Bursting a Bubble: Abstract Banking Demographics to Understand Tipping Points?

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Abstract. It has become popular to describe the behaviour of certain systems as "undergoing a tipping point". This is normally used as a description of a system that has rapidly changed from an apparently stable state to a new state with little or no warning. A wide range of complex systems can display tipping point behaviour, from climate systems to populations of people. Here we present preliminary work of using the British banking sector from 1559 to 2012 as a case study for the modelling of complex systems that show tipping point behaviour. We present a description of an abstract population model of the banking system. Once implemented we hope to use this model to test our assumptions about how systems undergo tipping points. In the future it might also help determine what the key drivers of the population trends seen in the British banking sector are, and what the possible implications were of past legislative interventions.

1 Introduction

The term tipping point is often used to describe a system that has undergone a rapid change in state. It is often applied when aspects of the change in state were not predictable before hand, such as the potential for very occurrence of the state change, the exact timing, or the nature of the final system state[9, 3]. We are interested in developing models and simulations of systems that could potentially experience a tipping point, avoiding the ever present danger of programming the tipping point into the model (and therefore the resulting simulation if implemented). Current best practise of building a simulation of this kind dictates that the system is simplified into a number of key interacting components. This is a difficult step as in a truly complex system it is difficult to identify the key causal components for an observed behaviour. Our informed opinions of what is or is not important might be very accurate, but may also be focused on the wrong part of the system altogether. Once identified these components are then given simplified versions of their *real* behaviour, the simulation is then started from a suitable initial condition and the resultant system behaviour observed. However, the very nature of the modelling process biases the modeller towards selecting components of the larger system being modelled that have at least the potential to produce desired behaviour. This is somewhat inevitable as a modeller is not going to included bits of a system that he/she believes to be irrelevant. The process therefore has an aspect of self-selection. In our case as researchers we look for systems that display what we consider to be tipping point behaviour. We then, in the background of already having decided that the system has displayed what we define as a "tipping point", make assumptions about the behaviour of the components of that system. When the model is then built care is taken not to build the solution into the model, but it is impossible to operate in a completely unbiased way.

What the current best practice does give us is some indication of how good our assumptions about a system are. If we have identified likely key system components that when given reasonable behaviours do go on to produce the system behaviour that we are interested in seeing, then we have at the very least learnt something about our understanding of that system. This understanding can be compared with that of other researchers, and also considered in the wider background of the field of study. In short, we can make some assessment of how good we think that model is and how good we think its underlying assumptions are. This knowledge of the model can then be taken into account when the model is used. Models of tipping points have an additional problem that often we have only one example of a system going through a tipping point. Therefore we don't have a good understanding of how that system truly behaves; we do not know what constitutes its normal state. Therefore when making assumptions about key components and key behaviours we do so with the additional assumption that it can go through a tipping point. Therefore it would be helpful to the modelling process that the modeller had no knowledge of what we define as a tipping point.

In this paper we approach this from a slightly different angle. Rather than commissioning a modeller (free of the burden of 'tipping point' knowledge) to build a model of a system with only information that does not give away that it is capable of undergoing a tipping point, and then observing what they determine as important components and behaviours. We have chosen a model system where the important determinates of the global behaviour are not clear, but what is clear is that the system has the potentail to undergo a tipping point. We have collected detailed population data on the banks present in British banking system from 1559 to 2012. The data includes useful demographic data, including the size of population of banks for each year, the number of bank failures, the number of bank creations, and also the number of mergers. Not only do we have the number of mergers but we are also able to track the flow of banks into one another by acquisition. The data suggests that in terms of population the banking sector undergoes a tipping point during this time period, but importantly it's a tipping point that we have so far being unable to satisfactorily discover the basis of. We therefore believe that we know a lot about the system, its components and behaviours, but we do not know which behaviours are producing the observed tipping point. Is this an opportunity to develop a simulation of a complex system and learn something about the modelling process itself, but also about the extent of our understanding of the banking system. The historical na-

