	Parameter Value
Roth-Erev experimentation factor	$\varrho = 0.90$
Roth-Erev exploitation factor	$\phi = 0.50$
Roth-Erev Gibbs-Boltzmann cooling parameter	$\tau = 1$
Roth-Erev update model type	Nicolaisen Variation
Roth-Erev number of actions/securitisation rate choices	$N = card\left(\mathbb{A}^{BANK}\right) = 101$
Roth-Erev number of trials	10,000
Initial securitisation rate*	$\alpha = 0.25$
Standard mortgage contract rate	$r^A = 0.05$
ARM mortgage contract rates	$r^A_{ARM} = 0.05/0.08$
Cash deposit rate of return	$r^L = 0.0252$
Regulatory capital ratio	$\varepsilon = 0.08$
Securitisation cost function	Non-linear
Demand driven credit enhancement charge	$\mu_{\gamma,t} = \begin{cases} 0.00 = 0.00\,(1.0 - 1.0)\,, & if\, w_{MBS} \geq 50\%\, of\, LAPF\, portfolio \\ 0.03 = 0.05\,(1.0 - 0.50)\,, & if\, 25\% \leq w_{MBS} < 50\%\, of\, LAPF\, portfolio \\ 0.11 = 0.15\,(1.0 - 0.25)\,, & if\, w_{MBS} \leq 25\%\, of\, LAPF\, portfolio \end{cases}$
Standard loan survival probability at origination	$\gamma = \begin{cases} 0.99, & if\, strong\, household\, credit\, quality\ (AA) \\ 0.90, & if\, moderate\, household\, credit\, quality\ (BB) \\ 0.85, & if\, weak\, household\, credit\, quality\ (BB-) \end{cases}$
ARM loan survival probability at origination	$\gamma_{pre} = \begin{cases} 0.99, & if\, strong\, household\, credit\, quality\ (AA) \\ 0.90, & if\, moderate\, household\, credit\, quality\ (BB) \end{cases}$
ARM loan survival probability at reset	$\gamma_{post} = \begin{cases} 0.85, & weak\, household\, credit\, quality\ (BB-) \end{cases}$
Total initial assets (US$ bn.)	$A_0 = 231$
Total initial liabilities (US$ bn.)	$L_0 = 212.52$

*Notes: * The Initial Securitisation Rate is an arbitrarily selected rate to initiate the simulations at time t=0. The value has no impact on the simulated results for later periods.*

Tab. 5: Life Assurance and Pension Fund Sector Model Parameters Settings

Life Assurance and Pension Fund Sector	
Parameter Description	Parameter Value
Weight change increments	$\Delta w = 0.05$
Range of permitted weight change	$-0.15 \leq \delta \leq 0.15$
Discount factor	$\lambda = 0.70$
Estimation error/Precision parameter	$\varpi = 10bps$
Utility improvement threshold	$\hat{\theta} \approx 4bps$
Liability pay-out rate	$\eta_t = 0.03$
State dependant return on RMBS (Benchmark: OMBAX)*	$r_{OMBAX} = \begin{cases} \{-0.0115, 0.0, 0.0113\}, & for\ 2000-2004\ period \\ \{-0.0171, 0.0, 0.0094\}, & for\ 2005-2009\ period \end{cases}$
State dependant return on traditional assets (Benchmark: S&P500 Index)*	$r_{S\&P500} = \begin{cases} \{-0.0583, 0.0, 0.0573\}, & for\ 2000-2004\ period \\ \{-0.0947, 0.0, 0.1096\}, & for\ 2005-2009\ period \end{cases}$
Rate of return on risk-free bond	$r_{rf} = 0.001$
Initial observation of RMBS credit risk at origination	$\gamma_0^{RMBS} = \begin{cases} 0.95, & if\ strong\ household\ sector \\ 0.90, & if\ moderate\ household\ sector \end{cases}$
Expectations of RMBS credit risk at reset	$\gamma_t^{RMBS} = \begin{cases} 0.97, & if\ Bullish \\ 0.85, & if\ Bearish \\ \gamma_0, & if\ Neutral \end{cases}$
Initial asset allocation	$a_0 = \begin{cases} \{w_{rf} = 0.1, w_{S\&P500} = 0.5, w_{OMBAX} = 0.4\}, & if\ single\ fund \\ random, & otherwise \end{cases}$
Cost function multiplier	$\Phi = 0.07$
Cost function type	Non-linear
Solvency margin	$\rho = \{0.17, 0.22, 0.30, 0.50\}$
TotaliInitial assets (US$ bn.)	$A_0^{LAPF} = 288$

