Three different ways synchronization can cause contagion in financial markets

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Abstract: We introduce tools from statistical physics, to capture the dynamics of three different pathways, in which the synchronization of human decision making could lead to turbulent periods and contagion phenomena in financial markets. The first pathway is caused when stock market indices, seen as a set of coupled integrate-and-fire oscillators, synchronize in frequency. The integrate-and-fire dynamics happens due to "change blindness", a trait in human decision making where people have the tendency to ignore small changes, but take action when a large change happens. The second pathway happens due to feedback mechanisms between market performance, and the use certain (decoupled) trading strategies. The third pathway can take place because of communication and its impact on human decision making. A model is introduced where financial market performance has an impact on decision making through communication between people. On the other hand the sentiment created via communication has an impact on the financial market performance.

Keywords: synchronization; human decision making; complex system; decoupling; self-organized criticality; opinion formation; agent-based modeling

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1. Introduction

Financial markets are generally thought of as random and noisy, beyond an understanding within an ordered framework. The elusive nature of the markets has been captured in theories like the efficient market hypothesis, basically considering price movements as random. Behind such a notion is the idea that price movements happening on a given day is a random phenomenon, basically taken from some probability distribution, describing in probabilistic terms what kind of event one should expect happening on a given day. The assumption seems natural and probably has its roots back in time, when people working in finance at the beginning of a work day, would turn on their radio, and register new financial events (again, the events assumed to be created by some higher instances). Such a descriptive framework also holds for more modern and general schema used in Finance, such as ARCH and GARCH models which are able to describe many of the stylized facts observed in empirical data. Socio-Finance [1] instead try to emphasize non-random human impact in the formation of prices in financial markets, in particular stressing the interaction taking place between people, either directly through communication or indirectly through the formation of asset prices which in turn will be seen to enable synchronization in decision making.

Synchronization in human decision making, and the impact it could have on financial asset price formation, is not a well understood topic. The term is more known in economics, where empirical studies have shown that international trade partners display synchronization in business cycles. Dées and Zorell [2] find that economic integration fosters business cycle synchronization across countries. Also similar production structure is found to enhance business cycle co-movement. By contrast, they find it more difficult pinpoint a direct relationship between bilateral financial linkages and output correlation. For other references that studies the topic of synchronization and business cycles across countries see for example [3-5]. With the recent global financial crisis questions have then been asked, as to what role financial market integration could have on synchronization of business cycles across borders [6]? However, very little research has been done on synchronization that is created endogenously by the financial markets themselves, without necessarily an economic cause. Still, such phenomena could be relevant for both the onset and continuation of financial crisis, see e.g. [7-8]. This leads naturally to the next question: could synchronization endogenously created in financial markets, spill over into the economy and thereby cause synchronization in business cycles across borders? A clear framework to understand its dynamics, as well as conditions for onset of synchronization in decision making, therefore seems highly relevant.

It should be noted that the term "synchronization" in this article covers a broader phenomenon than "herding", a related term often used in the financial literature. In finance "herding" usually refers to the simple case where people intentionally copy the behavior of others. It has been suggested that it is rational to herd [9]. For instance; portfolio managers may mimic the actions of other portfolio managers just in order to preserve reputation. It is easier to explain an eventuality failure when everybody else also fails, than expose a failure due to bold forecasts and deviation from the consensus. For a general review paper on herding see [10]

Here "synchronization" instead refer to the more general and complex case, where people don't necessarily try to imitate the behavior of others, but rather by observing the same price behavior, or through communication, end up in cases where a majority of a population synchronize in decision making. From this point of view the synchronization described in this article, is maybe closer to the idea of creation of conventions, put forward by Keynes [11].

Poledna et al. [7] highlights how the role of regulation policies could increase the amount of synchronized buying and selling needed to achieve deleveraging, which in turn then could destabilize the market. They discuss the new regulatory measures which have been proposed to suppress such behavior, but it is not clear whether these measures really address the problem? In addition they show how none of these policies are optimal for everyone: the risk neutral investors would prefer the unregulated case with low maximum leverage, banks would prefer the perfect hedging policy, and fund managers would prefer the unregulated case with high maximum leverage. Aymanns and Georg [8] instead consider the case when banks choose similar investment strategies, which in turn can make the financial system more vulnerable to common shocks. They consider a simple financial system in which banks decide about their investment strategy based on a private belief about the state of the world, and a social belief formed from observing the actions of peers. They show how the probability that banks will synchronize their investment strategies depends on the weighting between private and social belief.

