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# Emotional Agents Make a (Bank) Run

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**Abstract.** Agent-based Computational Economics (ACE) is an area that has gained significant attention, since it offers the possibility to model economic phenomena in a more fine-grained manner than other approaches. One such phenomenon is "bank panic" in which the term "panic" implies the existence of emotional bias towards to the sudden withdrawal of deposits from financial institutions (simultaneous bank runs). However, research towards complex emotional agents in ACE has not been extensively conducted. The paper employs a formal state-based model enhanced with explicit emotional states, mood and personality characteristics in order to describe the agents behavior. A NetLogo simulation of a multi-agent system in a limited economic environment is attempted in order to study the effects of emotions, emotion contagion and the role of various players in the genesis of a bank panic crisis. The aim is to investigate further whether such agent models that are already used in other areas, such as evacuation simulation, could also provide a better insight on the evolution of such economic phenomena.

**Keywords:** Agent Based Simulation · Emotional agents · Agent-based Computational Economics · Bank Runs

## 1 Introduction

Agent based Computational Economics (ACE) is a thriving area of research, offering the potential to model economic phenomena. Existing conventional methods are based on mathematical models, which describe a set of definitions and assumptions that lead to proofs of theorems. A number of economists consider such models too restrictive to address real problems and thus moved towards other computational alternatives [13]. ACE modelling has been applied to the same problems, for instance how an economic system reaches an equilibrium. ACE conveys a methodological novelty since the models consist of relatively simple agents that collectively exhibit rich behaviour with the overall outcome naturally emerging as a result of their interactions. Thus, agent-based modeling enables the development of macroeconomic models using a bottom up approach [28].

ACE can be applied to a broad spectrum of micro or macro economic systems, where agents can be represented as interactive goal-directed entities, i.e. BDI agents. However, in many economics applications, BDI agents need to be infused with emotions that may affect their reasoning and decision-making. Emotions affect an agent's goals, hence affecting their actions [18], that is common in the real world. In addition, incorporating human aspects such as personality and emotion leads to more believable simulations [17].

The paper aims to investigate further whether emotional agent models, used in other areas such as evacuation simulation, could provide a better insight on the evolution of economic phenomena. Our motivation was to demonstrate the potential of ACE in an emotionally intensive economic phenomenon, namely a bank panic. Thus, the main contribution of the paper is an agent model and the corresponding simulation based on a formal method that supports emotions including emotion contagion.

The rest of the paper is structured as follows. Section 2 presents an overview of the related work in ACE, bank runs and emotional agents; Section 3 provides a brief description of the emotions X-Machine model, which was used as the basis to specify the behaviour of agents in the simulation environment. Section 4 describes the agent model used, including the emotional inputs and how they affect agent behaviour, with Section 5 presenting the preliminary experimental results. Finally, Section 6 concludes the paper.

## 2 Background and Related Work

### 2.1 Emotions

Emotions are meant to be short, short term states of mind the individual passively experiences instigated by events or objects [7]. Mood, on the other hand, is used to describe a long standing emotional state. In psychological studies, the emotions that influence the deliberation and practical reasoning of an agent are considered as heuristics for preventing excessive deliberation [4]. Emotions affect an agent's goals, hence affecting their actions. Emotional effects on goals can manifest via reordering existing goals, or by introducing completely new goals. The goals' success or failure can affect emotional states.

In addition to emotions and moods, personality is an important aspect which affects perception and how quickly the emotional state changes. The final factor that is of great importance to communication intensive socioeconomic environments is contagion, i.e. how an agent's emotional state affect another agent's emotional state. All these integrated, make an individual's behaviour completely different from pure rational behaviour in the absence of emotions.

Agents can be potentially enhanced by infusing emotions in their functionality leading to Emotional-BDI agents, i.e. agents whose behaviour is guided not only by beliefs, desires and intentions, but also by the influence of emotions (such as fear, anxiety etc.) in reasoning and decision-making. The existing formal systems for rational agents [20] do not allow a straightforward representation of emotions. However, they have properties which can be inherited in order to properly model Emotional-BDI agents [18].

### 2.2 Emotional agents in Socioeconomic scenarios

Several models for emotions in agent systems have been reported. ESCAPES is a multi-agent simulation tool, that reproduces phenomena on evacuation scenarios, such as an escape scenario at the International Terminal of Los Angeles International Airport [29].

Elsewhere, a Group Decision Support System was developed focused on the negotiation process improvement through argumentation, by using the affecting characteristics of the involved parties [25]. The system uses both personality and emotional inputs in order to select the best arguments to reach a decision. The results revealed that aggressive agents achieve more preferred solutions than negotiator agents.

In [1], another agent based model of the financial domain was introduced; leveraged investors (banks) that used a Value-at-Risk constraint. This constraint was established on historical market data (e.g asset prices) to predict the portfolio risk. The model took under consideration pro-cyclical leverage (low risk results in high leverage). It was shown that it resulted in endogenous irregular oscillations. This means that when the stock prices were increased the market collapsed. When the leverage was regulated to correct the risk (using a counter-cyclical leverage policy) prices reached a plateau which stabilized the system.