*Notes: * These are mean returns accross all empirical observations in a given asset's state.*

In relation to the MDP model of LAPFs asset-allocation problem, model validating experiments were conducted to firstly ensure that, for all three classes of funds, the Bellman value iteration algorithm resulted in convergence. Secondly, behavioural patterns or optimal policies derived from the value iteration algorithm were assessed for coherence by comparing results from the two transition probability matrices for 2000-2004 and 2005-2009. In both tests the MDP derived behavioural rules for each class of LAPF appeared consistent with what would be expected. Moreover, observed behavioural rule differences when comparing LAPF choices under the 2000-2004 and the 2005-2009 transition models were easily explained by assessing the returns and state transition probabilities of both joint transition matrices. The final set of parameters used in the simulations are listed in Table 4 and Table 5 for the banking sector and LAPF sector respectively.

5.2 Main Findings

With respect to market clearing in the primary market for RMBS, the results show that, even with a high quality mortgage pool, if perceptions of credit risk are priced into the costs banks face for issuing residential mortgage-backed securities, the issuance levels differ dramatically. If the pricing of credit risk is linked to obligor concentration limits, in a bear market in which funds hold a pessimistic view of the future perfomance of the mortgage market, banks face higher securitisation costs despite the high-quality collateral. The loss of investor confidence leads to a rapid decrease in holdings of RMBS, and the requirement for larger credit enhancements to support issuance forces securitisation rates to fall as low as 1%.

By contrast, where institutional investors are bullish in terms of their expectations of RMBS notes performances, there is a correlated downward pressure on requirements to support these notes with credit enhancements which in turn leads to higher securitisations rates. Information embeded in the evolution of asset returns also give rise to the bullish, yet risk averse, LAPFs drastically altering their portfolio allocation choices between the 2000-2004 and 2005-2009 asset return regimes.

The consequence is that there is a declining of demand for RMBS and thus securitisation rates under the regime between 2005 and 2009 as opposed to the accelerated growth wittnessed in the regime between 2000 and 2004. Indeed, asset securitisation rates are consistently higher under the 2000-2004 regime than in the 2005-2009 regime. The results therefore, suggest that there is some degree of significance in the impact of the both economic regimes on the behaviour of both banks and LAFPs. Thus, as RMBS notes begin to experience losses in returns, the ACE model is able to track this evolving shift in regimes. This illustrates how ACE models are not only able to map the build-up of asset bubbles, but also the underlying microstructures that lead to market crises.

determining which of -greedy or softmax action selection performs better (Sutton and Barto 1998 pp. 31-32).