In the following we will place the emphasis on the fact that price formation is the result of human decision of buying or selling assets. Behind every trade is a human decision making, if not by direct action of a human, then indirectly through the decision making made into the programs that governs algorithmic trading made by computers. Socio-Finance [1] considers price formation as a sociological phenomenon. It defines price formation to result from either direct or indirect human interactions. Direct interaction covers the case where either individuals, or groups of individuals, communicate directly and thereby influences mutual decision making with respect to trading assets. At the first level, the individual level, indirect interaction covers the case where a trader submits an order to buy or sell an asset. The resulting price movement of the asset is observed by other traders, who in turn may change their decision making because of the price movement of the asset caused by the initial trade. At the second level, the group level, indirect interaction covers the case where whole markets have to wait on the outcome of pricing in other markets in order to find the proper pricing.

2. Three different ways synchronization can lead to contagion in financial markets

2.1. Synchronization through indirect interaction of traders

This section is divided into two parts: indirect interaction of market participants at the individual level (section 2.1.1) and indirect interaction of market participants at the collective level (section 2.1.2).

2.1.1. Synchronization through indirect interaction of individuals: the first level

The deed of traders in the past, has a direct influence of the action of traders at the present. Past buying and selling activities has led the market up to the present level, for which traders have to decide whether now is an opportune moment to buy or sell. This applies to traders using technical analysis, as well as traders instead using fundamental analysis. Technical analysis will give different buy/sell signals depending on the exact price history made by traders in the past, whereas fundamental analysis will make traders judge about whether the price level has become sufficient low in order to buy, or high enough in order to sell.

So, as traders take note of what happens in the market, and update their trading strategies accordingly, the new evaluations of their strategies will change their future prospects of how to trade in the market. Therefore as the markets change, the decision making of traders with respect to buying/selling change, and as they change, they thereby change the pricing of the market. This feedback loop is illustrated schematically in the figure below.

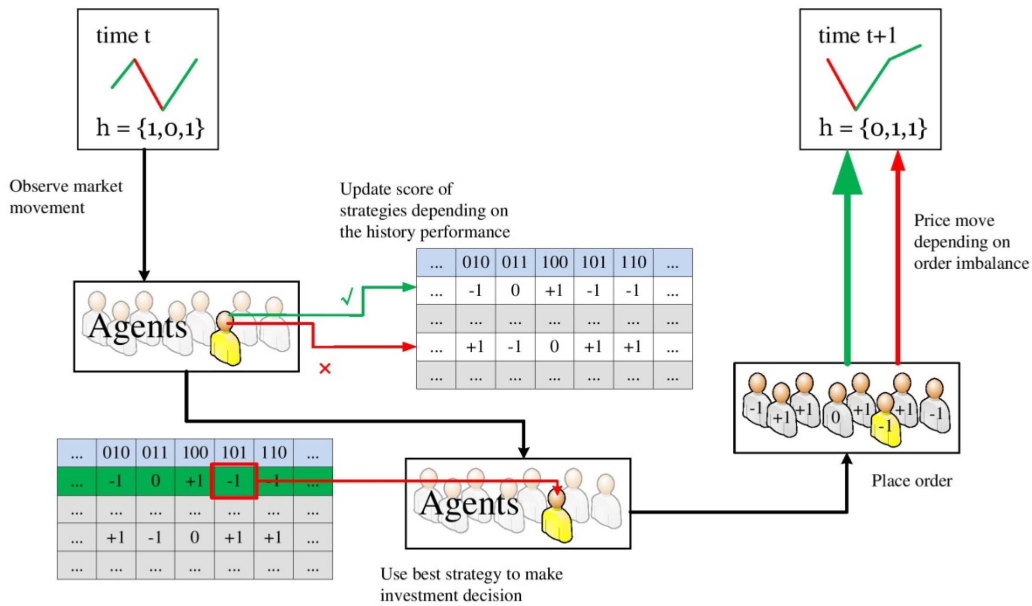

Figure 1. Representation of the price dynamics in the Minority-Game [12] and the $-Game [13]. Agents first update scores of all their strategies depending on their ability to predict the market movement. After scores have been updated, each agent chooses the strategy which now has the highest score. Depending on the price history at that moment, this strategy determines which action a given agent will take. Finally, the sum of the actions of all agents determines the next price move: if positive, the price moves up, if negative, the price moves down. The figure is taken from [14].

Under certain circumstances it can happen that traders inadvertently ends up in a state where their trading strategies “decouple” from the price history, so that over the next (evt. few) time step(s) their decision making become completely deterministic, independent of what happens next in the market. In order to illustrate this point, consider the table below which is one way of formalizing technical analysis trading strategies in a simple table form [12,13]. Considering for simplicity only the direction of each of the last market moves, the table below predicts, for each possible price history, the next move of the market. The table illustrates one technical analysis strategy that uses the last three time periods in providing a prediction, and can easily be generalized to any number of periods.