### 2.3 Bank runs

A bank run is defined as the situation "where depositors withdraw their deposits from banks because of fear of the safety of their deposits" [12]. The term "bank panic" is often associated with the existence of emotional bias towards a sudden simultaneous withdrawal of deposits from different financial institutions (simultaneous bank runs). Bank runs often appeared in the course of time, such as the Great Depression in the US. The 2007 global financial crisis, has also been characterized by bank runs internationally (e.g., Countrywide Bank, IndyMac Bank, Northern Rock Bank, etc.). To avoid bank runs, several actions have been taken, such as increasing deposit insurance in bank of the US and UK [12].

There have been several approaches in simulating bank run scenarios with ACE. The frequency of occurrence in bank runs has been studied in [27], where panic is spread among agents that focus on the neighborhood influence. The assumption is that different equilibria are likely to be established in different neighbourhoods. The model included synchronization effects which generate bank runs and is based on three important interacting factors which influence the patient agents' strategies (withdraw or wait), the proportion of patient agents (those that wait), the activation threshold and the interaction neighborhood of agents [6]. A similar approach with regards to focusing on neighborhood influence is taken in [26], which showed that the number of bank run incidents decreases with the size of the banks, i.e. number of clients. The work reported in [8] focuses on rumors spreading. The model described is predicated on dynamic rumor-based bank runs with endogenous information acquisition by incorporating bank liquidity uncertainties into a asynchronous awareness framework. The liquidity event triggers a rumor spread and therefore the bank can be exposed to a bank withdrawal. In such a case, depositors can withdraw or deposit at any time for a tiny low transaction cost, or wait so as to totally withdraw, then redeposit if the bank survives. The risk of collapse of a financial system has been studied in [19], which is calculated through an agent based model that suits the microeconomic framework for this economic analysis. In the model, there are heterogeneous agents that interact through two key channels: direct and informational contagion. Results showed that when bank runs are associated with contagion, then an increase in interconnectedness worsens the outcomes. In [11], the probability of bank runs is reported. Even when the economy is thriving, they proposed that agents' behaviour is influenced by non-favorable news and that can cause a bank run. Agents are modelled as rational or irrational with a wide range of learning models. Irrational thinking increases the chances of the system to collapse. An agent-based model for banking analysis is developed in [3]. The model includes agents types (savers, loans, and banks) which inhabit a world divided into different regions. Results showed that banks which are more vulnerable to credit shocks are also more likely to be under capitalized and eventually have to rely on the European Union's Emergency Liquidity Assistance.

Finally, agents behaviour in simulations can be predicted more accurately if artificial neural networks are utilised [11]. Taking into consideration the multi factorial facets of bank runs, the results demonstrate that if the agents are aware of the whole picture of market then bank run incidents only occur when the economy is at an extremely poor state. There exist a plethora of studies related to economic analysis of bank runs but they fall outside the context of this paper [12, 16, 5, 2].

The novelty of the current work is attributed to three factors: (a) our model is not based on a standard definition of a neighbourhood, e.g. lattice, but it adopts a more dynamic notion of neighborhood, one that depends on the spatial characteristics of the simulation platform, (b) our agents do not attempt to liquidify all their assets from the bank but instead their intention is to have enough cash to make them feel secure, i.e. we consider retail depositors agents relying on the assumption that deposit insurance is guaranteed by the government supervision of banks and (c) agents follow relatively complex behaviours and can be easily extended.

## 3 Modelling Agents using X-Machines & Emotions

### 3.1 A formal model of agents

X-Machines [9] are finite state machines that offer an elegant way to compact states $Q$ by allowing processing of a globally available memory structure $M$. In addition, transitions $F$ between states are each labeled by a function $\varphi$ (where $\varphi \in \Phi$) that is triggered by inputs $\Sigma$ and not just input values as in simple automata, i.e. $F : Q \times \Phi \to 2^Q$. Functions $\varphi$ also take into account the memory values, i.e. $\varphi : \Sigma \times M \to \Gamma \times M$, they generate an output and change the memory values. These characteristics give X-Machines some important advantages for formal agent modeling: (a) models have less states $Q$, (b) states, beliefs, goals etc. are nicely represented as $Q$ and $M$,(c) behaviors map well to transition functions $\varphi$ and (d) the formal model facilitate transformation to executable code but also is supported by a well established theory for complete testing. The formal definition of X-Machines can be found at [9].

In Figure 1 we show a partial X-Machine model of a rational (emotionless) agent. In this model, three states are depicted ("at the bank", "at store" and "at home"), four functions-behaviors ("withdraw some cash", "withdraw all cash", "go to store" and "go home") and a partial memory structure containing information that will trigger any behavior. For instance, in this particular case, "withdraw some cash" is triggered, which will allow the agent to get the appropriate amount of cash in order to go to the store.