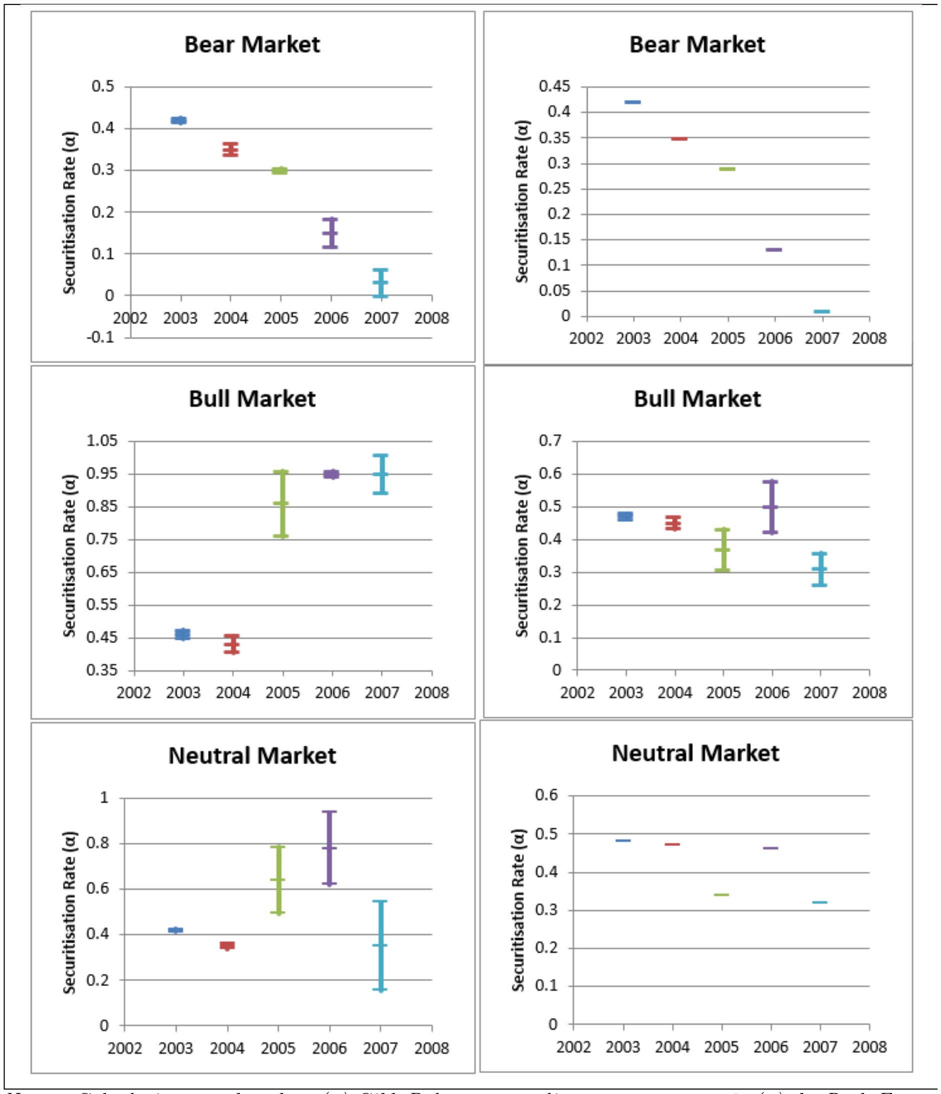
Tab. 6: Average Asset Securitisation Rate and Demand for Residential Mortgage-Backed Securities Consisting of High Quality Hybrid 2/28 ARM Loans

2000-2004 Transition Model						
	Bear Market		Bull Market		Neutral Market	
Year	Securitisation Rate(α)	RMBS Holdings (w_{RMBS})	Securitisation Rate(α)	RMBS Holdings (w_{RMBS})	Securitisation Rate(α)	RMBS Holdings (w_{RMBS})
2002	25%	0.40	25%	0.40	25%	0.40
2003	42%	0.25	46%	0.52	42%	0.46
2004	35%	0.10	43%	0.64	35%	0.46
2005	30%	0.08	86%	0.69	64%	0.39
2006	15%	0.08	95%	0.77	78%	0.40
2007	3%	0.08	95%	0.80	35%	0.34
2005-2009 Transition Model						
	Bear Market		Bull Market		Neutral Market	
Year	Securitisation Rate(α)	RMBS Holdings (w_{RMBS})	Securitisation Rate(α)	RMBS Holdings (w_{RMBS})	Securitisation Rate(α)	RMBS Holdings (w_{RMBS})
2002	25%	0.40	25%	0.40	25%	0.40
2003	42%	0.25	48%	0.37	48%	0.25
2004	35%	0.10	45%	0.24	47%	0.10
2005	29%	0.03	37%	0.19	35%	0.05
2006	13%	0.03	53%	0.16	46%	0.05
2007	1%	0.02	32%	0.17	32%	0.05

Notes: Calculations are based on (1) Gibb-Boltzmann cooling parameter $\tau = 1$, (2) the Roth-Erev RL algorithm outputs an action after 10,000 learning rounds (3) exploration rate $\varrho = 0.90$, (4) exploitation factor $\phi = 0.50$, (5) the value iteration algorithm assumes a utility improvement threshold $\hat{\theta} = 4bps$, (6) estimation error iterations $\varpi = 10bps$, (7) discount factor $\lambda = 0.70$ (8) Low quality is used to signify that upon reset of ARM loans, the original credit quality of the pool of mortgages that make up a RMBS issuance drops to a level of credit risk equivalent to a BB- rated note. (9) Traditional asset returns are the stochastic annual returns on the S&P500 index (i.e. random selection from -5.83%, 0%, and 5.73% for 2000-2004 and -9.47%, 0% and 10.25% for 2005-2009). (10) LAPF solvency margin $\rho = 0.17$ (11) Banks follow a 2-period average demand look back. (12) Results are the average over 20 simulation runs.