Table 1. Example of a strategy used in the Minority Game[12] and the $-Game[13]. Considering only up (1) and down (0) price movements of the market, a strategy issues a prediction for each given price history, here illustrated with price histories over the last m=3 days.

price history	prediction
0 0 0	1
0 0 1	-1
0 1 0	1
0 1 1	1
1 0 0	-1
1 0 1	-1
1 1 0	1
1 1 1	1

Consider now a given price history of the market, $\vec{\mu}(t)$ = (010), at time t, meaning that (as illustrated in the figure below) three time periods ago the market went down, then up, and then down. It should now be noted that *whatever* the price movement at the next time period t+1, the strategy in table 1 will *always* predict to sell at time period t+2. Therefore we don't need to wait for the market outcome at the next time step t+1 in order to know what the strategy will suggest following that time step: it will always suggest selling at time t+2. That such kinds of dynamics in the decision making of technical analysis strategies could be relevant for real market was suggested in [15]. In the terminology of [15] the strategy in table 1 is called "one time step decoupled conditioned on the price history $\vec{\mu}$ = (010) " and denoted $a_{\mu}^{decoupled}(t)$.

We can then divide trading strategies into two different classes: those coupled to the price history (i.e. conditioned on knowing $\vec{\mu}(t)$ one cannot know the prediction of $a_{\mu}^{coupled}(t)$ at time t+2 before knowing $\vec{\mu}(t+1)$), and those decoupled to the price history. Considering only the strategies actually used by the agents to trade at time t, the order imbalance, A(t), can therefore be written:

$$A(t) \equiv A_{\mu}^{coupled}(t) + A_{\mu}^{decoupled}(t) \qquad (1)$$

With $A_{\mu}^{coupled}(t) = \sum a_{\mu}^{coupled}(t)$ the sum over coupled strategies at time t and similarly for $A_{\mu}^{decoupled}(t) = \sum a_{\mu}^{decoupled}(t)$. The condition for *certain* predictability at time t, two time steps ahead is then:

$$A_{\mu}^{decoupled}(t+2) > N/2. \qquad (2)$$

If a majority of market participants hold decoupled strategies, this will ensure a deterministic future price movement of the market, independent of the choices made the minority that hold coupled strategies.

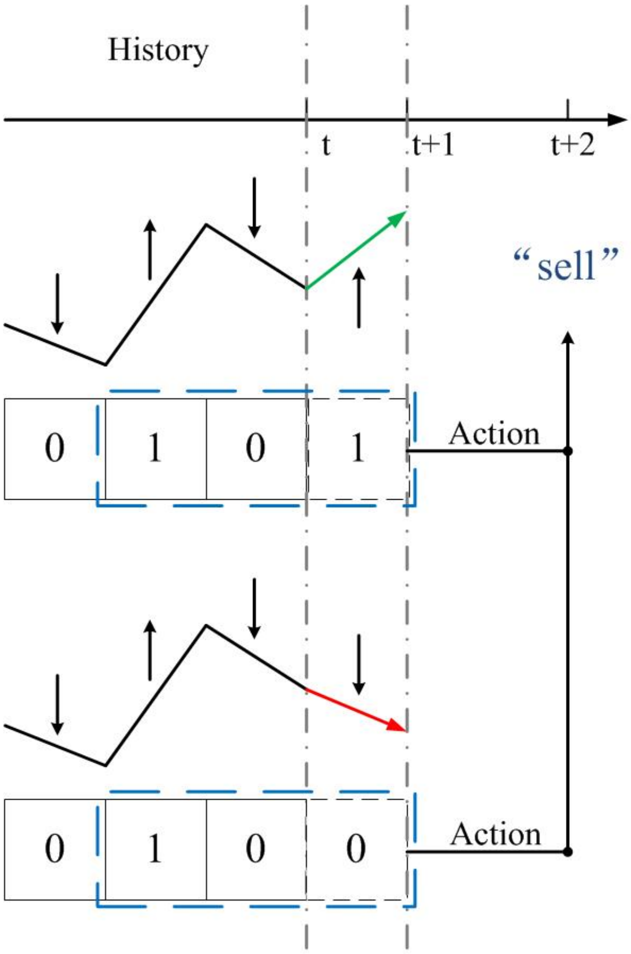

Figure 2. Representation of how the trading strategy in Table1 decouples at time t+2 conditioned on the price history $\vec{\mu} = (010)$ at time t. Figure taken from [14].

The condition (2) gives the condition for synchronization to happen via indirect interaction of traders through the price formation of an asset. Before considering synchronization in real markets [14], one obviously first have to show its presence in models as well as in experiments. Indeed, Figure 3 below proves synchronization via decoupling to be present in models like the Minority Game, a somewhat surprising result since these types of games by definition don’t support trend following strategies. For more literature covering the situation with respect to synchronization in experiments and markets, see [14-16].

