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Interpreting financial market crashes as earthquakes: A new Early Warning System for medium term crashes ☆

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ABSTRACT

We propose a modeling framework which allows for creating probability predictions on a future market crash in the medium term, like sometime in the next five days. Our framework draws upon noticeable similarities between stock returns around a financial market crash and seismic activity around earthquakes. Our model is incorporated in an Early Warning System for future crash days. Testing our EWS on S&P 500 data during the recent financial crisis, we find positive Hanssen–Kuiper Skill Scores. Furthermore our modeling framework is capable of exploiting information in the returns series not captured by well known and commonly used volatility models. EWS based on our models outperform EWS based on the volatility models forecasting extreme price movements, while forecasting is much less time-consuming.

1. Introduction

This paper proposes a modeling framework that draws upon the self-exciting behavior of stock returns around a financial market crash, which is similar to the seismic activity around earthquakes. Incorporating the tendency for shocks to be followed by new shocks, our framework is able to create probability predictions on a medium-term financial market crash. A large literature in finance has focused on predicting the risk of downward price movements one-step ahead with measures like Value-at-Risk and Expected Shortfall. Our approach differs however as we interpret financial crashes as earthquakes in the financial market, which allows us to develop an Early Warning System (EWS) for crash days within a given period. The EWS is tested on S&P 500 data during the recent financial crisis, starting from September 1, 2008. As will become apparent in later sections, our modeling framework differs from Extreme Value models as we allow dependencies across arrival times and magnitudes of shocks. At the same time, our framework differs from the conventional GARCH models by generating highly insightful medium term forecasts, while not having to make stringent assumptions on the tail behavior of error distributions. This makes our approach rather easy to implement and understand in practice.

The identification and prediction of crashes is very important to traders, regulators of financial markets and risk management because a series of large negative price movements during a short time interval can have severe consequences. For example, on Black Monday, that is October 19, 1987, the S&P 500 index registered its worst daily percentage loss of 20.5%. During the recent credit crisis, financial indices declined dramatically for numerous days, thereby suffering its worst yearly percentage loss of 38.5 % in 2008. Unfortunately, crashes are not easy to predict, and there still is a need for tools to accurately forecast the timing of a series of large negative price movements in financial markets.

To initiate the construction of our modeling framework for stock market crashes, we first focus on the potential causes of such crashes. Sornette (2003) summarizes that computer trading, and

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the increased trading of derivative securities, illiquidity, and trade and budget deficits and also overvaluation can provoke subsequent large negative price movements. More importantly, Sornette (2003) points out that speculative bubbles leading to crashes are likely to result from a positive herding behavior of investors. This positive herding behavior causes crashes to be locally self-enforcing. Hence, while bubbles can be triggered by an exogenous factor, instability grows endogenously. A model for stock market crashes should therefore be able to capture this self-excitation. Notably, such a self-excitation can also be observed in seismic behavior around earthquake sequences, where an earthquake usually generates aftershocks which in turn can generate new aftershocks and so on. For many academics (and perhaps practitioners), earthquakes and stock returns therefore share characteristics typically observable as the clustering of extremes and serial dependence.

Potential similarities across the behavior of stock returns around crashes and the dynamics of earthquake sequences have been noted in the so-called econophysics literature, in which physics models are applied to economics.[2] In contrast to the studies in the econophysics literature and also to related studies like Bowsher (2007) and Clements and Liao (2013), in our framework we do not model the (cumulative) returns but only the extreme returns. As such, we most effectively exploit the information contained in the returns about the crash behavior. As Aït-Sahalia et al. (2013) already show, only taking the jump dynamics of returns into account to approximate the timing of crashes gives more accurate results than using the full distribution of the returns. As is well known, the distribution of stock returns is more heavy-tailed than the Gaussian distribution as extreme returns occur more often than can be expected under normality. Furthermore, the distribution of stock returns is usually negatively skewed. As risk in financial markets is predominantly related to extreme price movements, we propose to model only extreme (negative) returns in order to improve predictions.

To model the extreme (negative) returns we use a particular model that is often used for earthquake sequences, and which is the so-called Epidemic-Type Aftershock Sequence model (ETAS). This model has been developed by Ogata (1988) and its use for earthquakes is widely investigated by geophysicists.[3] In the ETAS model a Hawkes process, an inhomogeneous Poisson process, is used to model the occurrence rate of earthquakes above a certain threshold. The jump rate of the Hawkes process increases when a jump (or shock) arrives after which the rate decays as a function of the time passed since the jump. As the probability of jumps increases after a jump has occurred, the Hawkes process is thus called self-exciting. The ETAS model has been exploited for crime rates (Mohler et al., 2011) and for the spread of red banana plants (Balderama et al., 2012). Interestingly, the ETAS model has also been applied to financial data, for example to model arrival data of buy and sell trades (Hewlett, 2006), the duration between trades (Bauwens and Hautsch, 2009) or the returns on multiple indices (Aït-Sahalia et al., 2013; Embrechts et al., 2011; Grothe et al., 2014).