Fig. 3: Bank Asset Securitisation Confidence Intervals (95%)

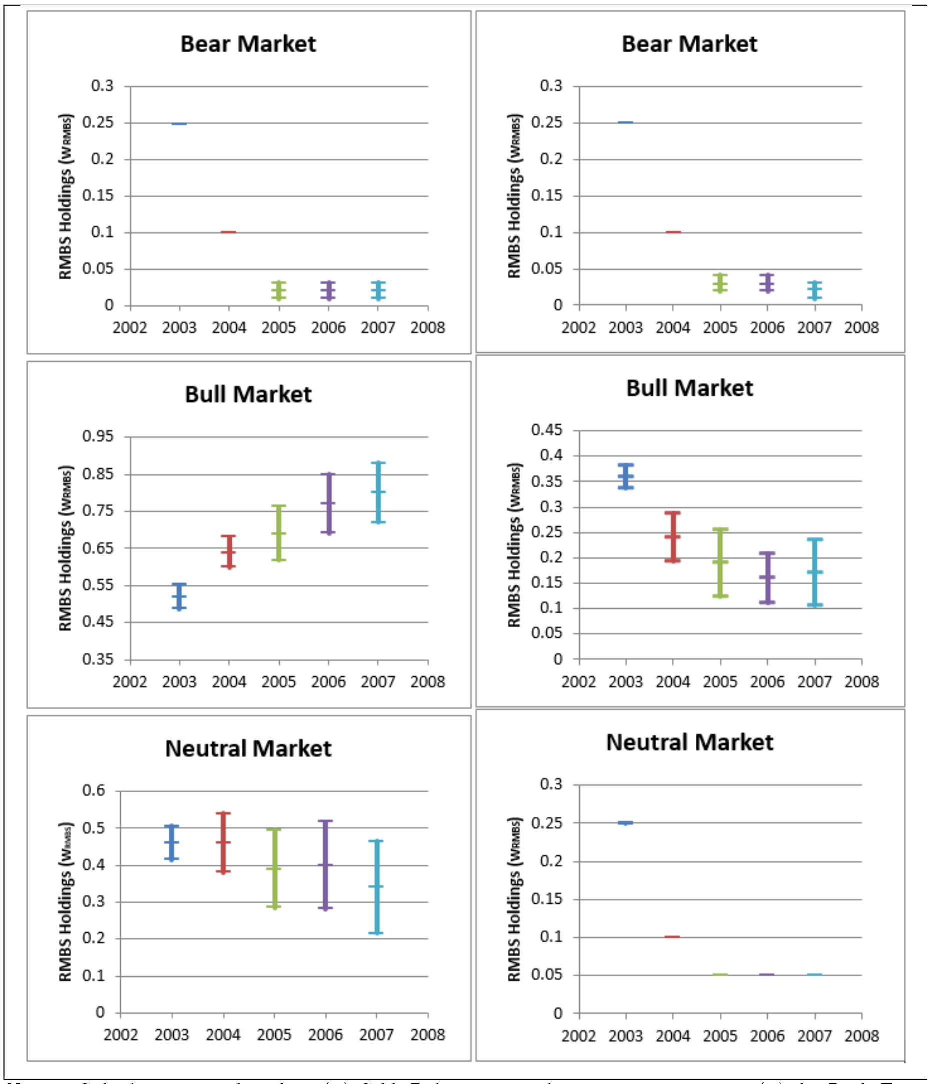
2000-2004 Transition Model	**2005-2009 Transition Model**



Notes: Calculations are based on (1) Gibb-Boltzmann cooling parameter $\tau = 1$, (2) the Roth-Erev RL algorithm outputs an action after 10,000 learning rounds (3) exploration rate $\varrho = 0.90$, (4) exploitation factor $\phi = 0.50$, (5) the value iteration algorithm assumes a utility improvement threshold $\hat{\theta} = 4$bps, (6) estimation error iterations $\varpi = 10$bps, (7) discount factor $\lambda = 0.70$ (8) Low quality is used to signify that upon reset of ARM loans, the original credit quality of the pool of mortgages that make up a RMBS issuance drops to a level of credit risk equivalent to a BB- rated note. (9) Traditional asset returns are the stochastic annual returns on the S&P500 index (i.e. random selection from -5.83%, 0%, and 5.73% for 2000-2004 and -9.47%, 0% and 10.25% for 2005-2009). (10) LAPF solvency margin $\rho = 0.17$

Fig. 4: LAPF Asset Allocation to RMBS Confidence Intervals (95%)