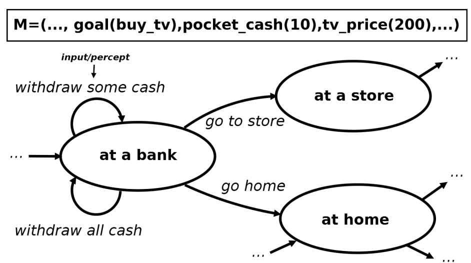


**Fig. 1.** A partial X-Machine model of a rational agent

### 3.2 A formal model of emotions

In order to facilitate a simulation of emotional agents, we adopt the formal model of emotions that was presented in [15], extended with a contagion mechanism [23], albeit with minor modifications. In the following, we briefly outline the approach reported in the previously mentioned work for completeness.

The representation of emotions follows the dimensional approach [21, 22], i.e. emotions are represented in a two dimensional space [15]. Thus, emotion is a tuple $(v_e, a_e)$, where $v_e \in [-1, 1]$ is the *valence* measure, that is how "pleasurable" it is to experience an emotional state and $a_e \in [-1, 1]$ the *arousal* measure, representing the likelihood to take some action in the specific state. The tuple defines the *emotional state E* of the agent and will be referred to as the *emotional state vector* of the agent.

Emotional states are subject to change due to *percepts*, *emotion contagion* (i.e. external stimuli) and *mood*. Thus, there are three stages in computing the overall emotional change in each execution cycle. They all share a similar mechanism for computing the resulting emotional state. The main characteristics of the mechanism is that the emotional state vector shifts closer to the input vector associated with either external stimuli or mood, and the rate of change is regulated by *personality traits* of the agent. The latter allows to represent population diversity in the simulation, i.e. model the fact that some agents might be more receptive to percepts than others.

The emotional effect of a *percept* is represented by a vector $(v_{prc}, a_{prc})$, i.e. each agent percept is associated with an input emotion vector. Given an emotional state $(v_e, a_e)$ the resulting vector $(v'_e, a'_e)$ is given in Equation 1.

$$(v'_e, a'_e) = \left( v_e + \frac{f_p^2 \cdot \Delta v}{1 + e^{-f_p \cdot (|\Delta v| - 1)}} \ , \ a_e + \frac{f_p^2 \cdot \Delta a}{1 + e^{-f_p \cdot (|\Delta a| - 1)}} \right) \tag{1}$$

where $\Delta v = v_{prc} - v_e$ and $\Delta a = a_{prc} - a_e$. The personality factor $f_p \in (0, 1]$ determines how quickly the emotion vector converges to an emotional percept.

The contagion model described in [23] is inspired by the ASCRIBE model [10], although simpler, and adapted to the vector representation of emotions. *Emotional contagion* is treated as a form of perception: agents perceive the emotions of other agents in their proximity. Thus, emotion contagion involves computing an overall emotion vector $(v_{cnt}, a_{cnt})$ based on the emotions of neighboring agents. In order to define the neighbourhood of each agent, it is assumed that agents inhabit a two dimensional world. However, extending the definitions to a three dimensional world is straightforward.

In order to model the spatial characteristics of such a perception, each agent has an *influence-crowd* $(IC_i)$ that consists of all other agents within a radius $d_{inf}$, i.e. $IC_i = \{Agent_j : d(Pos_i, Pos_j) \leq d_{inf}\}$.

*Contagion strength* $w_{ij}$ (Eq. 2) determines the strength by which an agent $j$ ($j \in IC_i$), influences agent $i$ and depends on the *expressiveness* of agent $j$, $expr_j$, a measure of how much the agent manifests its emotions, and the *channel*, that models that closer agents have a larger effect to the emotions of the agent $i$.

$$w_{ij} = expr_j \cdot \underbrace{\left( 1 - \frac{d(Pos_i, Pos_j)}{d_{inf}} \right)}_{channel_{ij}} \tag{2}$$

The overall contagion strength $w_i$ of agent $i$ by all agents in its influence is:

$$w_i = \sum_{j \in IC_i} w_{ij} \tag{3}$$

To form the emotional percept due to contagion $(v_{cnt}, a_{cnt})$, each emotion contagion vector coordinate is defined as the sum of the corresponding emotion vector coordinates of agents in the influence crowd multiplied by the normalised contagion strength $(w_{ij}/w_i)$:

$$(v_{cnt}, a_{cnt}) = \left( \sum_{j \in IC_i} (w_{ij}/w_i) \cdot v_j \ , \ \sum_{j \in IC_i} (w_{ij}/w_i) \cdot a_j \right) \tag{4}$$

The vector $(v_{cnt}, a_{cnt})$ is treated in a similar manner as other percepts (Eq. 1), however, the change now depends on the on the openness $(opn_i)$ of the agent $i$, i.e. how perceptive the agent is to other agents' emotions, and is given in Equation 5.

$$(v''_e, a''_e) = \left( v'_e + \frac{opn_i^2 \cdot \Delta v_{cnt}}{1 + e^{-opn_i \cdot (|\Delta v_{cnt}| - 1)}} \ , \ a'_e + \frac{opn_i^2 \cdot \Delta a_{cnt}}{1 + e^{-opn_i \cdot (|\Delta a_{cnt}| - 1)}} \right) \tag{5}$$

where $\Delta v_{cnt} = v_{cnt} - v'_e$ and $\Delta a_{cnt} = a_{cnt} - a'_e$, where $(v'_e, a'_e)$ is the emotion vector computed after the change due to perception (Eq 1).