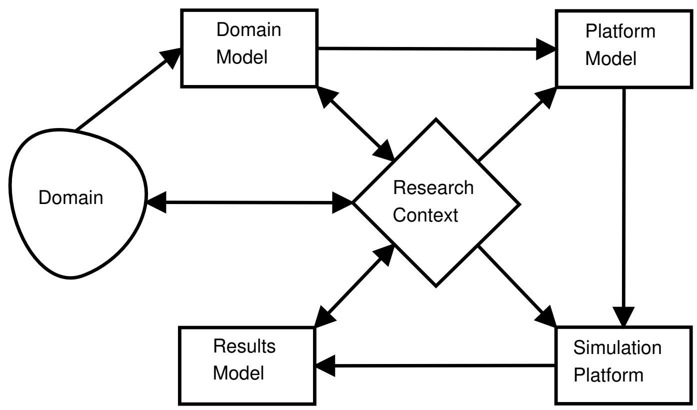

Fig. 1. The components of the CoSMoS process [1, fig.2.1]. Arrows indicate the main information flows during the development of the different components. There is no prescribed route through the process, in so far as going back a step at any point in the process is allowed and often useful.

ture of the data also allows us to make predictions about how the population of banks could have responded to changes to the regulation of the sector, allowing the testing of alternative regulatory interventions. Once fully implemented we might also be able to predicted the effect of present day interventions on the future banking populaiton.

We have made extensive use of the CoSMoS process[1] to guide the development of a number of different simulations of biological and behavioural systems[8, 7, 6]. This paper applies the CoSMoS process to building an abstract model of the population demographics of the British banking sector from from 1600 to 2012. We focus on the first step of this process where assumptions are made about what parts of the British banking sector need to be included in the model.

2 Background

2.1 CoSMoS Process: The modelling lifecycle

The CoSMoS process used for this work is described in full by Andrews et al. [1], and used is the same as used in our earlier work [8, 7, 6]. Summarised in figure 1, the version of the process used here contains the following components (summarised from [1], and the description of the process is taken from [7]):

Research Context: the overall scientific Research Context. This includes the motivation for doing the research, the questions to be addressed, and the requirements for success.

Domain Model: conceptual "top-down" model of the real world system to be simulated. The Domain Model is developed in conjunction with the domain experts, with its scope determined by the Research Context. The model may explicitly include various emergent properties of the system.

Platform Model: a "bottom up" model of how the real world system is to be cast into a simulation. This includes: the system boundary, what parts of the the Domain Model are being simulated; simplifying assumptions or abstractions; assumptions made due to lack of information from the domain experts; removal of emergent properties (properties that should be consequences of the simulation, rather than explicitly implemented in it).

Simulation Platform: the executable implementation. The development of the simulator from the Platform Model is a standard software engineering process.

Results Model: a "top down" conceptual model of the simulated world. This model is compared with the Domain Model in order to test various hypotheses. This part of the process is on-going research.

This work focuses on determined what parts of the Domain, the British banking sector, are included in the domain model. This is a particularly important part of the process for this model as we do not have a clear understanding of what causes the observed behaviour, but we believe we have a reasonable understanding of how the system is operating (on one level at least, Sect. 3).

3 The Research Context

The British banking sector is one of the oldest and most developed in the world. Starting in the 1550s it reached its maximal population of 1100 banks in 1810 before steadily declining to its current level of about 100 banks. Figure 2 shows data for the number of banks through time. The black line is the actual number, the long-dashed line is a exponential fit indicating a 2.7% increase year on year in the number of banks. The dashed-dotted line is a super exponential increase where an additional scaling factor is introduced to improve the fit to the real data. The short-dashed line as an exponential decrease of 1.5% year on year. Broadly the real data matches a exponential increase until the maximal population, after which the population decreases exponentially. The super exponential fit is interesting because these are often seen in situations where positive feedback is operating – perhaps indicating that creation of banks promoted the creation of more banks, discussed in Sect. 3.1. The last 200 years of the banking sector may have been dominated by a change in legislation and is discussed in Sect. 3.2.