2000-2004 Transition Model	**2005-2009 Transition Model**



Notes: Calculations are based on (1) Gibb-Boltzmann cooling parameter $\tau = 1$, (2) the Roth-Erev RL algorithm outputs an action after 10,000 learning rounds (3) exploration rate $\varrho = 0.90$, (4) exploitation factor $\phi = 0.50$, (5) the value iteration algorithm assumes a utility improvement threshold $\hat{\theta} = 4bps$, (6) estimation error iterations $\varpi = 10bps$, (7) discount factor $\lambda = 0.70$ (8) Low quality is used to signify that upon reset of ARM loans, the original credit quality of the pool of mortgages that make up a RMBS issuance drops to a level of credit risk equivalent to a BB- rated note. (9) Traditional asset returns are the stochastic annual returns on the S&P500 index (i.e. random selection from -5.83%, 0%, and 5.73% for 2000-2004 and -9.47%, 0% and 10.25% for 2005-2009). (10) LAPF solvency margin $\rho = 0.17$

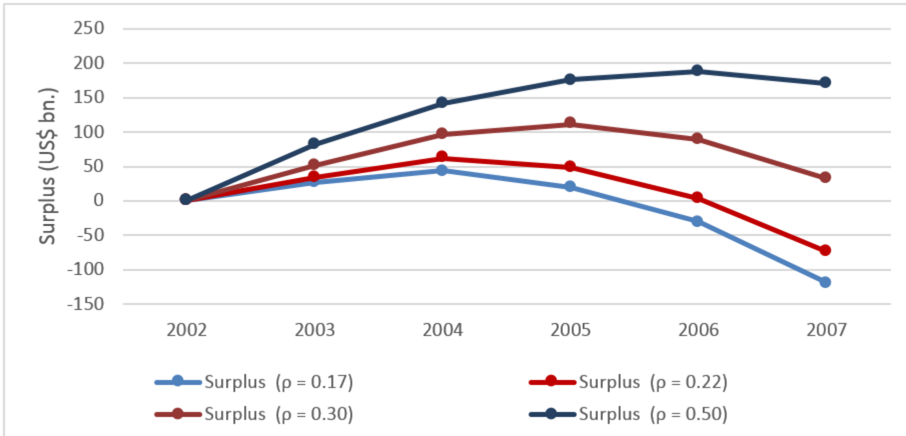
Whilst the ACE model is able to generate securitisation rates similar to those witnessed leading up to the 2007 financial crisis, the subprime mortgage origination rates predicted by the model, although close under the bull market, are substantially lower than the empirical data. Where banks issue subprime RMBS backed by high quality collateral to a market in which institutional investors hold neutral expectations about future evolution of credit risk and act purely on the information embedded in market returns, the simulated total outstanding notional value of mortgages peaks at US$1.72tn in 2007. This is in comparison to the US$2.5tn observed in the empirical data for the same year. Bullish sentiment by contrast gives rise to an estimated banking sector balance sheet growth from US$231bn in 2002 to US$2.03tn by 2007. Though not dismissed, it is not clear from the results that this growth entails the often cited moral hazard problems associated with aguements in the literature as to the asset securitisation and regulatory arbitrage.Rather it would appear the key driver is investors' yield seeking and sentiments on the future performance of the securitised assets.