Finally, the emotional state of agent is affected by its mood. Mood describes the long term emotional state of the agent, i.e that state in which the agent will eventually settle given that no external stimuli are present. Thus, mood provides the mechanism to model that the effects of a single emotion percept are reduced over time. Change due to mood is given by Eq. 6, where mood is the vector $(v_m, v_a)$, $\Delta v_{me} = v_m - v''_e$ and $\Delta a_{me} = a_m - a''_e$, $(v''_e, a''_e)$ the emotion vector computed in Equation 5 and $d$ is a discount factor that depends on the simulation model. The vector $(v^f_e, a^f_e)$ is the new emotional state of the agent.

$$(v^f_e, a^f_e) = \left( v''_e + \frac{d \cdot f_p^3 \cdot \Delta v_{me}}{1 + e^{-f_p \cdot (|\Delta v_{me}| - 1)}} \ , \ a''_e + \frac{d \cdot f_p^3 \cdot \Delta a_{me}}{1 + e^{-f_p \cdot (|\Delta a_{me}| - 1)}} \right) \tag{6}$$

### 3.3 A formal model of emotional agents

The emotional model described above is embedded in an X-Machine model resulting in Emotional X-Machines ${}^e\mathcal{X}$. The additional component in this model is an emotional structure formalisation $E$ that consists of emotional states ${}^eQ$, moods $\mathcal{M}$, personality traits $P$ and a contagion type mechanism $C$. In addition, there exist emotions revision functions ${}^e\varphi$ that given an emotional state, a mood, a contagion model, a personality trait and a memory tuple, it returns a new emotional state. Finally, inputs go through a revision function $\rho_\sigma$ which given an input transforms it into an emotional percept taking into account the current emotional state, the mood and the personality. The formal definition of Emotional X-Machines can be found at [14]. It should be noted that transitions functions of the original state machine (behaviors) take into account the emotional structure $E$.

The enhanced model (Emotional X-Machines) allows the description of the behavior of emotional agents which are developed on top of rational agents (simple X-Machines), offering a natural decoupling of the two types. For instance, consider again the partial model of Figure 1 now extended with the emotional structure as depicted in Figure 2. Under certain emotional state (e.g. panic due to rumors of financial crisis), the behavior which should be triggered is now "withdraw all cash" and not "withdraw some cash" as it was in the original case.

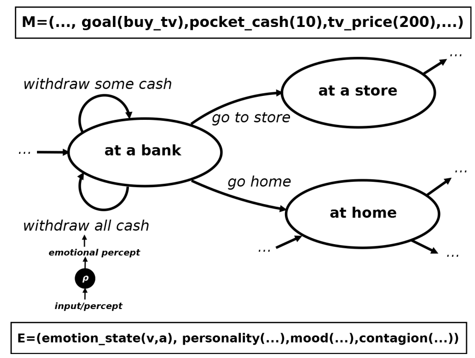


**Fig. 2.** A partial Emotional X-Machine model of an emotional agent

Emotional X-Machines have been used in a number of simulations involving evacuation scenarios [24]. In this work we focus on economic phenomena, as described in Section 4.

## 4 Modelling Bank Runs

Emotion X-Machines allow for a much richer bank depositor model, than those that have been explored in the literature. The model presented takes advantage of spatial characteristics of agent simulation platforms, since agents are expected to move in a two dimensional space, i.e. the world they inhabit and interact with. This presents the significant advantage of having agents interacting with a variable neighborhood, i.e. the underlying agent interaction links vary with respect to where the agent is located. More specifically, being at different locations during a single 24 hours simulation day, an agent interacts with "co-workers" sharing the same workplace, with a *different* set of agents in its home neighborhood, or with *other* agents located in a shopping area. Although the first two sets are invariant during the simulation, since they are fixed at initialisation, the third set allows the agent to form ephemeral links with agents that happen to visit the store at the same time. By interaction in this case, we refer to emotion contagion, i.e. the emotional change due the other agents included in an agent's influence crowd $IC_i$, which is computed dynamically in each time point.

### 4.1 Environment Setup

Agent movement also allows the opportunity to model the affect of *influencers* in the simulated world, for instance media that spread rumors regarding the imminent bank failure.