Our modeling framework entails that we use the ETAS model as a tool to warn for an upcoming crash (read: earthquake) in a financial market. As Herrera and Schipp (2009), Chavez-Demoulin et al. (2005) and Chavez-Demoulin and McGill (2012), already showed when deriving their Value-at-Risk and Expected Shortfall estimates, the ETAS model can contribute to the modeling and prediction of risk in finance. However, in contrast to Herrera and Schipp (2009), Chavez-Demoulin et al. (2005) and Chavez-Demoulin and McGill (2012) who do not provide a practical tool like an Early Warning System or an easily interpretable measure to quantify the risk of crashes, but instead we provide a ready-to-use application of the information from an estimated ETAS model by means of an EWS.

In somewhat more detail, we consider several specifications of the key triggering functions. The parameters of the ETAS models are estimated by maximum likelihood. And, to judge the fit of the different models, we compare the log-likelihoods and Akaike information criterion (AIC) values. We also develop simulation procedures to graphically assess whether data generated by the models can reproduce features of, for example, the S&P 500 data. The correctness of the ETAS model specification is further evaluated by means of the residual analysis methods as proposed in Ogata (1988). We review the performance of our Early Warning System using the hit rate and the Hanssen–Kuiper Skill Score, and compare it to EWS based on some commonly used and well known volatility models.

The estimation results confirm that crashes are self-enforcing. Furthermore we find that on average larger events trigger more events than smaller events and that larger extremes are observed after the occurrence of more and/or big events than after a tranquil period. Testing our EWS on S&P 500 data during the recent financial crisis, we find positive Hanssen–Kuiper Skill Scores. Thus as our modeling framework exploits the self-exciting behavior of stock returns around financial market crashes, it is capable of creating crash probability predictions on the medium term. Furthermore our modeling framework seems capable of exploiting information in the returns series not captured by the volatility models.

Our paper is organized as follows. In Section 2 the model specifications are discussed, as well as the estimation method. Estimation results are presented in Section 3. Section 4 contains an assessment of the models by means of simulations and residual analysis. The Early Warning Systems are reviewed in Section 5 and compared to EWS based on volatility models in Section 6. Section 7 concludes also with directions for further research.

2. Models

The Epidemic-Type Aftershock Sequence (ETAS) model is a branching model, in which each event can trigger subsequent events, which in turn can trigger subsequent events of their own. The ETAS model is based on the mutually self-exciting Hawkes point process, which is an inhomogeneous Poisson process. For the Hawkes process, the intensity at which events arrive at time t depends on the history of events prior to time t.

Consider an event process $(t_1, m_1), \ldots, (t_n, m_n)$ where t_i defines the time and m_i the mark of event i. Let $\mathcal{H}_t = \{(t_i, m_i) : t_i < t_g\}$ represent the entire history of events up to time t. The conditional intensity of jump arrivals following a Hawkes process is given by

$$\lambda(t|\theta; \mathcal{H}_t) = \mu + \sum_{i:t_i<t} g(t - t_i, m_i) \tag{1}$$

where $\mu > 0$ and $g(s - t_i, m_i) > 0$ whenever $s > 0$ and 0 elsewhere. The conditional intensity consists of a constant term μ and a self-exciting function $g(s)$, which depends on the time passed since jumps that occurred before t and the size of these jumps. The rate at which events take place is thus separated in a long-term background component and a short-term clustering component describing the temporal distribution of aftershocks. The conditional intensity uniquely determines the distribution of the process.

We consider the following specifications of event triggering functions

$$g_{pow}(t - t_i, m_i) = \frac{K_0}{(\gamma(t - t_i) + 1)^{1+\omega}} c(m_i) \tag{2}$$

$$g_{exp}(t - t_i, m_i) = K_0 e^{-\beta(t-t_i)} c(m_i) \tag{3}$$

[2] See amongst others: Sornette (2003), Weber et al. (2007), Petersen et al. (2010), Baldovin et al. (2011, 2012a,b) and Bormetti et al. (2013).

[3] See amongst others: Ogata (1998), Helmstetter and Sornette (2002), Zhuang et al. (2002), Zhuang and Ogata (2004), Saichev et al. (2005), Hardebeck et al. (2008) and Veen and Schoenberg (2008).