5.3 Credit Risk Transfer and Systemic Risk

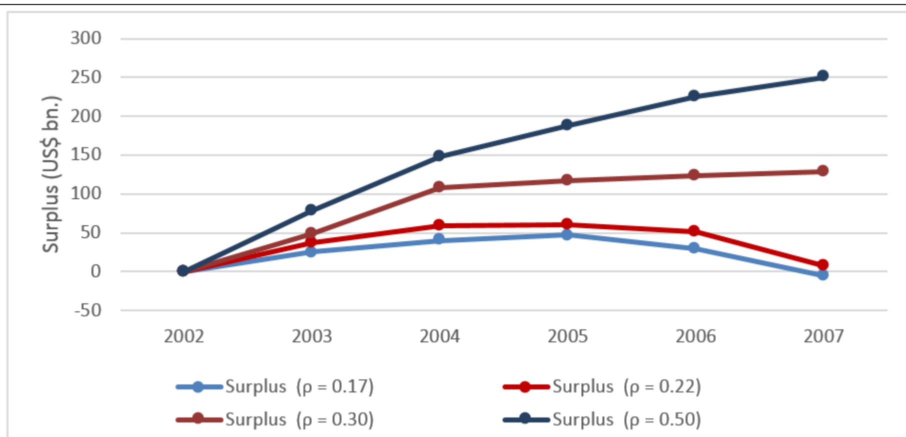
The impact of trade-off between risk aversion and yield seeking on LAPF surpluses is illustrated in Figure 6. In the Figure, LAPF surpluses are presented for bull markets in which funds utilise either one of the 2000-2004 or 2005-2009 state transition models under four different solvency margin regimes ($\rho = \{0.17, 0.22, 0.30, 0.50\}$). As previously noted, optimism towards future RMBS yields in the bull market is tempered to a much greater degree by risk information embedded in the 2005-2009 transition model than in the 2000-2004 model. This leads to substantially lower exposures to securitised assets by funds under the 2005-09 transition model. Consequently, as RMBS holdings begin to incur losses, these LAPFs perform better. The model estimates that by 2005 funds basing investment decisions on the 2000-2004 state transition model would have started recording losses, and by 2006 would be insolvent or close to insolvency. Funds under a solvency margin regime of 17% are estimated to be in funding deficits to the tune of US$118.8bn by 2007. Coincidentally, these funds would in fact be required to maintain solvency margins of 50% or more in order to be sufficiently cushioned from the losses on RMBS holding. Conversely, funds utilising the 2005-2009 state transition model are completely cushioned from losses and continue their surplus growth by maintaining a solvency margin of 30%.

Fig. 5: Simulated Bull Market Average LAPF Surpluses

2000-2004 Transition Model



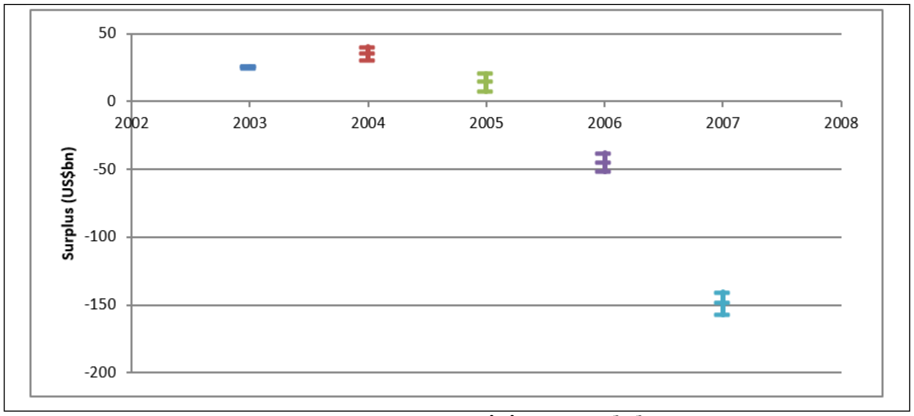
2005-2009 Transition Model



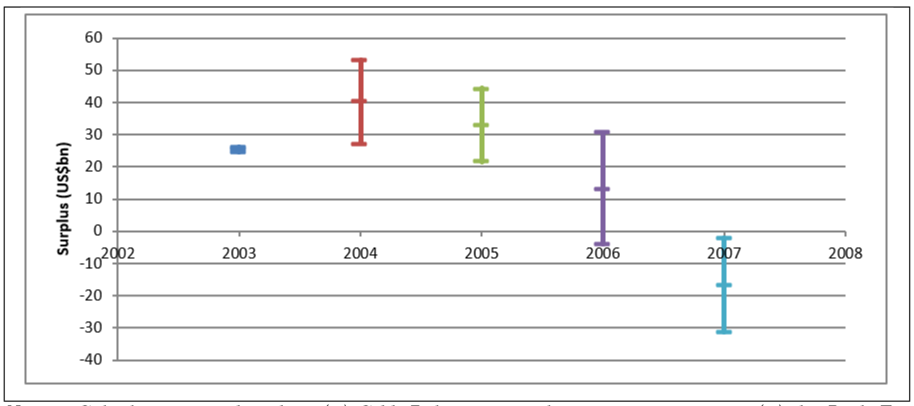
Notes: Calculations are based on (1) Gibb-Boltzmann cooling parameter $\tau = 1$, (2) the Roth-Erev RL algorithm outputs an action after 10,000 learning rounds (3) exploration rate $\varrho = 0.90$, (4) exploitation factor $\phi = 0.50$, (5) the value iteration algorithm assumes a utility improvement threshold $\hat{\theta} = 4$bps, (6) estimation error iterations $\varpi = 10$bps, (7) discount factor $\lambda = 0.70$ (8) Low quality is used to signify that upon reset of ARM loans, the original credit quality of the pool of mortgages that make up a RMBS issuance drops to a level of credit risk equivalent to a BB-rated note. (9) Traditional asset returns are the stochastic annual returns on the S&P500 index (i.e. random selection from -5.83%, 0%, and 5.73% for 2000-2004 and -9.47%, 0% and 10.25% for 2005-2009). (10) LAPF solvency margins $\rho = \{0.17, 0.22, 0.30, 0.50\}$ (11) Banks follow a 2-period average demand look back. (12) Results are the average over 20 simulation runs.