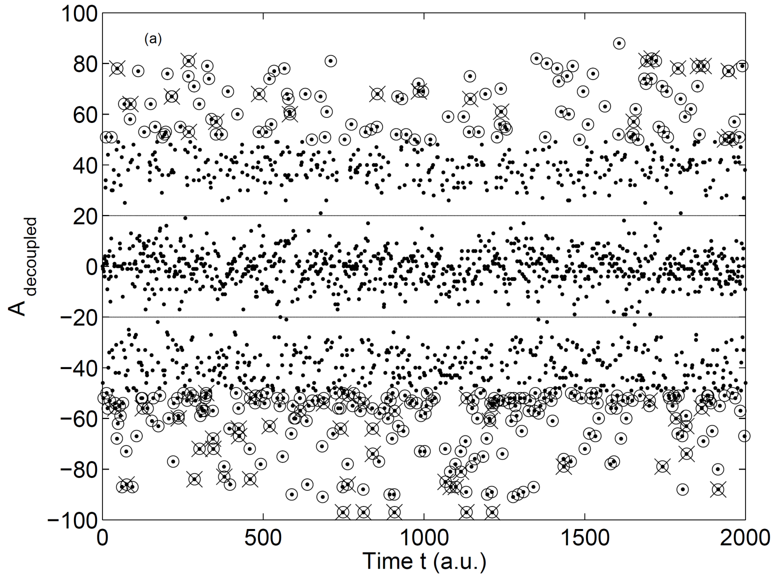

Figure 3. An example of $A_{decoupled}$ defined from (1) as a function of time for a simulation of the Minority Game. Circles indicate one-step days which are predictive with probability 1, crosses are the subset of days starting a run of two or more consecutive on-step predictive days.

2.1.2. Synchronization through indirect interaction of groups of individuals: the second level

Having discussed how indirect interaction of individuals through financial indices can lead to synchronization, let us next consider how the phenomenon can appear through indirect interaction of groups of individuals. In this case we consider the reaction of one market to the pricing created in another market. That is, we consider how one given market (i.e. a pool of traders) reacts to prior price formation in another market (created by another pool of traders).

To illustrate this point, consider the figure below which shows how large price movements of large capital stock indices, can have a particular impact on smaller capital stock indices. The figure illustrates the effect of both a world market return (calculated as a weighted sum of returns of stock indices) and the US market return on the following price movements of individual stock indices. Using the open-close return of the U.S. stock market, gives a particular clear case to see a ''large-move'' impact across markets: since the Asian markets close before the opening of the U.S. markets, they should only be able to price in this information at their opening the following day. That is, one can consider the impact in the ''close-open'' of the Asian markets that should follow *after* an ''open-close'' of the US market. An eventual ''large-move'' U.S. open-close should therefore have a clear impact on the following close-open of the Asian markets. From the figure below this is indeed seen to be the case. On the contrary, the European markets are still open when the U.S. market opens up in the morning, so the European markets have access to part of the history of the open-close of the U.S. markets. An eventual ''large-move'' U.S. open-close would therefore still be expected to have an impact on the following close-open of the European markets, but with larger variation in the response than for the Asian markets, since part of the U.S. move would already be priced in when the European markets closed. This is seen to be the case.

