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Analysis of non-stationary dynamics in the financial system

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HIGHLIGHTS

- We develop two novel approaches to detect instability in financial time series.
- The methods use functional PCA and Synchrosqeezing analyses.
- Both procedures successfully detect key historic periods of instability.
- Our analysis is applicable to finding gradual changes as well as structural breaks.

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ABSTRACT

Novel data-driven analyses, appropriate for detecting economic instability in non-stationary time series, are developed using functional principal component analysis (fPCA) and Synchrosqueezing. fPCA is applied in a new way, aggregating multiple financial time series to identify periods of macroeconomic instability. Synchrosqueezing, a technique which generates a time-series' time-dependent spectral decomposition, is modified to develop a new quantitative measure of local dynamical changes and structural breaks. The merit of this integrated technique is demonstrated by analyzing financial data from 1986 to 2012 that includes equity indices, securities and commodities, and foreign exchange. Both procedures successfully detect key historic periods of instability. Moreover, the results reveal distinctions between periods of long-term gradual change in addition to structural breaks. These tools offer new insights into the analysis of financial instability.

1. Introduction

The financial crisis and subsequent world-wide economic and financial developments have made clear the importance of developing additional econometric tools for the analysis of financial and macroeconomic data. Since the seminal work of Engle (1982) on modeling conditional variances by autoregressive conditional heteroskedasticity (ARCH), substantial research in financial economics has been centered on modeling and simulation both to gain insight into mechanisms of events, such as asset bubbles or crashes, as well as to characterize a system's stability (Beale et al., 2011; Branch and Evans, 2013; Chib et al., 2002; Gonçalves, 2011; Maldarella and Pareschi, 2012; Pagan, 1996; Raberto et al., 2001; Zhou and Sornette, 2007). At the same time, scholars in financial economics continue to develop novel mathematical and statistical techniques (Billio et al., 2012; Hansen and Scheinkman, 2009; Huang et al., 2009; Lo et al., 2000; Mercurio and Spokoiny, 2004), and the importance of continued effort in this area is well-recognized (Bisias et al., 2012; Worrell et al., 2013). In this letter we describe a new approach for detecting financial instability in non-stationary time series. We apply our approach to financial time series, where non-stationarity is widely acknowledged (Hinch and Roll, 1981; Khandani et al., 2013); our approach is useful to any interested in the analysis of non-stationary data.

Our approach builds on two previously established techniques. First, functional principal component analysis (Ramsay and Silverman, 2005) is used in a unique way to aggregate multiple time series and derive macroeconomic instability signatures. Second, a recently developed time–frequency algorithm called "Synchrosqueezing" (Daubechies et al., 2011; Thakur et al., 2013) is used to develop a new quantitative indicator of system-level changes in a time series. This method is broadly applicable and can identify both structural breaks as well as more gradual changes in a time series. We demonstrate these approaches by analyzing

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financial data spanning 1986–2012. Our data include equity indices, securities and commodities, and foreign exchange.

The remainder of this paper is organized as follows. Section 2 describes the data, and Section 3 details the methods. Section 4 describes the results, and the final section concludes.

2. The data

Publicly available financial time series data covering 1986 through 2012 are obtained from http://research.stlouisfed.org/fred2/ (6222 points over 26.84 years). These daily data cover three sectors: equity indices (Dow Jones Industrial Average, S&P 500 Stock Price Index, Wilshire 5000 Total Market Full Cap Index, FTSE 100 Index, Nikkei 225 Index, Dow Jones Composite Average); securities and commodities (10-Year Treasury Constant Maturity Rate, Crude Oil Prices: West Texas Intermediate Gold Fixing Price 3:00 P.M. (London time), 3-Month London Interbank Offered Rate (LIBOR)); and foreign exchange (Trade Weighted US Dollar Index: Major Currencies, US–Japan Foreign Exchange Rate, US–UK Foreign Exchange Rate, US–Canada Foreign Exchange Rate, US–Australia Foreign Exchange Rate, US–Switzerland Foreign Exchange Rate).

3. Analysis methods

Our work builds on two approaches. First, we implement functional principal component analysis (fPCA) in a novel way (see supplement for details). In brief, empirical time series data are coded by functional basis sets. As with standard PCA, for well-behaved input functions the first eigenvalue explains a high percentage of the variation (of the functions) and reconstruction accuracy is stable over time as well. Intuitively, sudden changes (typically reductions) in reconstruction accuracy reflect instability in the behavior of the data. Consequently, we use the period-by-period reconstruction accuracy of a moving-window fPCA analysis as an evolving metric of a system's stability, where "system" refers to the aggregate of participating time series.

