Lending to Small and Medium Enterprises: A Novel Approach to Credit Portfolio Management

András Kővári – a.kovari@student.tudelft.nl – Delft University of Technology, The Netherlands

Erik Pruyt – e.pruyt@tudelft.nl – Delft University of Technology, The Netherlands

Abstract

There is a vast unmet demand for credit from SMEs in emerging markets, while banks need novel ways of approaching their risk strategies. These inspired a pilot project within a major commercial bank. The goal of the project is to investigate in what ways exploratory system dynamics (SD) could support lending decisions and monitoring of a SME credit portfolio. This paper reports on this project as a practical application of SD modeling for a bank. The first stage of the project consists of `quick and dirty' modeling and analysis intended to illustrate the possibilities of this approach. A generic model of a company with debts was modeled to explore plausible dynamics given the assumptions about how the company's environment may affect its performance. The 2nd and 3rd stage – modeling of actual companies and aggregating them into a portfolio for stress testing – is work in progress due before the summer.

Keywords: SME credit, portfolio risk management, System Dynamics, Exploratory Modelling & Analysis

1. Introduction

Small and Medium-sized Enterprises (SMEs) are the backbone of growth and employment in emerging economies. They represent 95% of all companies, and employ two thirds of the labor force. A report by McKinsey & Co. estimated that SMEs in emerging markets (EM) account only for 7% of the total value of loans, bonds and public equity outstanding (Stein, Goland, & Schiff, 2010). Despite their huge share in job creation, SMEs' capital employed in some form of credit is just a fraction of the loans that the large corporations use. This is found by some to be the biggest constraint on these companies' growth (Beck & Demirguc-Kunt, 2006).

Lending to SMEs is riskier, but the yields that investors can get from larger companies have long reached a plateau. There is a huge unmet credit demand from the SME side. Therefore, banks that can develop a sound business model for lending to them could find great alternatives for future revenue streams while contributing to economic development and job creation. However, confidence in banks' sound business models and risk management in general has hardly ever been lower. Bankruptcies and bail-outs during the crisis to high-profile scandals[1], all threatened to undermine bank's credibility in proper risk management. Angered economists also talk about financialization of industry, warn about debt deflation and call for the restoration of banks' role as a service to industry (Hudson, 2012). KPMG reports on the expectations of risk management being outpaced by capabilities (KPMG and The Economist, 2013), while another survey calls for the rethinking of risk strategies within banks (Ernst & Young, 2010). The European Central Bank stated that there is an enormous need for further research into the management of financial systems and systemic risks (ECB, 2010). Novel analytical tools aiding banks' decision-making could help restoring confidence and reconcile finance and industry.

[1] Think of insider trading, HSBC money-laundering, Barclay's Libor fixing, JP Morgan's recent 6bn losses

Banks' need for novel ways of risk approaches and a vast unmet demand for credit from SMEs in emerging markets inspired a pilot project within a major commercial bank. This paper reports on this project as a practical application of SD modeling. A small group within this bank[2] is considering alternative ways to extend credit to SMEs in one of the booming countries of the emerging markets, and wants to combine this with innovation in its approach to uncertainty and risk. The goal of the project is to investigate in what ways SD modeling combined with an exploratory approach could support lending decisions and monitoring of an SME credit portfolio.

The rest of this paper is organized as follows. In section 2 we start with contrasting the current practices of lending decisions with the approach envisioned in this project. Then we mention some of the background literature that supports our work. Section 3 illustrates the exploratory analysis method using a simple SD model[3]. Finally Section 4 looks ahead at what still needs to be done to further develop the project.

2. A Novel Approach?

Access to finance by SMEs is low for various reasons, but a lack of credit history and detailed archives of performance documentation is a major barrier. When an SME *does* get into the negotiations, an examination of the cash flow perspectives follows usually on spreadsheets. The models built are then usually linear and contain expectations about the future values of parameters and coefficients. There are also assumptions about how these parameters might change in the future. However, the resulting forecasts can be as good as the assumptions that generate them. Modifying these assumptions one-by-one can give a sense of sensitivity, but there is hardly a systematic evaluation of possible future scenarios. Assessing all the uncertainty space and then deriving meaningful insights is virtually impossible. Such an attempt would quickly run into the limitations of linear modeling and multiple regression analyses that provide some of the coefficients.

Performance of a company through time is driven by delays and regenerative feedback loops in its processes and interactions with its environment. Current modeling approaches do not reflect these features, therefore they can be misleading especially when a broad range of uncertainties must be evaluated. These limitations were already documented by Forrester in his early years of studying industrial models and applying his control systems background. A seminar note from 1956 published almost 50 years later contains the original ideas (Jay W. Forrester, 2003). SD modeling can capture the feedback loops of a dynamic system and its stock-flow approach is well suited for representing company operations and the developments of a balance sheet.