By allowing influencers to "move", they interact for short periods with different sets of agents, thus providing a varying perceptual input to the latter. This, we believe, leads to a better modelling of the impact that influencers have to the general population. For instance, in order to be affected by public media an agent could follow some of their broadcasts; since this is not expected to happen continuously during the course of a day, a model should be able to accommodate such an interaction. Additionally, not all agents follow the same media, thus one could model the impact of a highly influential news channels by increasing its number of influencers.

The current model has a very fine grain representation of time, with 15 min corresponding to a single simulation step. Under this assumption, agents stay at their working place for 8 hours a day and commute to work for 45 mins (please see Section 4.2). Such a fine grain simulation, facilitates experimentation with the evolution of phenomena that occur rather rapidly.

The model simulates a limited part of the economic environment: we consider only retail banks, a market (shops), workplaces, houses, influencers and individual depositors. In this model we are only interested in cash flow and we do not model transactions that occur with electronic forms of money (i.e. credit cards). This restriction of the model was due to the fact that we are concerned about bank panic, i.e. a significant amount of banks failing, a problem that can manifest when depositors withdraw cash for safe keeping at their home. The model has entities that represent:

- *Banks*: Each bank has an initial amount of retail depositor savings (see below) and maintains a 10% fractional reserve in cash. Each retail depositor maintains an account in one of the available banks. Each bank maintains a number of ATMs that "spread" its presence in the environment. It can serve a limited number of customers in each step, thus *queues* can be formed outside banks (a phenomenon common in bank runs).
- *Shops* stand for the marketplace. Shops provide goods to individuals (for the obvious exchange of cash) and at the end of each day deposit their profits to the banks, thus contributing to maintaining adequate cash levels of banks.
- *Influencers*: are agents that move randomly in the experiment world, and "spread rumors" regarding bank solvency. They act as perceptual input to bank depositors, i.e. the latter perceive their presence and form the corresponding emotional percept (see Section 4.2).

### 4.2 Agent Parameters Setup

The main actors are the *Retail Depositors* and we are going to refer to the latter as the *agents* hereafter. The latter have a number of parameters, stored as *memory values* in the corresponding X-Machine:

– *savings* in one of the banks, that is initially set to three times the agent's *salary*,
– the current amount of cash in their *Wallet* ($W_i$),
– a desired level of cash the agent "feels" safe to have, i.e. its *Cash-Level* ($Cl_i$),
– a ratio of *Wallet/Cash-Level* ($r_i^{w/cl}$) that determines when the agent needs to withdraw money from the bank.

Obviously the ratio $r_i^{w/cl}$ determines the amount of cash that exist off the system, i.e. cash held outside banks. We define the 10% of their salary as the *Original Cash Level* ($OC_i$) and initially $Cl_i = W_i = OC_i$.

Agents follow a daily cycle, that consists of an 8-hour working day, after which they return home. When their goods level is low, they visit the market, and when the level of cash in their wallet drops below the threshold $r_i^{w/cl} \cdot Cl_i$ ($W_i < r_i^{w/cl} \cdot Cl_i$), they visit the bank to withdraw money. Agents do not move between locations instantly, but commute so that each transportation requires are least three time steps (45 mins): this allows agent to perceive the status of the environment, as for instance whether a queue is formed in front of a bank, etc. The behavioural model outlined above, was encoded as an emotions X-Machine, with states and transitions depicted in Figure 3.

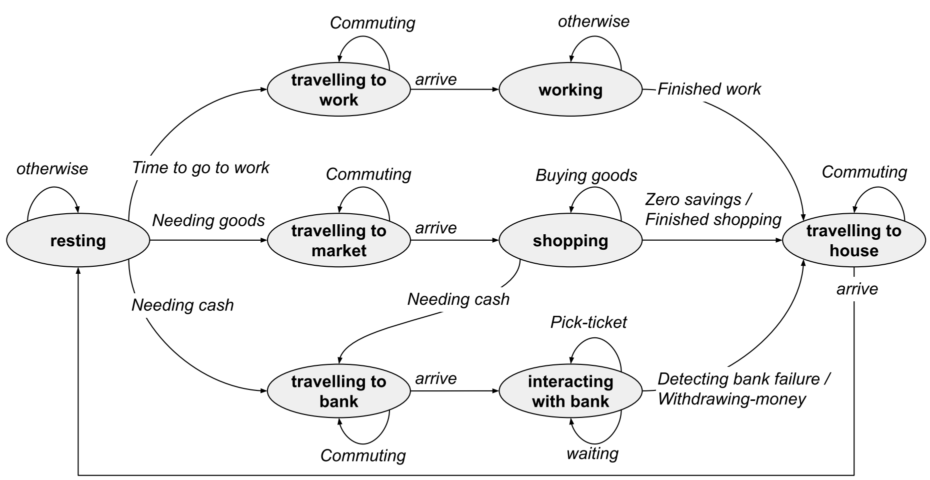


**Fig. 3.** The Agent state transition X-Machine Model

Following the description of Section 3, a subset of the agent percepts is mapped to emotions, i.e. they produce a change to the emotional state of the agent. In the current model, three percepts belong to this subset:

– Perception of an influencer in the agent's proximity, which is mapped to the emotional percept $E_{ifl} = (-0.5, 0.7)$. In the model ifluencers spread negative rumors regarding the solvency of banks and thus cause a negative affect on

the agent's valence (value -0.5) and at the same time urge agents to withdraw money from the failing banks (arousal value 0.7).
- Perception of any queues in a bank, mapped to $E_{bankQ} = (-0.5, 0.8)$. Such a perception confirms the negative valence of the emotion attributed to the influencer and further alerts the agent to take some action w.r.t. money withdraw (arousal 0.8).
- Finally, perception of agent's bank failure is mapped to the emotion $E_{bankF} = (-1, 1)$, i.e. the minimum valence and the maximum arousal value, i.e. what could be described as panic.

The above emotional percepts lead to changes to the emotional state of the agent, which affect in the current model, memory values of the X-machine. In particular, the two dimensions of the emotion state vector affect the *Cash-Level-* $Cl_i$) and a ratio *Wallet/Cash-Level* ($r_i^{w/cl}$) of the agent.

Equation 7 shows how the cash level changes with respect to the arousal of the agent. Since arousal measures the incentive of the agent to take action, i.e. withdraw money from the bank, an increase in the arousal coordinate of the emotion vector leads to an increased cash level. As shown in Equation 7, we define the latter to be at most 5 times the original $OC_i$, i.e. at most 50% of their monthly salary.

$$Cl_i(a_e) = \begin{cases} OC_i & : a_e \leq 0 \\ (1 + 5 \cdot a_e) \cdot OC_i & : a_e > 0 \end{cases} \tag{7}$$

Valence controls the Wallet/Cash-Level ratio of agents. The rationale behind this choice is that in unpleasant economic situations, agents feel safer if they have more cash in their disposal. Thus, Equation 8 provides the ratio change with respect to value (obviously lower valence leads to a higher ratio).

$$r_i^{w/cl} = -0.25 \cdot v_e + 0.75 \tag{8}$$

As a final note, the model includes a consumption rate that decreases the level of goods in all agents in every simulation step. The section that follows (Sec. 5) presents the results of our experiments.

## 5 Experimental Results

We implemented the model[3] using NetLogo [30]. According to our experience, NetLogo can successfully deal with such simulations, even at large scale. We divided the experiments into two phases: (a) experiments in order to calibrate the model, and (b) experiments to show the effect that influencers have on the population. The calibration phase is required to setup appropriate parameters in a state where an equilibrium is achieved, far from any potential bank failures. These parameters are then used in the second phase.

The number of agents is set to 250, the number of banks to 5, with 10 ATMs and 15 workplaces in total. The salary is set to 600 monetary units for all agents.

[3] The code can by found at https://github.com/isakellariou/NetLogoBankRun

The original cash level for each agent was set to 10% of the salary. As mentioned, each agent has three times its salary as savings in one of the banks minus its cash level.

The personality characteristics of the agents are as follows. The personality factor $f_p$ (Eq. 1), ranges between 0.5 and 0.75, while expressiveness $expr_i$ (Eq. 2) and openness $opn_i$ (Eq. 5) have a minimum value of 0.2 with the maximum being 0.4. Agents receive randomly a value within the range mentioned above for each parameter.

### 5.1 Calibration

In the first set of experiments related to calibration, we expect that the system is in equilibrium, i.e. no bank run event occurs. We set the maximum time period for the experiment to 25 days. The number of influencers is set to 0, meaning that no "bad news" on bank solvency is spread within the simulation world. We test the environment for two cases. The first concerns experiments with no contagion, and as shown in Fig 4, the system is in equilibrium, i.e. bank reserves are well over the amount of cash desired by the agents. The fluctuations observed are attributed to the fact that agents withdraw money from the bank to cover the needs in market goods by paying in cash, which at the end of each simulation day are deposited by the shops back to the bank. Almost identical results occur for the case of agents interacting under the contagion model described in Section 3. Values reported in Figure 4 are the average values over a set of 10 experiments.