Synchrosqueezing is a time–frequency algorithm that decomposes a time series into its constituent *instantaneous frequencies*(IFs), which is not possible with a conventional Fourier or windowed Fourier spectral decomposition (Daubechies et al., 2011; Thakur et al., 2013). We use this methodology to derive a new indicator of structural breaks in a time series, called the *density index* (see supplement for details). The density index describes the distribution of IFs in a dynamical system over time, with smaller or larger values respectively corresponding to the system being in a stationary state or undergoing a structural break. The density index involves no dynamic model specification and is especially well-suited for studying non-stationary time series.

4. Results

4.1. Ensemble behavior of financial system by moving window functional PCA

The moving window fPCA is applied on the sixteen daily data sets stated above, using a *B*-spline basis. Fig. 1 shows the reconstruction accuracy for different eigenfunctions; the loss of accuracy is a measure of system instability. The blue trace in Fig. 1 shows the first eigenfunction to be dominant. The effect of the first two eigenfunctions is shown in green, and the first three in red. All critical financial events over 1986–2012 are identified. If the threshold for reconstruction accuracy is set at 0.75 as shown by the horizontal red line (on a scale of 0–1), many major economic events cross this threshold. The occurrence of the respective events is labeled as A through F in Fig. 1.

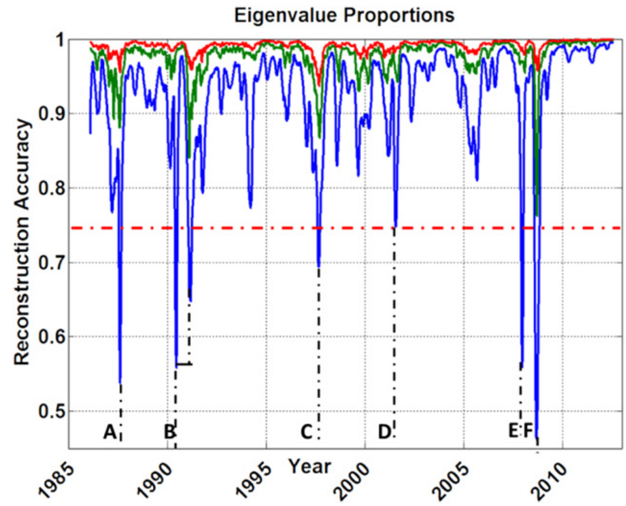

Fig. 1. fPCA identifies all financial crisis events. A threshold for reconstruction accuracy at 0.7 distinctly identifies: September 87 crash (A); Gulf War (B); Asian Financial Crisis (C); 9/11 (D); Bear-Stern (E) and Lehman Brothers (F) crises. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2. Local dynamics using synchrosqueezing and the density index

The Synchrosqueezing and density index methodology is applied to the sixteen time series after preprocessing (discussed in supplement), and it provides insights into the local dynamics of each data series.

Shown in Fig. 2 are the Synchrosqueezing and density index plots for four representative time series (out of sixteen), namely, the Dow Jones Composite Average (DJCA), the Treasury yield, Oil and the dollar index. We find a few distinct oscillatory components with low but variable instantaneous frequencies, between 0 and 3 cycles/year (c/y). These components form and/or break up at different times and represent the slow, trend-like dynamics in the systems. The overall trends and long-lasting changes in the density indices are a leading indicator of instability (e.g., structural breaks) in the systems. These are far from apparent in the data itself and in some cases appear long before the change is seen in the data. Some illustrative cases are discussed below.

The equity indices, except for the Japan-focused Nikkei 225, generally have similar behavior, which is reflected in their Synchrosqueezing plots and density indices, as shown in Fig. 2(a) for the DJCA. The dominant trend is described by two oscillatory modes: one 0.31–0.6 c/y component that is present from 1986 to 1991 and another that starts (or is first detectable) in mid-1994 at 0.037 c/y and continues to the present day at 0.18 c/y. A third component appears at 0.17 c/y in March 2006, grows to 0.34 c/y until July 2008, disperses until October 2008, and finally coalesces again into a 0.72–1.05 c/y component. This can be interpreted as a new underlying economic dynamic that is distinct from the long-term trend. In contrast, similar behavior around other crises such as Black Monday is much less pronounced and dissipates quickly after the crisis. The trend in the density indices is largely flat until mid-2002, when the equity markets first started to recover from the dot-com crash and 9/11. At that point, they show a gradual decrease until mid-2005, followed by a similar increase up to the crisis in October 2008, and finally followed by a decrease again. This shows that a structural break occurred around October 2008 and reflects the behavior of the third, higher frequency component during this period.

These equity results (Fig. 2(a)) imply that past crises such as Black Monday were largely exogenous events that did not change the fundamental dynamics of the financial system, despite having