Coupled Market Behavior Based Financial Crisis Detection

Wei Cao, Longbing Cao and Yin Song

Abstract— **Financial crisis detection is a long-standing challenging issue with significant practical values and impact on economy, society and globalization. The challenge lies in many aspects, in particular, the nonlinear and dynamic characteristics associated with financial crisis. Most of existing methods rely on selecting individual indicators associated with one market indicator, and the linear assumption is often behind the models for prediction. In practice, a linear assumption may be too strong to be applicable to the real market dynamics. More importantly, instruments in different markets such as gold price and petrol price are often coupled. A financial crisis may significantly change the couplings between different market indicators. In addition, such couplings in cross-market interaction are likely nonlinear. In this paper, we present a new approach for financial crisis detection by catering for the often nonlinear couplings between major indicators selected from different markets, called *coupled market behavior analysis*, to detect different coupled market behaviors at crisis and non-crisis periods. A Coupled Hidden Markov Model (CHMM) is built to characterize the coupled market behaviors of equity, commodity and interest markets as case studies. The empirical results show the need of catering for nonlinear couplings between various markets and the proposed approach is much more effective in capturing the coupling and nonlinear relations associated with financial crisis compared with other traditionally used approaches, such as Signal, Logistic and ANN models.**

I. INTRODUCTION

THE impact of financial crisis is often disruptive on multiple perspectives, including economy, living, society and globalization. As we just experienced, the subprime mortgage crisis triggered in the US in 2007 has causes a chain of destructive effect on instruments in the US, global financial markets, and other markets and areas [1]. This clearly discloses the need of substantial efforts to be made on early prediction of financial crisis.

However, the effective detection of possible financial crisis is not a trivial task. Firstly, crisis has a strong transfer effect from one aspect to another, namely we can not use the change of a single indicator to represent the crisis. This is because each indicator would reflect differently to a crisis. It indicates that the simple signal approach illustrated by Kaminsky and Reinhart in [3] is not operable. Secondly, the financial crisis is a rare event with non-linear feature, which means that it is difficult for some approaches with linear assumption (for example, logistic approach) to capture the nature of crisis. Thirdly, financial crisis is a complex problem triggered, associated or reflected via many factors. Even with multiple indicators, it is essential to consider the coupling relationship between the indicators. Often there are dependency between indicators from various financial

Wei Cao, Longbing Cao and Yin Song are with the Advanced Analytics Institute, University of Technology, Sydney, Australia (email: {Wei.Cao,Yin.Song}@student.uts.edu.au,longbing.cao@uts.edu.au).

markets, crisis effect is passed from one market to another reflected through the couplings and indicator dynamics. It is assumed that the coupling and indicator dynamics behave significantly differently between the crisis and non-crisis periods, as the drivers triggering the crisis likely change the coupling from 'normal' to 'abnormal' status. Currently, there is limited work reported on capturing the couplings and coupling changes cross market indicators. Lastly, most of existing models rely on the selection of proper indicators. A corresponding issue how to select discriminative indicators that are sensitive to crisis.

The above issues surrounding the existing work make it very necessary to develop new approach for effectively selecting the appropriate indicators, catering for the nonlinear dynamics, and considering their coupling relationships. For this, we propose a coupled market behavior based framework to detect financial crisis. The coupled market behaviors refer to behaviors of different market instruments, such as gold and petrol prices, which show strong coupling relationships. The framework works on the assumption that financial crisis is better reflected through coupled market behaviors rather than single indicators without coupling relationship, and the couplings change with the occurrence of financial crisis, namely sharing different coupling dynamics during and outside the crisis period. This is acceptable according to domain knowledge and the cross-market theory.

The framework consists of three stages. It firstly converts the common transnational data into a new data structure better fitting the model used in the second stage. The second stage captures the couplings between market behaviors and model the coupling difference during and outside crisis respectively through a Coupled Hidden Markov Model (CHMM). The CHMM captures the non-linear coupling relationship in multiple processes and its transitional effect from one state to another. Subsequently, the third stage detects financial crisis by observing significant difference occurring between the crisis and non-crisis periods.