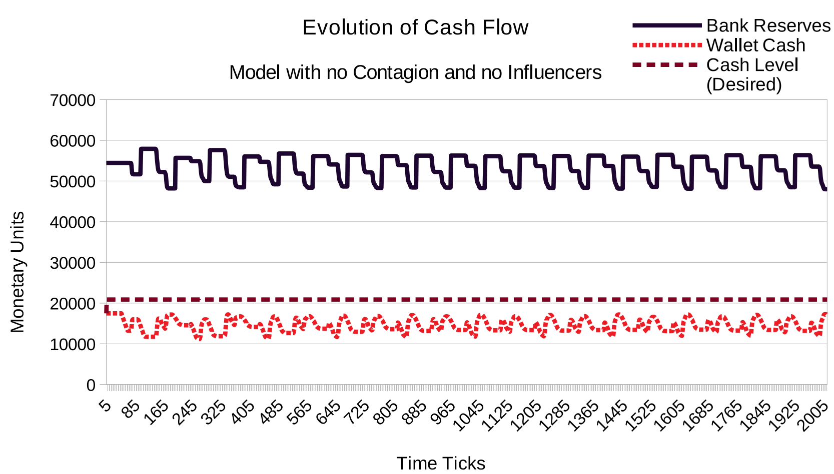


**Fig. 4.** Experimental Results during calibration (No Contagion and No Influencers).

### 5.2 The Effect of Influencers

Having a set of initial conditions that form an equilibrium, the next set of experiments involves increasing the number of influencers in the simulation world. We consider this number to reflect how strong rumors regarding bank failure are, thus we vary the number of influencers from 5 to 15. Table 1 summarizes the results over a set of 12 runs for each combination of influencers and contagion model, with the column "Failure Rate", reporting the number of experiments over those 12 runs where all banks failed, i.e. the manifestation of the "bank panic". For each set of runs, the column "Simulation Step" reports the time point when the last bank failed with the associated standard deviation. Results, as expected, confirm the belief that stronger bank failure rumors increase likelihood that banks will fail.

**Table 1.** Bank Failures w.r.t. the number of influencers

| | No Contagion Mechanism | | | with Emotion Contagion | | |
|---|---|---|---|---|---|---|
| Influencers | Failure Rate | Sim. Step | StdDev | Failure Rate | Sim. Step | StdDev |
| 5 | 25 % | 1388.33 | 414.31 | 0 % | - | - |
| 6 | 33.3 % | 1370.25 | 679.02 | 16.7 % | 1271.00 | 170 |
| 7 | 75 % | 1088.22 | 314.50 | 33.3 % | 1136.50 | 158.86 |
| 8 | 91.7 % | 816.64 | 171.33 | 50 % | 762.83 | 406.25 |
| 9 | 100 % | 581.33 | 58.38 | 66.7 % | 848.50 | 376.51 |
| 10 | 100 % | 423.50 | 174.53 | 83.3 % | 782.50 | 491.01 |
| 11 | 100 % | 393.75 | 37.01 | 100 % | 421.83 | 37.71 |
| 12 | 100 % | 293.67 | 63.88 | 100 % | 434.08 | 98.05 |
| 13 | 100 % | 309.25 | 117.43 | 100 % | 343.33 | 147.51 |
| 14 | 100 % | 221.92 | 39.37 | 100 % | 301.67 | 51.53 |
| 15 | 100 % | 243.83 | 44.64 | 100 % | 269.67 | 160.23 |

It is interesting to note that in simulations using the contagion model, the number of total failures (all banks fail) is less compared to no contagion mechanism simulations, and at a much slower rate. Although this appears counter intuitive, it can be explained by the fact that, interaction with neighboring agents reduces the effect to the population, at least in the early stages of spreading rumors, i.e. the effects of influencers are reduced due to interaction among individuals. Recall that according to the emotions model (Section 3), emotions induced by influencers and contagion are both treated as percepts, however with a different factor (personality factor vs. openness).

Figure 5 presents the behaviour of agents under emotion contagion, when the number of influencers is 15. Again values reported are averaged over all experimental runs. Note that the desired level of cash increases rather rapidly and thus this leads eventually to banks failing. The steep rise of the desired cash level at the final steps of the simulation is attributed to the fact that once agents

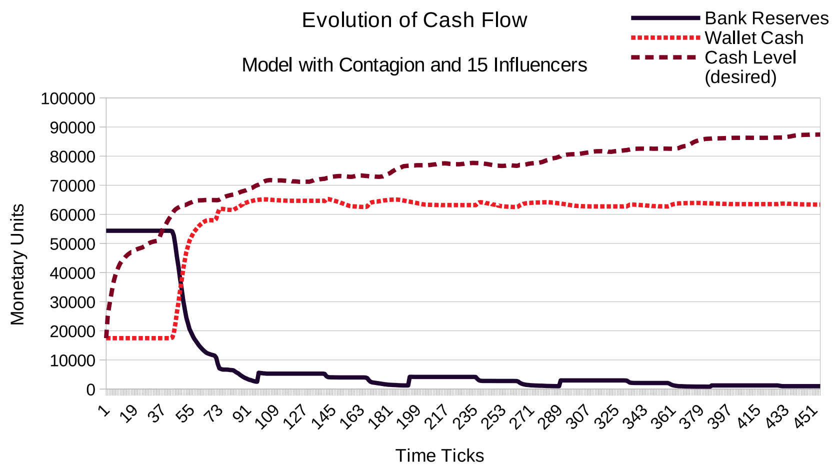


**Fig. 5.** Experimental Results with the Emotion Contagion Model and 15 Influencers.

learn that their bank has failed, they simply panic, spreading this emotion to other members of the population.