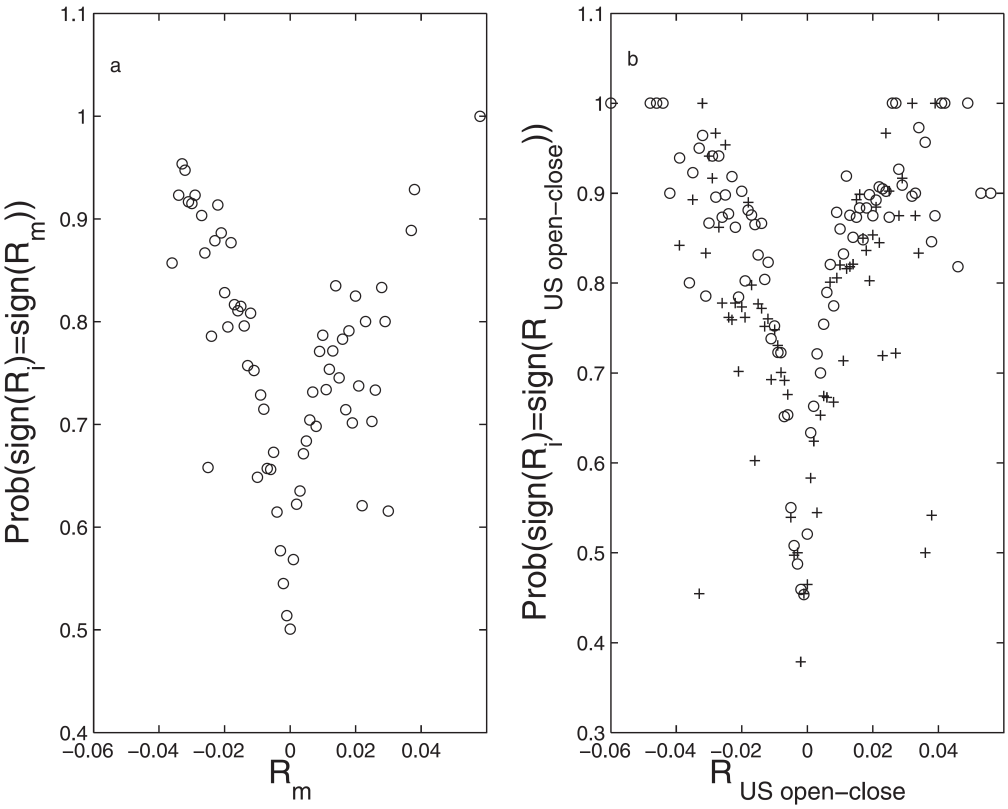

Figure 4. Illustration of change blindness: a large world market return (fig a) or US market return (fig b) impacts a given stock exchange, whereas small returns have random impact. a) Conditional probability that the daily return Ri of a given country's stock market index has the same sign as the

world market return. b) Conditional probability that the close-open (+: European markets; circles: Asian markets) return Ri of a given country's stock market index following an U.S. open-close, has the same sign as the U.S. open-close return. The figures were created using almost 9 years of daily returns of 24 of the major stock markets worldwide. For more information see [17-18]

To see how synchronization can happen across markets, consider the illustration in Figure 4.a below which shows three Integrate-And-Fire (IAF) oscillators with the same frequency over one time period (or equivalently one IAF oscillator over three time periods). An IAF oscillator is characterized by an accumulation (i.e. "Integrate") in amplitude A(t) (e.g. "stress") over time t, up to a certain point A_C, after which it discharges (i.e. "Fires"). The complexity of models of IAF oscillators arise when the oscillators are coupled (i.e. the amplitude of one oscillator influences the amplitude of other oscillators), and have different frequency (see Figure 4.b) and/or thresholds A_C^i. Peskin [19] introduced IAF oscillators in neurobiology to describe the interactions of neurons, but IAF oscillators have been introduced in many other contexts, for network studies of IAF oscillators see e.g. Mirollo and Strogatz [20], Kuramoto [21], Bottani [22]. The link between certain, types of integrate-and-fire oscillators are earthquake models has also been noted by e.g. Corral et al. [23].

As mentioned in [17], one can consider each financial market index as an IAF oscillator that influences other market indices (i.e. other IAF oscillators). The impact, or "stress", from index i on index j accumulates up to a certain point, after which it becomes priced-in. The justification for such a behavior, can be seen from Figure 4, which shows that small price changes of index i has no immediate influence on index j (but is assumed to accumulate over time), whereas large price changes at index i, have an impact and thereby becomes priced-in at index j.

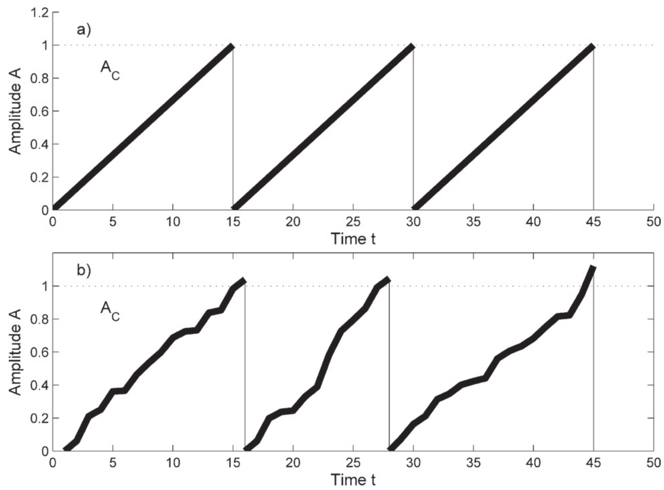

Figure 5. Illustration of an IAF oscillator. a) Illustrates the case where the amplitude A(t) of an IAF oscillator integrates linearly in time until it reaches a critical value Ac, after which it discharges by setting A(t) = 0. The case in a) can be viewed as one IAF oscillating over three periods of time, or equivalently, three identical and uncoupled IAF oscillators oscillating over one period of time. b) An IAF oscillator with random frequency over three time periods, or equivalently, three different unit oscillators with random frequency over one time period. The figure is taken from [18].