The plan of approach for this project is illustrated in Figure 1. High-level SD models of the companies' main operations are built for each of the SME that constitute a portfolio. The models should capture the main drivers behind the performance of the company. Some of these factors will be external variables that are not under the direct control of the company (or the creditor for that matter). Examples are availability of a key resource, demographics of the client base or the stability of a major supplier. These form the immediate environment in which the company operates, and they are in turn influenced by shifts in the macroeconomic level. In what way and to what extent

[2] References to the details of the project will remain vague due to confidentiality

[3] Acknowledgements to Santiago Braje for inspiration on this section

these factors influence the other is uncertain. Exchange rates, oil price and emigration can have direct or indirect effect on a company's performance, and this effect can also take different forms from strongly positive through mixed to very negative.

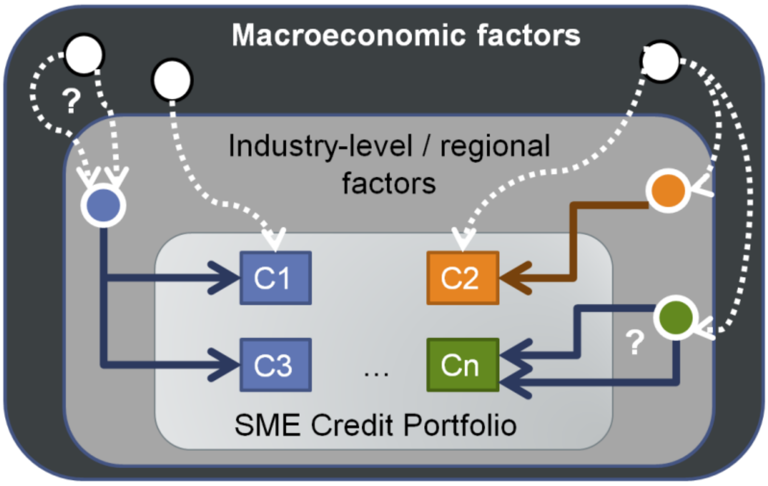


Figure 1: Conceptual model of the portfolio stress testing bench

An exploratory approach tries to consider all the possible hypotheses about how factors in the company's environment influence its performance. These hypotheses are then turned into alternative 'models of the future'. Combining the plausible ranges for the external parameters and switching between alternative structures a large number of plausible future scenarios can be generated. The portfolio then can be 'stress-tested' for extreme circumstances or interesting combinations of events.

A similar methodological approach is called Exploratory Modeling and Analysis (EMA) and was extensively described by (Agusdinata, 2008; Lempert, Popper, & Bankes, 2003). EMA treats questions like: *"what is the range of plausible future dynamic developments of a phenomenon of interest? Under what circumstances can we expect which dynamic developments?"* (Jan H. Kwakkel & Pruyt, 2013) Treating such questions would support the risk approach towards volatile SMEs that can be very much influenced by events in their operating environment. Analysis tools that can help answering these questions are readily available open source[4] and a growing number of works demonstrate their use (Auping, Pruyt, & Kwakkel, 2012; Hamarat, Kwakkel, & Pruyt, 2013; Kővári & Pruyt, 2012; J H Kwakkel & Timmermans, 2012)

This modelling project involves building small models of company operations and industry dynamics. This effort is supported by a vast SD literature from (Jay Wright Forrester, 1961) through (Sterman, 2000) to (Warren, 2008). There are also some papers that deal with bank-related modelling with SD. Some of them describe banking crises, bank runs and build models that could (or could have been) used for crisis management (Pruyt & Hamarat, 2010; Pruyt, 2009; Rafferty, 2008). However, there are also a few published SD works related to risk management of a commercial bank (Chaim & Castellano, 2012) and stress testing of a financial system from the point of view of a central bank (Anderson et al., 2011). (Gramlich & Oet, 2012) give a comprehensive overview of the modelling works related to systemic financial feedbacks (SFFs). They find that SD is a suitable

[4] For example R packages or the EMA workbench at http://simulation.tbm.tudelft.nl/

modelling approach for such systems and problems. However they note that *"The scarcity of SD modelling for SFFs may be attributed to the lack of required economically-sound foundations for theoretical modelling"*. An exploratory approach circumvents this problem by looking at all plausible model versions rather than coming up with *the* model of the true theory.

3. A simple SD model for illustration

In this section we illustrate the above presented approach with a simple SD model of a company that tries to grow while initially taking on a loan.