Fig. 6: Simulated Bull Market LAPF Surpluses

2000-2004 Transition Model



2005-2009 Transition Model



Notes: Calculations are based on (1) Gibb-Boltzmann cooling parameter $\tau = 1$, (2) the Roth-Erev RL algorithm outputs an action after 10,000 learning rounds (3) exploration rate $\varrho = 0.90$, (4) exploitation factor $\phi = 0.50$, (5) the value iteration algorithm assumes a utility improvement threshold $\hat{\theta} = 4bps$, (6) estimation error iterations $\varpi = 10bps$, (7) discount factor $\lambda = 0.70$ (8) Low quality is used to signify that upon reset of ARM loans, the original credit quality of the pool of mortgages that make up a RMBS issuance drops to a level of credit risk equivalent to a BB- rated note. (9) Traditional asset returns are the stochastic annual returns on the S&P500 index (i.e. random selection from -5.83%, 0%, and 5.73% for 2000-2004 and -9.47%, 0% and 10.25% for 2005-2009). (10) LAPF solvency margin $\rho = 0.17$ (11) Banks follow a 2-period average demand look back.

6 Conclusions

This paper presented a two-sector ACE model of systemic risk and credit risk transfer arising from asset securitisatioin. The model considered both banks' and institutional investors' profit maximisation as being contrained by insolvency risk. Optimal behavioural rules are then derived using the evolutionary computational method of machine learning known as reinforecment learning. For the banking sector this entailed using the Nicolaisen variation of the

Roth-Erev reinforcement learning algorithm with a Gibbs-Boltzmann probability model to handle negative rewards. Whereas, for the institutional investors whose portfolio sellection problem was reduced to a Markov decision problem, the more conventional artificial intelligence reinforcement learning algorithm augmented with market sentiment based rule of thumb adjustments was employed. The results show that, in an environment where risk capital is binding but banks are able to securitise assets, the issuance rates of asset-backed securities ultimately depends on the pricing of the associated credit risk.
Aligning RMBS credit risk and securitisation costs with the demand for securitised assets, the ACE model shows that, where agents make decisions on the basis of behavioural rules, securitisation rates witnessed in the empirical data are attainable. The model further illustrates how the loss of confidence in a bear market or through the evolution of asset returns, leads to funds offloading RMBS notes from their portfolios and give rise to large downward swings in the rate at which these securitises are issued. This is a consequence of banks having to assume a greater share of the credit risk through the provision of increasing amounts of credit enhancement on their securitisations. Thus, the extent to which CRT is possible depends on the market pricing of risk, not necasserily the moral hazard problem associated with arguments made as to the importance of regulatory arbitrage in the securitisation process. Where investor demand for securitised assets is sufficiently high and the implied provision of credit enhancements low, banks are able to transfer a great amount of the credit risk to investors. This outcome conforms with Duffies (2008) argument regarding CRT and reinforces the results of Gorton and Souleles (2005), Solano et al. (2006) and Jiangli, et al. (2007), all of whom found that investor perceptions of the credit worthiness of banks, or the quality of the reference assets, drive the profitability of securitisation for banks.
From a policy standpoint, the results show that regulatory arbitrage does not fully explain securitisation rates leading up to the subprime crisis. Rather as noted by Calomiris and Mason (2004) and Minton et al. (2004), the avoidance of capital requirements is a consequence of securitisation rather than the motivation. As such, the requirement, as stated in the European Commissions 2006 Capital Requirements Directivethe European Unions Basel II implementationfor credit institutions to demonstrate to authorities that the decision to securitise is made consistently and is not determined by regulatory arbitrage considerations appear redundant.
The sustainability of the O&D operational model and associated systemic risk implications of credit risk transfer was illustrated to be linked to the extent to which institutional investors decisions foster the mispricing of the underlying credit risk. Under the ACE model, the persistence of losses is found to be conditional upon the trade-off between institutional investors risk aversion and yield seeking. Moreover, as the balance is tilted towards perceptions of future yield increases in RMBS, especially in a bull market, funds are seen to require higher solvency margins to shield against potential losses.
The findings point to a key implication for banking regulations such as Basel II that rely on market discipline. That is, such regulations are predicated on the