3.1 The Banking Sector Pre 1810

The period of exponentially increasing numbers of banks could have a number of possible causes. During this time banks operated as partnerships; each bank had a number of partners and they brought with them the money that could be invested. During this period banks were limited to a maximum of six partners. This builds into the system a mechanism for the growth in the number of banks via an increasing population of available partners. Its is reasonable to assume

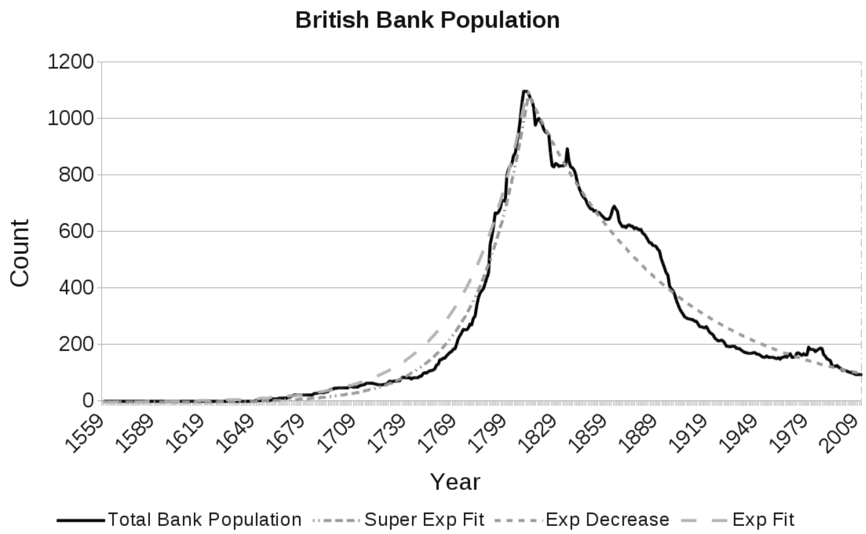

Fig. 2. The changing number of banks through time from 1559 to 2012. The black line is the actual number, the long-dashed line is a exponential fit indicating a 2.7% increase year on year in the number of banks. The dashed-dotted line is a super exponential increase where an additional scaling factor is introduced to improve the fit to the real data. The short-dashed line as an exponential decrease of 1.5% year on year.

that during this period of sustained economic growth there was a requirement for more banks, not only that there would also have been a supply of potential partners that wanted to invest money to make money. As the number of new potential partners increased so did the number of banks. The fact that the real growth of banks more closely matches a super exponential curve is interesting as it suggests that there was an element of positive feedback in the system. One possible explanation for this feedback is that people believed that there was money to be made in banking and therefore looked for opportunities to set up banks. They saw others making money by setting up banks and therefore copied that behaviour. Positive feedbacks (or herd behaviour) in financial systems can turn out to be unstable[5, 2, 11], creating a bubble that is destined to burst at some point in the future, and could be one possible cause for the eventual decline in the number banks.

3.2 The Banking Sector Post 1810

Post 1810 the number of banks starts to decline exponentially year on year. The actual date of the decline is interesting as it is close to a number of potentially significant historical events. The Napoleonic Wars ran from 1803-1815 and are likely to have been a source of economic disruption; there was also a significant financial crisis in 1825 [10]. Of particular interest is the Amalgamation Movement that describes a long peroid of banking history. In 1825 the rules governing banks changed and banks were able to expand via amalgamation, allowing the formaiton of joint stock banks [12]. This could explain a lot of the changes in the population of banks post 1810 as we have evidence that banks were rapidly increasing in size via amalgamation during this period, essentially by copying the behaviour of other banks in the population [12, 4]. The Amalgamation Movement was brought to a halt in 1925 is it was feared that the population of banks would fall too low [12].

There is evidence for a number of underlying processes at work in the British banking sector that might account for many of the trends seen in the changing population of banks. A long period of growth in the British economy coupled with a restrictive policy limiting the size of banks suggests a mechanism for the expansion of the bank population. Add to that an interest in forming banks to make money increasing the population beyond what is strictly required and we are starting to identify possible components and behaviours to explain the growth in the population of banks. At some point (perhaps due to internal pressure or external drivers) new rules are introduced into the banking system that allow banks to increase in size via merging together. Once the rules are changed there follows a long period of bank amalgamation that results in an exponential decrease in the population of banks and dominating its development for the next 200 years. This poses a number of questions. Can we develop an abstract model of banking demographics and then implement a simulation based on these these basic rules? What behaviours will we observe using this simulation and how do they compare to the real banking population data? In order to see the observed tipping point in the banking system will we have to drive the system externally, or would the model require much more fine-grained detail about the economy and individual banks to reproduce the population trends through time?