This can be formalized in the following expression which expresses the set of stock market indices worldwide as a set of coupled IAF oscillators:

$$R_I(t) = \frac{1}{N_i^*} \sum_{j \neq i}^{N} \alpha_{ij}\, \theta\left(\left|R_{ij}^{cum}(t-1)\right| > R_C\right) \times R_{ij}^{cum}(t-1)\beta_{ij} + \varphi_{ij}(t) \qquad (3)$$

$$R_{ij}^{cum}(t) = \left[1 - \theta\left(\left|R_{ij}^{cum}(t-1)\right| > R_C\right)\right] \times R_{ij}^{cum}(t-1) + R_j(t),\ j \neq i \qquad (4)$$

$$\alpha_{ij} = 1 - \exp\left[-K_j/(K_i\, \gamma)\right]\ ;\ \beta_{ij} = \exp\left[-|\ z_i - z_j|/\tau\right] \qquad (5)$$

In expression (3) R_i(t) is the return of stock index j, which at time t receives a contribution from stock index j, whenever the "stress" R_{ij}^{cum} exceeds a certain threshold R_C. α_{ij} describes the coupling between the two stock indices, expressed via (5) in terms of the relative weight of capitalizations K_i. A large γ, $\gamma \gg 1$, corresponds to a network of the world's indices with dominance of the index with the largest capitalization Kmax. On the contrary a small γ, $\gamma \ll 1$, corresponds to a network of indices with equal strengths since α_{ij} then becomes independent of i, j. In addition it is assumed that countries which are geographically close, also have larger interdependence economically, as described by the coefficient β_{ij}, with $|\ z_i - z_j\ |$ the time zone difference of countries i,j. τ gives the scale over which this interdependence declines. Small τ, $\tau \ll 1$, then corresponds to a world where only indices in the same time zone are relevant for the pricing, whereas large τ, $\tau \gg 1$, describes a global influence in the pricing independent of the difference in time zone.

It is seen from (4), that it is the tensor R_{ij}^{cum}, that places the role of an IAF oscillator. Returns from index j, R_j, accumulates stress on index i by continuously adding to R_{ij}^{cum}, up to a certain point, $\left|R_{ij}^{cum}\right| > R_C$, after which the oscillator discharges, $R_{ij}^{cum} \to 0$, and the stress becomes priced-in via (3).

Once the IAF network is in a state of synchronization, it is possible to identify contagion effects throughout the network. One example is given in Figure 5 below, showing the propagation of a large price movement taking place in the Japanese stock market on the 23/05/2013. For more examples on real market data see [18]

Figure 5. "Price-quake". One of the main advantages of the non-linearity in the integrate-and-fire oscillator model is that it enables a clear-cut identification of cause and effect; The figure shows one example of a price-quake, following an initial minus 7% price movement on the Japanese stock market on 23/05/2013. The figure is taken from [18].

2.2. Synchronization through direct interaction of traders

2.2.1. Synchronization through direct interaction of individuals and groups of individuals: the first and second level.

Having discussed how synchronization can immerge through indirect interaction through financial market indices of individuals, or groups of individuals, we now instead consider the case of direct interaction, that is, how decision making is influenced by direct communication between people or groups of people. The idea is to see how discussions among market participants, can influence their decision making with respect to buying/selling assets, which in turn can influence the market performance. On the other hand, we will show how the market performance itself can be a relevant factor in the process of decision making, thereby creating another feedback loop between the decision making of people and market performance.

To see how this can take place consider Figure 6.a below, which illustrate a population of market participants with different views of the market, which we for simplicity will take either to be positive, bullish, or negative, bearish. Figure 6.a illustrates an example where initially half the population is bearish, the other half bullish. One could for example imagine a morning meeting taking place in a major bank or brokerage house, and so at the beginning of the day, we let people meet and discuss around tables in groups of different sizes Figure 6.b. To illustrate how communication between people can influence their decision making, consider first the simple case where consensus making is determined by the majority opinion Figure 6.c. As seen in Figure 6.d, at the end of the day the opinion of the population has changed as a result of their meetings (direct interaction), with now only 45% of the population being bullish.