Similar results can be observed in Figure 6, although the time it takes for the banks to fail is much larger.

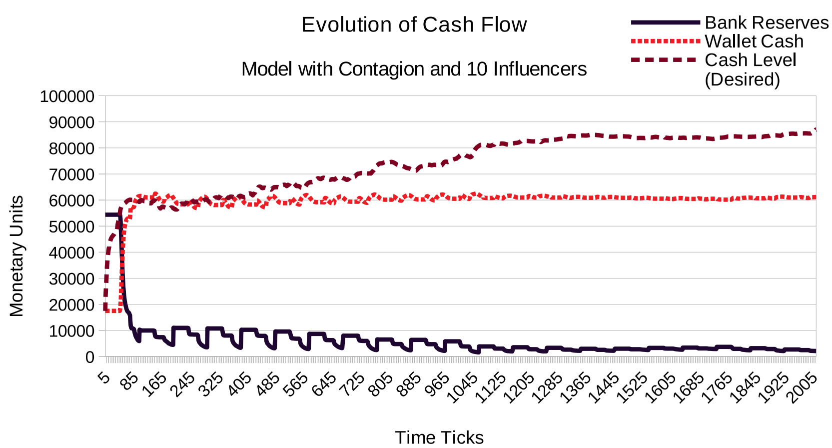


**Fig. 6.** Experimental Results with the Emotion Contagion Model and 10 Influencers.

It is also interesting to see the time relation between successive banks failures in the world, since not all banks fail at the same time. Figure 7 shows, the average time point of each bank failure in the corresponding set of experiments, i.e. the time point when the first bank fails, the second, etc. As it can be easily observed, experiments with no contagion (labeled as *No-Cont*) fail earlier compared to those with contagion (labeled *Contagion)* for both cases of 10 and 15 influencers, due to the same reasons reported earlier in the section. Another interesting point to note is that when one bank fails, then others follow in a rather short time period, again due to the fact that agents not being able to withdraw money are pushed to a panic state, and this has an effect through the contagion mechanism to all other agents.

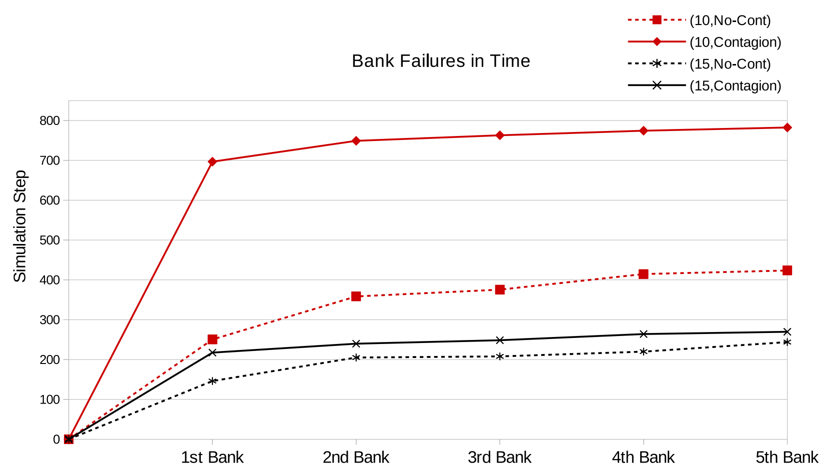


**Fig. 7.** Bank failures vs. Simulation Time.

Although the present experimental evaluation of the bank run phenomenon is preliminary, it is noticed that a relation exists between strong rumors of bank failures incidents and actual bank panic. However, to reach a safe conclusion, a more thorough experimental evaluation is required, one that might take into account more parameters of the system, as for example no-retail depositors and interbank links. However, given the expressive power of X-Machines, modelling more agents, other influencers, global broadcasting models, is not expected to present significant difficulties.

## 6 Conclusions

Incorporating human aspects such as personality and emotion can be an important research direction for ACE, since it allows modelling of emotionally intensive economic phenomena and can lead to more engaging and believable simulations. The present work attempts, for the first time to the best of our knowledge, to use a formal emotional agent model towards a simulation of bank panic, a phenomenon that is often associated with the emotional state of involved stakeholders. In that direction, the paper presents an emotions X-Machine model, together with an implementation in a well known simulation platform. The experimental results confirm that a relation exists between public opinion influencers (e.g. public media) and the manifestation of such phenomena.

There are a number of research directions towards which this work can be extended. These include a more in-depth analysis of the current experimental model and adding different types of stakeholders in the domain, such as government officials. Finally, it is interesting to build a more complete model of the banking system and include a wider range of economic activities, such as inter-bank links and strategic investors. In all cases, we believe the introduction of formal emotional agent modelling could provide ACE with a set of tools that can increase its potential.

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