Economic Modelling 59 (2016) 224–236

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Contagion in the world's stock exchanges seen as a set of coupled oscillators

Lucia Bellenzier[a], Jørgen Vitting Andersen[b], Giulia Rotundo[c,*]

[a]Department of Statistics and Quantitative Methods, University of Milano-Bicocca, Piazza dell'Ateneo Nuovo 1, 20126 Milano, Italy
[b]CNRS, Centre d'Economie de la Sorbonne, Université Paris I Panthéon-Sorbonne, Maison des Sciences Economiques, 106-112 Boulevard de l'Hôpital 75647 Paris Cedex 13, France
[c]Department of Methods and Models for Economics, Environment and Finance Sapienza University of Rome, via del Castro Laurenziano 9, Rome 00161, Italy

ARTICLE INFO

Article history:
Received 10 December 2015
Received in revised form 2 July 2016
Accepted 4 July 2016
Available online xxxx

Keywords:
Contagion
World's stock exchanges
Change blindness
Integrate-and-fire oscillators

ABSTRACT

We study how the phenomenon of contagion can take place in the network of the world's stock exchanges when each stock exchange acts as an integrate-and-fire oscillator. The characteristic non-linear price behavior of integrate-and-fire oscillators is supported by empirical data and has a behavioral origin called change-blindness. One advantage of the integrate-and-fire dynamics is that it enables a direct identification of cause and effect in price movements, without the need for statistical tests such as Granger causality tests, often used in the identification of causes of contagion. Our methodology can thereby identify the most relevant nodes with respect to onset of contagion in the network of stock exchanges, as well as identify potential periods of high vulnerability of the network. Over the time period of study, our method is able to identify the importance of the U.K. and U.S. markets as sources for propagation of positive returns, whereas, more surprisingly, the Swiss and some Asian markets (China, South Korea) seem to play a particular role with respect to propagation of downturns across markets. The model is characterized by a separation of time scales, brought about by a slow build-up of stresses, for example, due to (say monthly/yearly) macroeconomic factors, and then a fast (say hourly/daily) release of stresses through "price-quakes" in price movements across the world's network of stock exchanges.

1. Introduction

The turmoil on the financial markets resulting from the 2008 sub-prime crisis has been a wake-up call for academics and policy-makers to detect and understand the linkages and vulnerabilities of the financial system. Much of the ensuing effort has focused on systemic risks and contagion phenomena. However, the issue of instability is not new and has been much discussed since the great depression of the 1930s by, e.g., Fisher (1933) and Keynes (1936). On the other hand, the subject is not without controversy. Some argue that the use of the term contagion is misplaced and that the financial markets in fact show a high level of co-movement at all times, whence one ought to speak instead of market "interdependence" (Forbes and Rigobon, 2002).

There exist several ways of defining 'contagion' in the economic literature[1] . "Pure" contagion is often understood as "a significant increase in cross-market linkages in different markets during a crisis period", above and beyond what can be explained by fundamentals, trade, and exchange rate arrangements. Then there is the "wake-up-call" contagion, in which the crisis is initially restricted to one country, providing new information that prompts investors to reassess the default risk of other countries. And the "shift" contagion, which occurs when the normal cross-market channel intensifies after a crisis in one country with an increased sensitivity to global risk factors, rather than country-specific factors. For other types of transmission channels appearing in the literature (the liquidity channel, the cross-market hedging channel, and the wealth effect channel), see Chiang et al. (2007) for a survey of the literature regarding contagion. We stress that the contagion studied in this paper is generated dynamically by the interaction between all the different markets. Such a contagion can have a local origin, but can only

* Corresponding author.
E-mail addresses: lucia.bellenzier@unimib.it (L. Bellenzier), Jorgen-Vitting.Andersen@univ-parisl.fr (J. Andersen), giulia.rotundo@uniroma1.it (G. Rotundo).

[1] We thank an anonymous referee for pointing this out for us.

http://dx.doi.org/10.1016/j.econmod.2016.07.002
0264-9993/

be understood globally from the way it spreads, i.e., it can only be understood by considering the response of the system as a whole. The fact that a system of interacting elements dynamically organizes into a state that can only be understood by considering the whole was called “self-organized criticality” by P. Bak (1996).

A significant fraction of studies on contagion relate to correlation-based networks. For instance, in Chiang et al. (2007), contagion is detected by statistical analysis of the correlation among markets, and it is viewed from a behavioral perspective, interpreting the continued high correlation as herding. As mentioned in Aloui et al. (2011), studies of the transmission of return and volatility shocks from one market to another, together with studies of cross-market correlations are essential in finance, because they have many implications for portfolio allocation. Their paper used a multivariate copula approach to examine extreme co-movement across markets, the aim being to study the harmful consequences of contagion effects on portfolio selection. In the context of systemic risks and contagion phenomena, it becomes very important to understand and control the so-called tail risk in equity markets. van Oordt and Zhou (2013) found that assets with higher tail betas were associated with significantly greater losses during future extreme market downturns, thereby suggesting that tail betas could be used to detect sensitivity to future systematic tail risk. Kinateder (2015) found the VIX to be one of the important drives of equity tail risk, a mechanism which is incorporated in the model presented in this paper.