3.1 The Model

At this high level, the business is seen as a circular flow of money that tries to create profits by constantly investing its available money into assets. Assets are then partly monetized (sold), thereby generating revenues, possibly at a margin. Assets that are not monetized usually depreciate. There is also a debt that the business takes or considers to take. Traditionally an amount of loan is given that bears interest. Experience shows that "it is never the right time" for companies to repay part of their debt, mostly only paying the minimum required by their contract, or taking on new loans to pay (only) the interest on an old loan. Therefore they face uncertainty in terms of what interest rate they can secure.

Three additional hypotheses are proposed (illustrated on Figure2):

- The bigger the company becomes the lower monetization rate it can achieve on its assets.
- As the company grows bigger, the fluctuations in the monetization rate are reduced
- As the company grows, the interest rates at which loans can be refinanced also tend to reduce

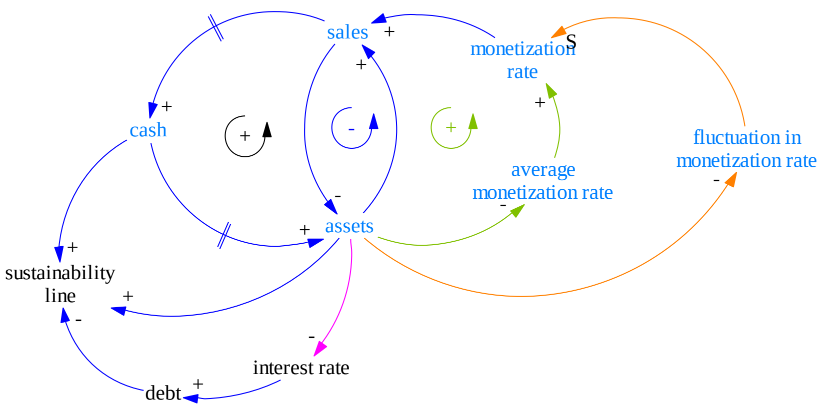
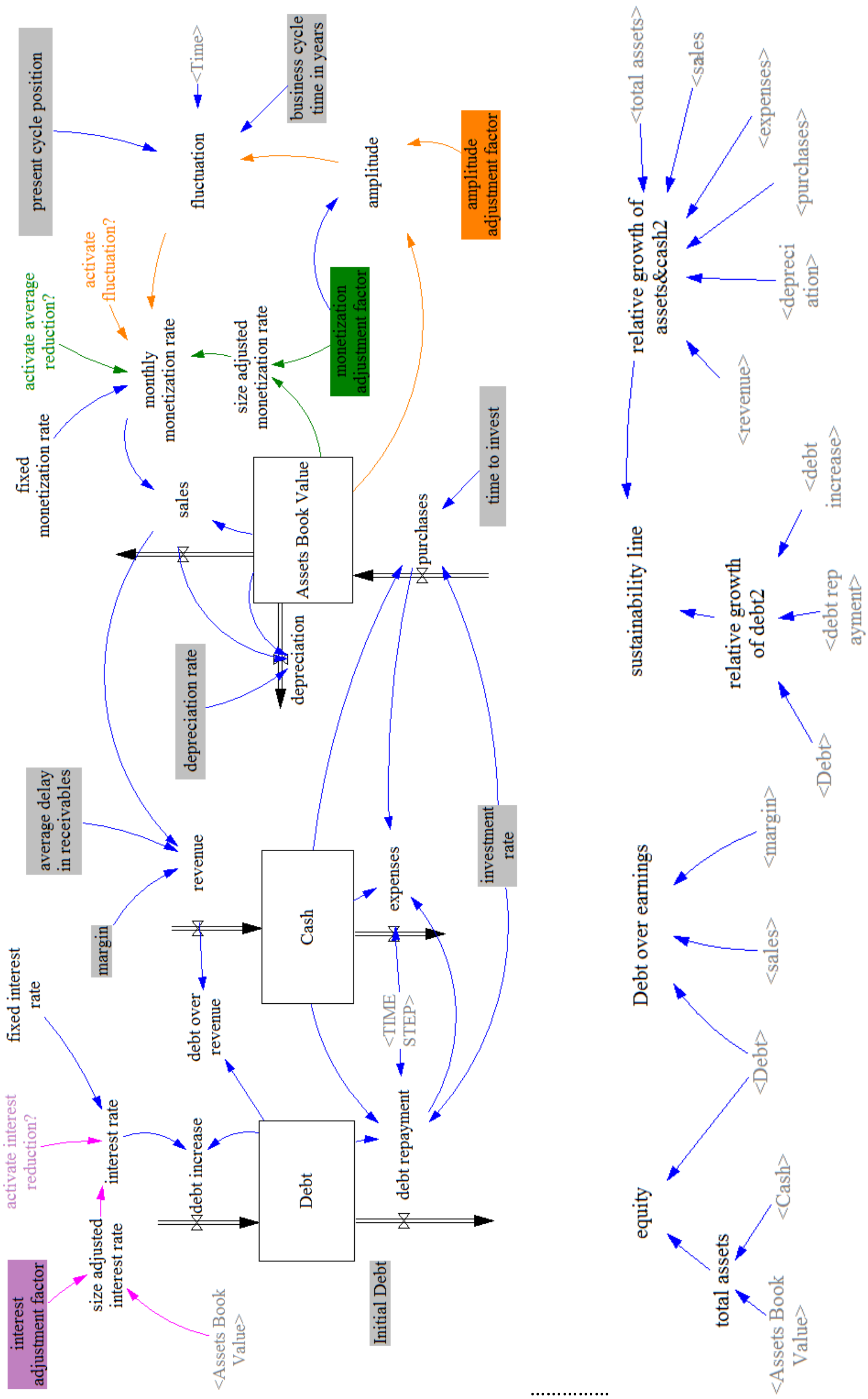