4 The Domain Model: the banking sector

We intend to develop an agent-based model of an abstract banking sector based on the components and behaviours identified from studying the British banking sector. From the domain we can determine a number of key components to the model, we can also develop simplified behaviours for the components. These components and behaviours will be mapped to "agents" in the model and ultimately implemented in the simulation. We intend to evolve the components and their possible behaviours starting from a very simple initial set. This is to see how the introduction of new components affects the results from the simulations, allowing us to incrementally develop our understanding of the abstracted banking system.

Figure 3 shows the domain class diagram. A description of the agents (and their starting behaviours) and other components of the initial system follows:

Partners: Prior to 1825 Partners are central to the banking sector as they are the source of funds in the system. Agents representing Partners will have the following behaviours. New Partners enter into a pool of Partners; from

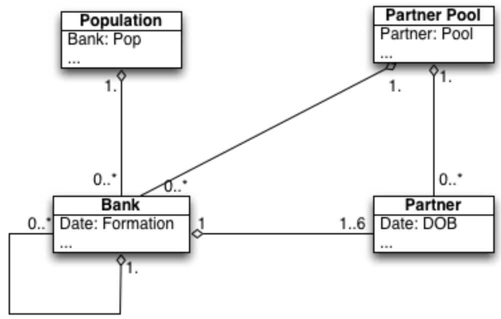

Fig. 3. Domain class diagram showing the relationship between the Bank and Partner classes. The Population starts with 0 Banks, supply of money causes the creation of Partners which are held in the Partner Pool. Banks are created by Partners and held in the Population. A Partner can be in only one Bank, each Bank can have a maximum of 6 Partners. A Bank can contain 0 or more acquired Banks.

here they can either join an existing Bank (initiated by the Bank) or form a new Bank. Existing Partners in a Bank can decide to leave their current Bank and form a new one; they can either do this individually or as a group. Partners can exit the population. Figures 4 and 5 represent the behaviour of the Partners.

Banks: Banks are container for Partners. A Banks can contain between 1 and 6 Partners. A Bank with less than 6 Partners can attempt to attract new Partners. Banks can also acquire other Banks to increase in size, they are therefore a contaion for Banks. A number of possible behaviours could be tested here. Including the effect of keeping the 6 Partner limit, this limit would block any merger of Banks that resulted in more than 6 Partners. Alternatively the Partners of the acquired banks could either exit the population, or return to the pool of Partners. Banks can only be formed by Partners and do not arise spontaneously. Banks can fail and exit the population, or they if a Bank's only Partner exits the population the Bank leaves too. Figure 6 shows the activity diagram for the basic bank behaviours. The size of a Bank could be determined by the number of Partners, the number of acuired Banks or a combination of both.

GDP: The simulation needs a method for introducing new Partners into the system. The population of Partners is increased in line with growth in estimated United Kingdom (UK) Gross Domestic Product (GDP).

There are few key differences between the domain model for the initial simulator implimentation and the domain. Firstly, Partners remain key to the formation of Banks throughout the simulation. In the real system post 1825, banks are not only owned by partners. We are making this alteration to the system to see if the changes that bring about the Amalgamation Movement are responsible for the declining population of banks. There is an approximate 10 year cap between the

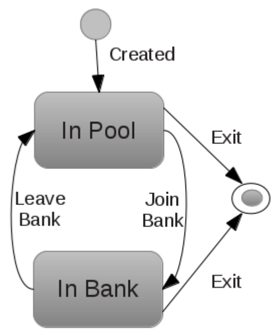

Fig. 4. State Diagram for the the Partners. Partners can occupy two different states, in the general pool of Partners, or in a Bank. The Partners can leave the simulation from both the In Bank state and the In Pool state.

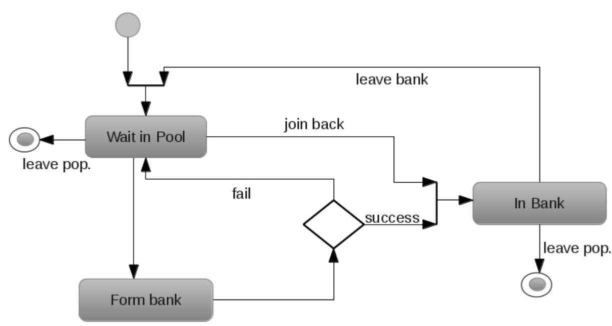

Fig. 5. Activity diagram for the Partners. The behaviours of the Partners drive the initial model.