In Bekaert et al. (2003), contagion is defined as correlation between markets in excess of what would be implied by the fundamentals. However, this definition makes actual measurement quite difficult, because there is no common agreement on the definition of fundamentals, although the model may explicitly consider macroeconomic variables (Syllignakis and Kouretas, 2011).

In Caporale et al. (2005) and Chiang et al. (2007), contagion is detected through co-movements of the correlation. Thus, the main issue is modeling the correlations (Celik, 2012; Dimitriou et al., 2013; Gjika and Horvath, 2013; Mensi et al., 2013) or the cointegration Hong et al. (2009). Hong et al. (2009) tested whether a large downside risk in one market would Granger-cause a large downside risk in another market, in a very similar spirit to the study of this paper. In our study, however, spill-over effects can be detected directly via the non-linear terms in the model, from which one can deduce cause and effect. In principle, this could provide a way to improve trading strategies, such as pairs trading. The debates in the aforementioned publications led to a general discussion of the difference between interdependence and contagion (Ahmad et al., 2013; Aloui et al., 2011; Corsetti et al., 2005).

Bae et al. (2003) proposed to consider contagion as a phenomenon associated with extreme returns: if there is contagion, small return shocks propagate differently from large return shocks. In their study, they focused on counts of coincidences of extreme returns rather than on correlations of joint extreme returns. The different roles of propagation of small versus large returns will turn out to be a key ingredient in our model, and indeed it will be one of the main mechanisms behind the creation of contagion.

Another issue relates to cause and effect in contagion. For example, a study by Yang and Bessler (2008) was able to use a vector auto-regression analysis to pinpoint the origin of the 1987 crash in the U.S. markets, and identify a following upward movement of the Japanese market as important for the subsequent recovery. However, a clear-cut conclusion about what starts market turmoil and what makes it end is often difficult. For example, Roll (1988) came to a different conclusion in his analysis of 23 of the major markets worldwide, and argued that the international stock market crash of 1987 started rather in Asian countries, but not Japan, and spread from there to Europe and the U.S., before finally reaching Japan. A different way to obtain information about cause and effect is through surveys. In Shiller (1989), a survey identifies the U.S. as playing the dominant role in the international crash of 1987.

Other advanced techniques for analyzing contagion have appeared in the literature during the last few years. For example, Cappiello et al. (2006) introduced a generalized GARCH model to allow for specific news impact and conditional asymmetries in correlation dynamics. The model was used to investigate asymmetries in conditional variances and correlation dynamics for a broad cross-section of equity and government bond returns. Jondeau and Rockinger (2006) applied a copula-GARCH model of conditional dependencies to four major stock markets. Their results suggest that conditional dependency depends on past realizations alone. Other copula-GARCH type studies can be found in Kenourgios et al. (2011), Okimoto (2008), Pelletier (2006), Samarakoon (2006), Tamakoshi and Hamori (2013), Xu and Hamori (2012), Yang and Hamori (2013), and Yang et al. (2015). For a longer overview, see also Patton (2006, 2009).

In contrast to these studies, we propose to take a new look at network analysis of contagion by introducing a model in which cause and effect is inherently defined without the need for statistical tests such as Granger causality tests. The possibility of doing such cause and effect analysis is an artifact of the non-linearity introduced via the pricing. However, the non-linearity also makes it difficult to compare our approach directly with most linear types of models, like most GARCH-type models, and this is the reason why we refrain from introducing this in our analysis. We will address new issues in network analysis in order to get a statistical understanding of the pathology of contagion and we will also consider the question of cause and effect, something which the structure of the model allows us to identify directly, without the need for statistical tests on correlations.

In the following, we consider the world's network of stock exchanges as a network of coupled oscillators. The idea is to consider each exchange as an oscillator of a “force field” (to be defined below) which can influence the other oscillators in the network. Our methodology enables a new understanding of the way impacts generated through non-linear price dynamics can propagate across markets, and it can be used to study the origins of contagion effects in stock exchange networks. In such a picture, contagion can be seen as a synchronization of the network of stock exchanges as a whole, largely caused by exchanges which adjust their “rhythms” (by pricing according to price movements at the other exchanges), thereby producing a global aggregate signal. One of the main features of our model is a separation of time scales, with a slow price dynamics due to economic fundamentals for a given country, and a fast price dynamics due to cross-market impacts. Fig. 1 shows an example illustrating the way the method identifies the network of propagation after a large stock movement on the Japanese stock market on 23/05/2013.

2. Empirical methodology

2.1. Models of coupled integrate-and-fire (IAF) oscillators

Fig. 2a shows an IAF oscillator schematically. The amplitude $A(t)$ increases constantly versus time t until it reaches a threshold $A_C = 1$, after which it discharges and its amplitude A is reset to zero. The process then repeats until a new discharge takes place, and so on. Fig. 2a could equally well be seen as three identical and independent IAF oscillators operating with the same constant frequency. Furthermore, assuming independence of the different unit oscillators, the oscillator system is trivially described by the same oscillation as a single unit oscillator. Fig. 2b illustrates an IAF oscillator with random frequency over three time periods, or equivalently, three different unit oscillators with random frequency over one time period. In this case, the aggregate response of a system with several units is trivially less, especially if there exists a coupling, i.e., dependence, between the units.