Figure 2: Conceptual model of a growing company with a loan

The stock-flow diagram of the model is shown in Figure 3. For illustration the initial data can be arbitrary, *Cash* and *Debt* are initialized at 200 and 100 respectively, while *Assets Book Value* is 1 only to avoid division by zero at the outset. The business starts by investing all its money into assets, meaning that the *investment rate* is 100%. Selling assets will generate *sales* with a so called *monetization rate,* while this will create an inflow of money possibly at a *margin*. An *average delay in receivables* is added, to examine the effect of late payments. The parameters of the model are summarized and explained in Table 1.



....

Figure 3. Stock-Flow Diagram of the simulation model with some possible indicators at the bottom

Uncertainty	Description	Range
activate interest reduction?	Will the interest rate decrease with the growth of the company?	y/n
fixed interest rate	If size-related reduction is deactivated, a fixed interest rate can be used	0-50%
interest adjustment factor	A parameter setting how fast will interest rate decrease	1-100
activate average reduction?	Will the average monetization rate reduce as the company grows?	y/n
monetization adjustment f	A parameter setting how fast will the monetization reduce	1-100
fixed monetization rate	If feedback reduction is deactivated, a fixed rate can be used	0-100%
time to invest	the time it takes for assets to be acquired	1-6 months
investment rate	share of cash is invested into assets instead of debt repayment	80-100%
average delay in receivables	delay in the actual inflow of money from sales	0,2-6 months
depreciation rate	How fast will the unsold assets depreciate?	0-100%
margin	Uncertainty in the margins that the company can reach	1-1000%
amplitude adjustment f	A parameter setting how fast will fluctuations reduce	1-100
activate fluctuation?	Will fluctuation reduce as the company is growing?	y/n
business cycle length	From yearly to decade long fluctuation - depending on the case	1-10years
present cycle position	0=middle of upturn; π/2=top of the wave; π=middle of downturn; 3π/2=depth of crisis-facing upturn	0-1,5-3,1-4,7

Table 1: External parameters and their range considered in the analysis

The switch -parameters with question marks can be used to deactivate their respective loops. This can help assessing the impact of the three hypotheses mentioned above. Each of these hypotheses takes the *Assets Book Value* as a proxy for the size of the company and influences the *fluctuation*, *interest rate* and *monthly monetization rate.* However, there is uncertainty about how quickly the growth of the company can be felt on these rates. Therefore an adjustment factor is used to vary the actual effect (see Figure 5). For example: *size adjusted interest rate* $= adjustment\ factor/Asset\ Book\ Value$. Table 1 also contains suggestions for the ranges of each parameter that can be analyzed. Some of them represent what is physically possible (like *depreciation rate*), others are just suggested plausible ranges (like *margin*).

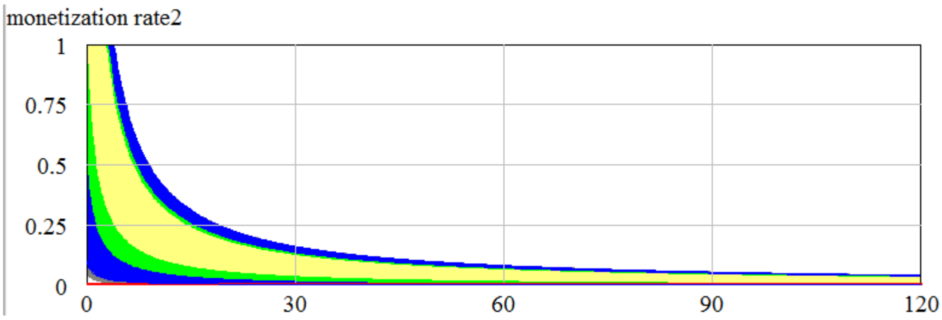


Figure 5. Varying the adjustment factors can change speed at which monetization rate decreases due to growth.