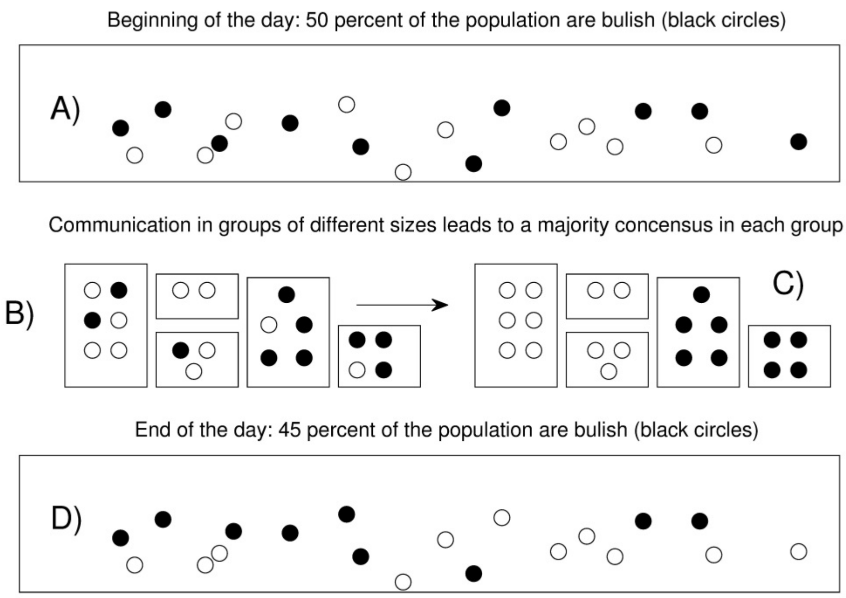

Figure 6. Changing the "bullishness" in a population via communications in subgroups. (a) At the beginning of a given day t a certain percentage B(t) of bullishness. (b) During the day communication takes place in random subgroups of different sizes. Panel (c) illustrates the extreme case of complete polarization $m_{k,j} = \pm 1$ created by a majority rule in opinion. In general $m_{k,j} \simeq j/k$ corresponds to the neutral case where in average the opinion remains unchanged within a subgroup

of size k. (d) Due to the communication in different subgroups the "bullishness" at the end of the day is different from the beginning of the day. The figure is taken from [25].

In the context of decision making with respect to trading assets in financial markets, it is natural to assume that the market performance itself could influence the decision making of the market participants, whereas this in turn could influence future market performance. In order to capture such kinds of feedbacks, a model was suggested in [25]. The main idea is to let the market performance influence the decision making, instead of the simple majority rule seen in Figure 6.b-c. This is done by assuming a certain *probability* for a majority opinion to prevail. Thereby under certain conditions, a minority could persuade a part of the majority to change their opinion. The probability for a majority opinion to prevail, will depend on the market performance over the last time period.

Specifically, let B(t) denote the proportion of bullishness in a population at time t, the proportion of bearishness is then $1 - B(t)$. For a given group of size k with j agents having a bullish opinion and $k - j$ a bearish opinion, we let $m_{k,j}$ denote the transition probability for all (k) members to adopt the bullish opinion, as a result of their meeting. After one update taking into account communications in all groups of size k with j bullish agents, the new probability of finding an agent with a bullish view in the population can therefore be written:

$$\mathbf{B(t+1) = m_{kj}(t) C_j^k B^j [1 - B(t)]^{k-j}} \qquad (6)$$

with

$$\mathbf{C_j^k \equiv \frac{k!}{j!(k-j)!}} \qquad (7)$$

It should be noted that the transition probabilities $\mathbf{m_{k,j}}(t)$ depend on time, since we assume that they change as the market performance changes.

The link between communication and its impact on the markets, can now be taken into account by assuming that the price return r(t) changes whenever there is a change in the bullishness. It should now be noted, that it is the *changes* in opinion that matters for the market performance, rather than the *level* of a given opinion. Empirical data supporting this idea, can for example be found in [26]. The reasoning behind this, is that people having a positive view of the market would naturally already hold long positions on the market. It is therefore rather when people change their opinion, say becoming more negative about the market, or less bullish, that they will have the tendency to sell. Assuming the return to be proportional to the percentage change in bullishness, RB(t), as well as economic news, $\boldsymbol{\varphi(t)}$, the return r(t) is given by

$$\boldsymbol{r(t)} = \frac{\boldsymbol{RB(t)}}{\boldsymbol{\mu}} + \boldsymbol{\varphi(t)}, \ \boldsymbol{\mu > 0} \qquad (7)$$

Here $\boldsymbol{\varphi(t)}$ is a Gaussian distributed variable with mean 0 that described a standard deviation that varies as a function of time depending on changes in sentiment:

$$\boldsymbol{\sigma(t)} = \boldsymbol{\sigma_0} \, \mathbf{exp}\left(\frac{\boldsymbol{RB(t)}}{\boldsymbol{\beta}}\right), \ \boldsymbol{\sigma_0} > \mathbf{0}, \ \boldsymbol{\beta} > \mathbf{0}. \qquad (8)$$

The impact from the market performance on the decision making, can then be taking into account by letting $\mathbf{m_{k,j}(t)}$ depend on the market performance via:

$$\boldsymbol{m_{k,j}(t)} = \boldsymbol{m_{k,j}(t)} \, \mathbf{exp}\left(\frac{\boldsymbol{r(t)}}{\boldsymbol{\alpha}}\right), \boldsymbol{\alpha} > \mathbf{0}, \boldsymbol{m_{kj}} \leq \mathbf{1} \qquad (9)$$

In this way the transition probabilities for a change of opinion, (9), depend directly on the market return over the last time period. The reasoning for such dependence, is that if for example the market had a dramatic downturn at the close yesterday, then in meetings the next morning, those with a bearish view will be more likely to convince even a bullish majority about their point of view.