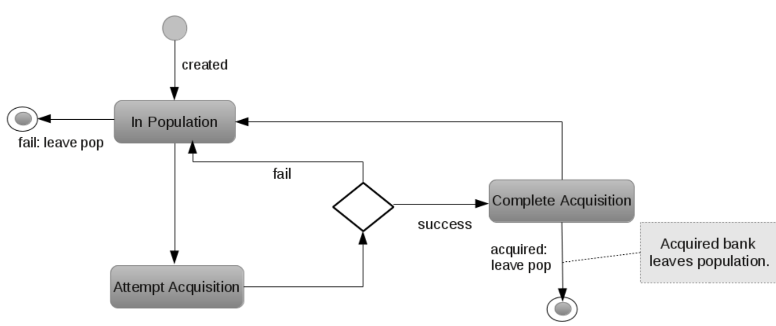

Fig. 6. Activity diagram for the Banks. Banks are formed by one or more Partner. Banks will also be able to acquire, or be acquired, by other banks. Acuired banks leave the general population but remain 'in side' the acquiring Bank.

start of the decline of banks and the 1825 change in regulation, suggesting that the relationship between the obversed decline and the regulation is not clear. If the change in regulation had not been made what would the banking sector look like based on our simple rules? Initially we will not introduce any external drivers to the system, such as economic disruption or regulatory change. This domain model represents the base model for the system to which additional processes will be added.

4.1 Drivers of Change

As it stands our domain model describes two distinct behaviours that look to dominate the simulated banking system at two different periods of time. During the early part of the development of the banking sector, from 1600s to 1810 the system is driven by the behaviour of partners. The supply of partners into the system should drive the formation of new banks, the growth phase. In the second time period, merger and acquisition dominate the system, the decline in population and the rise of super banks (banks that have acquired large numbers of other banks). These two systems are similar in some respects, they are both about generating sucessful banks that are as large as possible. In the case of the partner model, banks (created by partners) attempt to grow by attracting new partners from the pool. In the second phase, banks grow more by acquiring other banks. Modelling the swtich between these two methods of growth of banks present a challenge, and is largerly dependant on our assumptions about the evolution of the real banking system.

One possibility is to allow both behaviours to operate in parallel. Under this system it would be interesting to see under what conditions the behaviour of the simulation changes and how sensitive it is. When there is an abundence of available Partners (stable money supply, condition of economic growth), is possible to produce a simulation where growth by attracting Partners from the pool dominates? However, if the economic conditions became more difficult (unstable money supply, poor or no economic growth), would a swtich to merger and acquisition behaviour take place? How stable would this switching be, and would the banks need to have the possibility of copying "successful" members of the population (follow the herd) for the behaviour to diffuse throughout the population? This would suggest that regulatory change might have legitimised a behaviour that was already starting to occur in the population of banks. Alternatively, to achieve the two distinct phases of population change might require external influence, indicating that the second phase was in response to regulation. What would be the effect of initially only allowing merger if the limit on six partners is respected?

5 Discussion

Developing a model and simulation of a tipping point is challenging as it is hard to take an unbiased view of a system as the system is often of interest because it seems to display tipping point behaviour. Here we approach a system, the population demography of the British banking sector, that appears to display tipping point behaviour but where the exact cause is unclear. We have identified the key aspects of the banking system for inclusion in the model that could be responsible for the general population trends seen in the population. The initial model is a highly simplified version of the real system. This is deliberate and is an attempt to produce a null model for the banking sector, with much of the complexity removed, that is still capable of matching the general trends. This model could be used to test the effect of internal drivers on the population of banks, but also if external drivers are required to match the general population trends.

We also hope to gain insight into modelling tipping points. The banking system appears to undergo a tipping point in its population in around 1810. Using the simulation we can test if when we model the components of the system as we assume them to work if the modelled system can undergo tipping points. We are also able to test the effect of introduced legislation on the behaviour of the modelled banking system. The two phase nature of the system could potentially help us understand how population of organisations might flip bewtween two possible but distinct behaviours. Under what conditions this flips occur and how often they occur. It is also possible that tipping points could be caused by behaviours no longer happening, forcing a system into one behaviour.

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