Fluctuations in the sales can be modeled to represent long-term business cycles, or seasonal variations. Some well-known key performance indicators were modeled to track the changes over time. The sustainability line is the difference between the relative growth in the company's assets and cash and the relative growth of debt. Above zero on this indicator means that on the long term the company is on a sustainable track. The model could be further decorated with many assumptions as one wishes, similarly to the above presented ones. This selection of features and hypotheses is plausible, but is not meant to represent 'the most important things' that can happen to a company. They are selected somewhat arbitrarily for illustration.

Figures 5 and 6 show the result of four simulation runs. The first is the result of fixed rates with all the 3 hypotheses turned off. Since depreciation is relatively low, the company goes on an exponential growth path. Once the balancing effect is turned on in the 2nd run, the growth becomes limited.

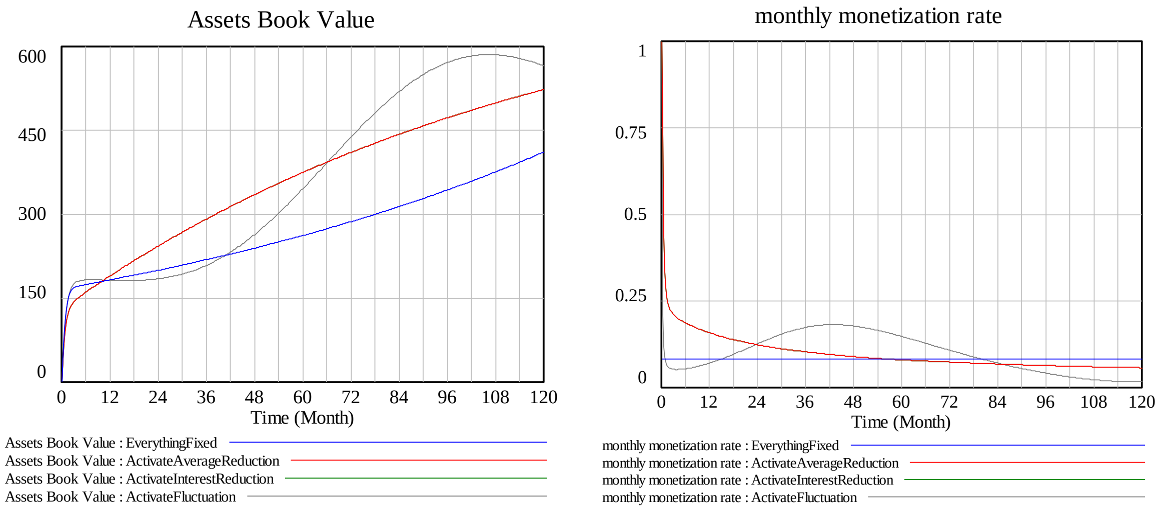


Figure 5. Simulation results of activating the hypotheses one by one. The 2nd and 3rd runs are overlapping

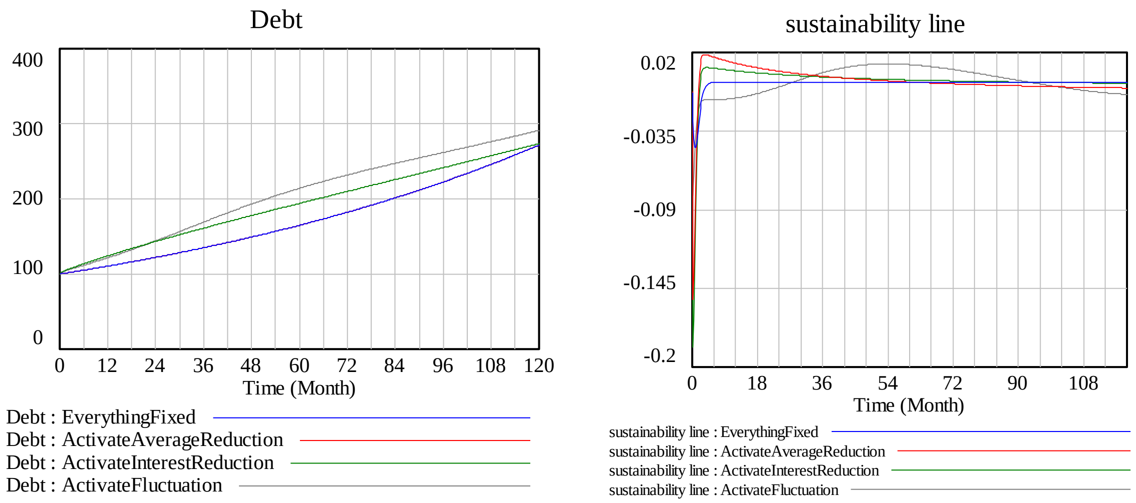


Figure 6. Simulation results of activating the hypotheses one by one. 1st and 2nd runs are overlapping for Debt