Synchronization in the decision making due to communication between people, can now be studied via for example tipping point analysis. Once extreme sentiment, B=0,1, has been created via synchronization, this can be used to identify a tipping point of the market: when say $\mathbf{B} \rightarrow \mathbf{1}$ any further increase in B is limited, which in turn limits further price increases in the market. However, any negative economic news, $\boldsymbol{\varphi(t)}$, will then lead to a decrease in B(t) through (7) and (9). The cases of B=0,1 therefore acts as reflection points of the model, enabling thereby an identification of tipping points of the price dynamics of the markets. One illustration of such tipping point dynamics in real markets, can be seen in the figure below taken from [27]. In [27] maximum likelihood methods were used to estimate the parameters of the model, after which an out-of-sample analysis was performed on EUBanks index around the time of the financial crisis in 2008. As can be seen from Figure 7.a,c prior peeks, $\boldsymbol{B} \cong \mathbf{1}$, in the estimated sentiment indeed announce a tipping point in the performance of the return of the index.

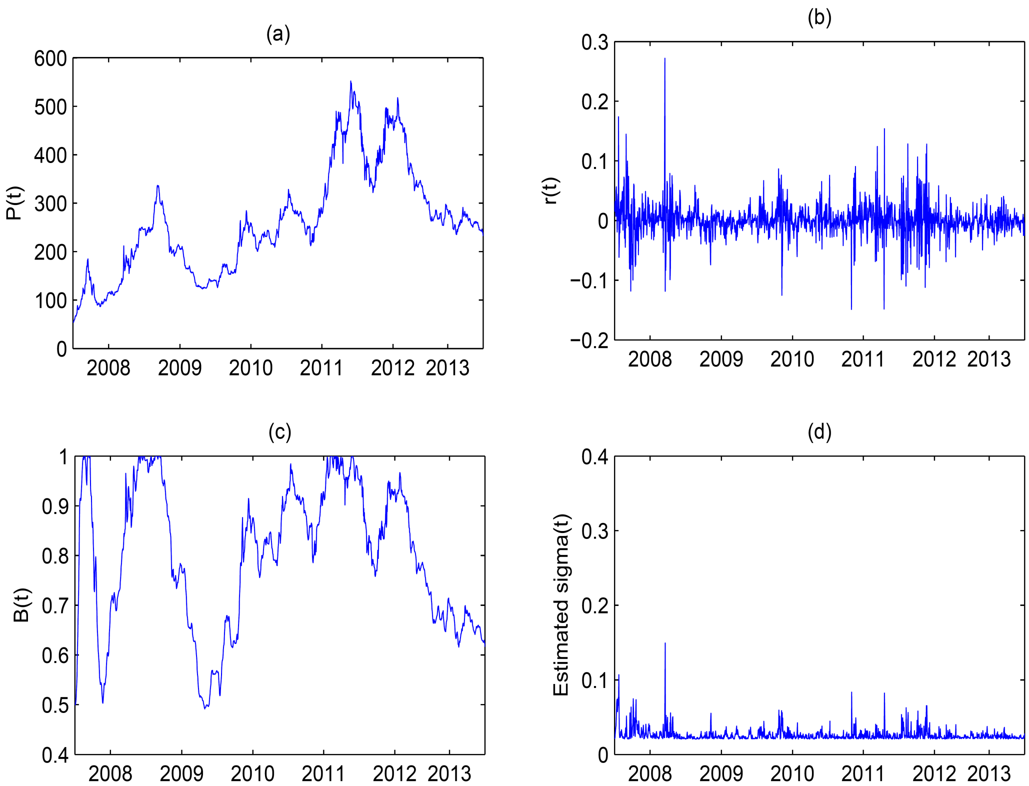

Figure 7. This figure presents EUBanks index prices and returns, as well as the corresponding estimated conditional volatilities and bullishness proportions under the assumption of conditional Student-t distribution. (a) EUBanks index price P(t), (b) EUBanks index returns r(t), (c) Estimated bullishness proportions B(t), (d) Estimated conditional volatilities σ(t). The figure is taken from [27]

3. Discussion

We have introduce three different models from Socio-Finance in order to capture three different pathways in which the market participants in financial markets could synchronize in decision making, and thereby create the route to contagious and volatile market phases. One pathway is caused when stock market indices, seen as a set of coupled integrate-and-fire oscillators, synchronize in frequency. Another pathway happens due to feedback mechanisms between market performance, and the use certain (decoupled) trading strategies. Finally a third pathway could take place because of communication and its impact on human decision making.

Synchronization is a well know phenomenon used in economics, to describe how trading partners can introduce synchronization in business cycles across international borders. With the recent global financial crisis, one question is to what role financial market integration could have on synchronization of business cycles across borders? Another question is whether synchronization created endogenously in financial markets could spill over into the economy and thereby cause synchronization in business cycles across borders? It should be noted, that very little research has been done on synchronization that is created endogenously by the financial markets themselves, without necessarily an economic cause. It is the hope of the authors that the preset article could help fuel awareness and interest on the topic.

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