very strong assumption that investors are not only able to correctly assess the risks associated with bank lending, but also that investors remain immune from market sentiment and the search for yields that ultimately drive the mispricing of the underlying credit risk. As observed under conditions where market sentiment-based yield seeking outweighs investors risk aversion, mispricing of risk implies that market discipline will fail to have the desired influence on the issuance of trade receivables securities such as RMBS regardless of the quality of the reference assets.

It should nevertheless be noted that the model does not consider banks' access to, and the dynamics, of short-term funding through wholesale money markets and leverage finance. Inclusion of these markets may affect the results. Adrian and Shin (2007), Northern Rock (2008), Milne (2009) and Shin (2009) reported that banks routinely funded their loan originations through wholesale market exposures. The collapse of Northern Rock was, for example, tied to the substantial outflow of over GBP15bn in liquidity from the wholesale market during the second half of 2007 (Northern Rock, 2008). At the start of 2007, wholesale market exposures of GBP26.71bn accounted for 25% of Northern Rocks funding. Further research will be required to incorporate the impact of external sources of funding into the models. A further extension would entail introducing a more dynamic model for the quality of bank loans and their ability and willingness to monitor those loans. Such a model of loan monitoring would involve capturing various classes of borrowers and the factors that influence their credit worthiness and decisions to default on loans.

Likewise, the MDP model of LAPF solvency optimisation may be extended to include a wider pool of assets classes to choose from. The returns on the benchmark indices upon which funds base their investment decisions were also assumed to be independent. The model can therefore be further refined to allow for correlation between asset classes. These extensions to the model will undoubtedly have an impact on the results, as would the improved calibration of market clearing conditions to capture more of the realities of price discovery in the over-the-counter trading of RMBS. Though out of the scope of the current analysis, these can prove to be valuable areas for further research.

7 Appendix A

Banking Sector	
Parameter Description	Parameter
Roth-Erev experimentation factor	ϱ
Roth-Erev exploitation factor	ϕ
Roth-Erev Gibbs-Boltzmann cooling parameter	τ
Roth-Erev action selection probability	$\hat{p_i}\,(t)$
Roth-Erev action selection propensity	$\hat{q}\,(t)$
Roth-Erev experience function	$\hat{E_i}\,(\varrho, i, j, t)$
Roth-Erev reward for selecting action i at time t	$\hat{r_i}\,(t)$
Roth-Erev number of trials	$\mathbb{A}^{BANK}$
Roth-Erev number of actions/securitisation rate choices	N
Securitisation rate	$\alpha \in \mathbb{A}^{BANK}$
Conventional mortgage contract rate	r^A
ARM mortgage contract rates	r^A_{ARM}
Cash deposit rate of return	r^L
Regulatory capital ratio	ε
Asset accumulator function	q
Demand driven credit enhancement charge	$\mu_{\gamma,t}$
Standard loan survival probability at origination	γ
ARM loan survival probability at origination	γ_{pre}
ARM loan survival probability at reset	γ_{post}
Total assets	A
Total liabilities	L

8 Appendix A

Life Assurance and Pension Fund Sector	
Parameter Description	Parameter
Weight change increments	Δw
Range of permitted weight change	δ
Discount factor applied to past reinforcement learning rewards	λ
Estimation error/Precision parameter	ϖ
Utility improvement threshold	$\hat{\theta}$
Liability pay-out rate	η_t
State dependant return on asset k	r_k
Rate of return on risk-free bond	r_{rf}
Rate of return on risk-free bond	r_{rf}
Time t observation/expectations of the performance of asset k	γ_t^k
Expectations of RMBS credit risk	γ_t
Asset allocation action	$a \in \mathbb{A}^{LAPF}$
Cost function multiplier	Φ
Cost function of aquiring asset k	$f\left(w_k\right)$
Regulatory solvency margin	ρ
Total assets	A^{LAPF}
Total liabilities	L^{LAPF}
Fixed component of LAPSs' net present value of future liabilities	C
Risk capital or equity reserve	K
Fund surplus at time t	S_t

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