Many pages could be spent continuing with exploring the effects of individual parameters asking the 'what if?' question. Programs such as Vensim that can display the simulation results 'on the fly' as parameters are varied are useful tools to give a good sense of the influence each external parameter has on the model. However, the aim was a more systematic approach. In what follows, the full uncertainty ranges mentioned in Table 1 are explored.

3.2 Beyond 'What if?' Questions

One question that the commissioner of this project found important is: what can possibly happen? In some cases the future evolution of external parameters is uncertain, but we can have information on what is the possible range within which they can vary. Or it might be insightful to see what are the possible dynamics that can occur in extreme circumstances. Figure 7 presents the outcomes: hundreds of scenarios generated sampling through the given uncertainty ranges. A blue envelope shows what the ranges of possibilities are at a glance. Visual inspection of the individual lines can indicate what kinds of dynamics occur. However, recent techniques such as time series clustering (Warren Liao, 2005) can make the process automated.

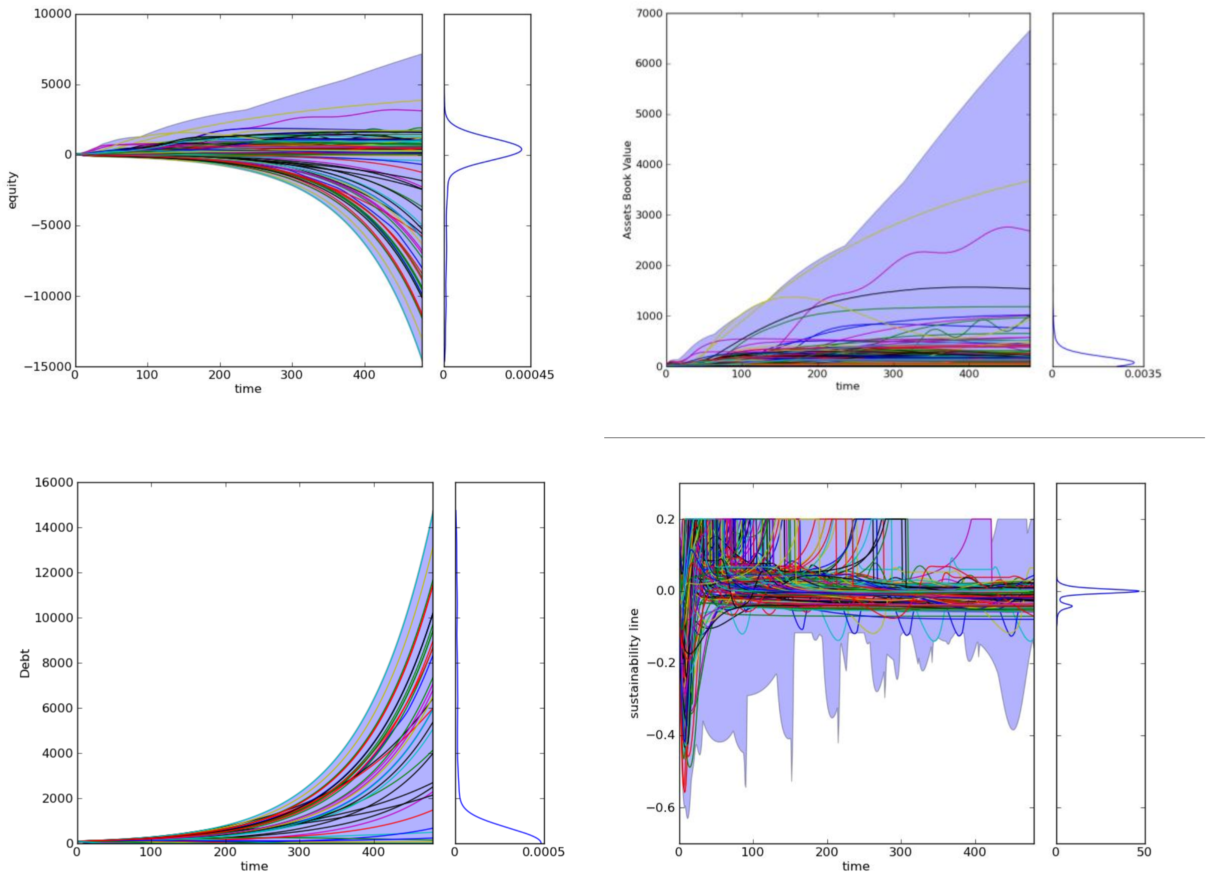


Figure 7. Possible dynamics with a full-range exploration

On the graphs presented in Figure 7 the distribution of the end states for the scenarios are also displayed. This gives an indication of how many of the scenarios end up in a particular state. Debt for example will mostly be below 2000 after 10 years, but there are still quite a few runs that go way above that.

Once we see the range of possibilities, the next logical question is: what combination of parameters can lead to which scenario? What leads to a debt higher than 5000 after 10 years? Another analysis tool, the PRIM algorithm can reveal the answer. The algorithm searches among the uncertainty ranges for combinations of parameters that lead to a given end state. Its answer to the question of what leads to debt greater than 5000 at the end of the runs is displayed on Figure 8. The combination of ranges is displayed on normalized scales. The result is not very surprising: investment rates at the high end (meaning little expenditure to repay debt) are the defining factor. Margins at the lower end, and slowly decreasing interest rates also contribute. The 5 parameters are ordered according to the length of the lines displayed. It is a ranking of how crucial that parameter is in leading to the undesired state.

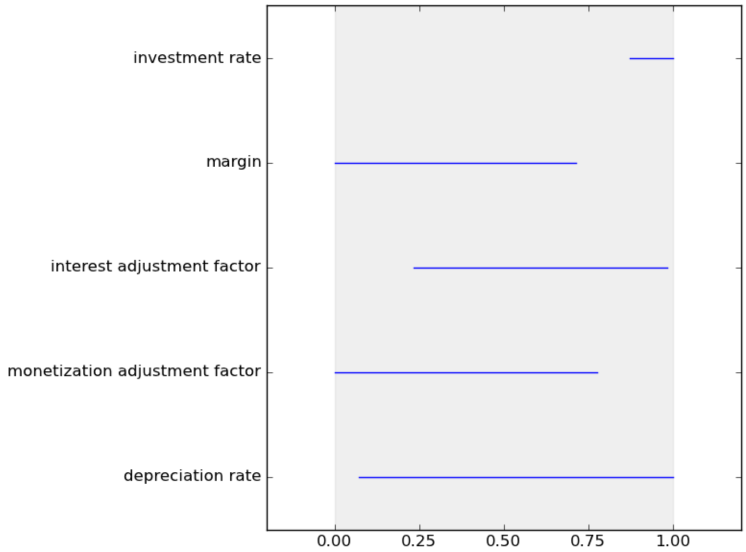


Figure 8. PRIM: the combination of parameter ranges that lead to high Debt

4. Next steps

The above presented model and analysis is a metaphor to a company. It was used to show how EMA can help exploring the risks involved in a commercial loan. The model used was simple and abstract, therefore the results of the analysis also somewhat unsurprising. It was used to illustrate the tools available and to build confidence in the potential of this method to the commissioner. We have to turn from this abstract model to a more operational representation of the actual companies and their environment to make the analysis relevant for use in decision-making.

The second stage of this project is to turn to the descriptions of the companies within the existing portfolio and modeling them. There the challenge is to find a balance between detailed modeling of a company and simplicity for the sake of efficiency in use. After all the modeling should not take too much time, but it should be just enough to facilitate a meaningful discussion that adds real value to the already existing practices. A possible road is aiming for a handful of generic types of SMEs, and then trying to find ways of quick customization for the individual aspects of the actual companies that make up a portfolio. Similar efforts are documented in (Winch & Arthur, 2002).

The third stage is then the exciting part: aggregating the models into a portfolio, building hypotheses about external effects and stress-test the resulting model. Then a debate can follow about what insights can be gained from the analysis that is relevant for the actual case.

5. Conclusions

An innovative approach towards risk and uncertainty in a bank was presented and illustrated on a simple SD model. It is a first stage of a work in progress due before the summer. The goal is to find ways in which the presented exploratory approach can support lending decisions and portfolio monitoring within the bank. The discussion in this paper already points to potentially valuable tools.

The tools and analysis methods presented in this paper were mostly taken from the EMA literature: "*EMA … can be used to address 'beyond what if' questions…Because of this focus, EMA* *stimulates 'out of the box' thinking and can support the development of adaptive plans or policies."*(Jan H. Kwakkel & Pruyt, 2013). We find such an approach helpful and desirable for the evaluation and monitoring of credit portfolios. The portfolio stress-testing workbench developed might not fully replace existing investment analyses, but it could provide valuable support to build a robust business model for future lending to SMEs. Further work from this project will be included in this paper.

As with any exploratory research, the outcome of this project is unknown: will it be worth doing all the modeling and analysis? Does it really add value to the existing practices? Future research could try to measure that. Such an inquiry can also help to find analysis methods that *do* make an impact and could point to directions in which the EMA toolkit could be extended.

References

Agusdinata, D. B. (2008). *Exploratory modeling and analysis: A promising method to deal with deep uncertainty*. Delft University of Technology.

Anderson, S., Long, C., Jansen, C., Affeldt, F., Rust, J. W., & Seas, B. (2011). Dynamically Stress Testing Financial Systems. *Proceedings of the International Conference of the System Dynamics Society*.

Auping, W., Pruyt, E., & Kwakkel, J. (2012). Analysing the Uncertain Future of Copper with Three Exploratory System Dynamics Models. *Proceedings of the International Conference of the System Dynamics Society*.

Beck, T., & Demirguc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance*, *30*(11), 2931–2943. doi:10.1016/j.jbankfin.2006.05.009

Chaim, R. M., & Castellano, M. (2012). ERM quantitative risk analysis methods and techniques applied to a small commercial bank. *Proceedings of the International Conference of the System Dynamics Society*.

ECB. (2010). Towards Macro-Financial Models with Realistic Characterizations of Financial Instability. *Financial Stability Review*, (December), 138–146.

Ernst & Young. (2010). Recover , adapt , advance - Back to business in an uncertain world. Retrieved from http://www.ey.com/Publication/vwLUAssets/Recover,_adapt,_advance:_back_to_business_in_an_uncertain_world/$FILE/Recover-adapt-advance_back-to-business-in-an-uncertain-world.pdf

Forrester, Jay W. (2003). Dynamic models of economic systems and industrial organizations. *System Dynamics Review*, *19*(4), 329–345. doi:10.1002/sdr.284

Forrester, Jay Wright. (1961). *Industrial Dynamics* , Productivity Pr.

Gramlich, D., & Oet, M. V. (2012). Systemic Financial Feedbacks – Conceptual Framework and Modeling Implications. *Proceedings of the International Conference of the System Dynamics Society*.

Hamarat, C., Kwakkel, J. H., & Pruyt, E. (2013). Adaptive Robust Design under deep uncertainty. *Technological Forecasting and Social Change*, *80*(3), 408–418. doi:10.1016/j.techfore.2012.10.004

Hudson, M. (2012). *THE BUBBLE AND BEYOND*. ISLET.

Kővári, A., & Pruyt, E. (2012). Prostitution and Human Trafficking : A model-based exploration and policy analysis Prostitution and Human trafficking 2012. *Proceedings of the International Conference of the System Dynamics Society*.

KPMG and The Economist. (2013). Expectations of Risk Management Outpacing Capabilities - It's Time For Action. Retrieved from http://www.kpmg.com/Global/en/IssuesAndInsights/ArticlesPublications/risk-management-outpacing-capabilities/Documents/expectations-risk-management-survey.pdf

Kwakkel, J H, & Timmermans, J. S. (2012). Safe Operating Spaces for Human Water Use : Applying Exploratory Modeling and Patient Rule Induction to ANEMI.

Kwakkel, Jan H., & Pruyt, E. (2013). Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. *Technological Forecasting and Social Change*, *80*(3), 419–431. doi:10.1016/j.techfore.2012.10.005

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis*. (RAND, Ed.). Santa Monica, California.

Pruyt, E. (2009). Saving a Bank ? Cracking the Case of the Fortis Bank ? A High-Level System Dynamics Simulation Model. *Proceedings of the International Conference of the System Dynamics Society*.

Pruyt, E., & Hamarat, C. (2010). The Concerted Run on the DSB Bank : An Exploratory System Dynamics Approach. *Proceedings of the International Conference of the System Dynamics Society*.

Rafferty, M. (2008). Northern Rock plc: A case study in banking policy during times of duress. *Proceedings of the International Conference of the System Dynamics Society*.

Stein, P., Goland, T., & Schiff, R. (2010). Two trillion and counting. Retrieved from http://www.mspartners.org/download/Twotrillion.pdf

Sterman, J. D. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World*. McGraw-Hill/Irwin.

Warren, K. (2008). *Strategic Management Dynamics*. John Wiley & Sons, Ltd.

Warren Liao, T. (2005). Clustering of time series data—a survey. *Pattern Recognition*, *38*(11), 1857–1874. doi:10.1016/j.patcog.2005.01.025

Winch, G. W., & Arthur, D. J. W. (2002). User-parameterised generic models: a solution to the conundrum of modelling access for SMEs? *System Dynamics Review*, *18*(3), 339–357. doi:10.1002/sdr.252