The rest of the paper is organized as follows. Related work is presented in Section II. In Section III, the coupled market behaviors are illustrated by a case study in financial markets and the corresponding problem of coupled market behavior based crisis detection is defined. The framework of our model is described in Section IV. Empirical outcomes and evaluation are illustrated in Section V. Conclusions and future work are discussed in Section VI.

II. RELATED WORK

This paper aims to detect financial crisis from the coupled market behavior aspect. This section discusses the related work as well as background knowledge. The first part of this

section is about the related approaches for detecting financial crisis. A brief introduction of coupled behavior analysis and CHMM are then provided, which serves as the base for our design of the crisis detection framework.

A. Related Approaches

There are many literatures addressing financial crisis analysis. Generally, the recent efforts on detecting financial crisis can be categorized into three types. The first type is using the signal approach to detect financial crisis. It was proposed by Kaminsky and Reinhart in [3], which identifies the difference of the economic behaviors during financial crisis when compared with normal period. Variables such as the exchange rate and stock market index are often used as indicators. If they exceed a user specified threshold, then a crisis signal is produced [6]. An issue here is that each indicator behaves differently during a crisis. In order to combine all the information and various indicators at the same time, Kaminsky proposed four methods for information integration in [4], but it cannot handle couplings. Authors in [2] illustrated that there would be a very high noise-to-signal ratio if the indicators are strongly correlated.

The second type of methods use limitedly dependent regression models. Two basic models are logistic and probability models [5] [10]. The models are used to predict the probability of the occurrence of the financial crisis based on some selected explanatory variables. Although such models can capture all the information contained in the selected variables, the linear assumption may lead to unsatisfactory results given the non-linear characteristics of variables associated with financial crisis.

The third type of approaches adopt artificial intelligence and machine learning techniques to detect financial crisis [2]. Techniques such as artificial neural network (ANN) and fuzzy logic are taken. Some recent work reveals that ANN is a popular method with promising results [7][8]. For instance, authors in [9] adopt ANN to predict bank crisis in emerging financial markets. However, the ANN-based methods also have limitations: the black-box nature leads the difficulty to disclose the relationships among the indicators; also, the results rely on the selection of indicators, which may not be easy to obtain in the real life.

B. Coupled Behavior Analysis

Coupled behaviors refer to the activities from the same or different actors with inter and intra-relationships between the activities. While behavior analysis is not a new topic [11][12][13], most of them mainly pays attention to intra-relations between behaviors. The problem of coupled behavior analysis is formally defined in [14].

Suppose there are I actors $\{\mathscr{E}_1, \mathscr{E}_2, \ldots, \mathscr{E}_I\}$, an actor $\mathscr{E}_i$ undertakes J_i behaviors $\{\mathbb{B}_{i1}, \mathbb{B}_{i2}, \ldots, \mathbb{B}_{iJ_i}\}$, actor $\mathscr{E}_i$'s j^{th} behavior $\mathbb{B}_{ij}$ is a K-variable vector, its variable $[p_{ij}]_k$ reflects the kth behavior property. Then a Behavior Feature Matrix $FM(\mathbb{B})$ is defined as follows:

$$FM(\mathbb{B}) = \begin{pmatrix} \mathbb{B}_{11} & \mathbb{B}_{12} & \ldots & \mathbb{B}_{1J_{max}} \\ \mathbb{B}_{21} & \mathbb{B}_{22} & \ldots & \mathbb{B}_{2J_{max}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{B}_{I1} & \mathbb{B}_{I2} & \ldots & \mathbb{B}_{IJ_{max}} \end{pmatrix}$$

Where $J_{max} = max\{J_1, J_2, \cdots, J_I\}$, for every behavior set $\{\mathbb{B}_{ij} | J_i < J_{max}\}$, the corresponding element $\mathbb{B}_{ij}$ is recognized as $\emptyset$ when $J_i < j \leq J_{max}$. Further, each (i, j) element of this matrix $FM(\mathbb{B})$ is actually a row vector, expressed as $\overrightarrow{\mathbb{B}}_{ij} = ([p_{ij}]_1, [p_{ij}]_2, \cdots, [p_{ij}]_K)$, where $[p_{ij}]_k$ $(1 \leq k \leq K)$ is the kth property of the behavior $\mathbb{B}_{ij}$. The intra-coupling is the relationship within one row of the above matrix, while how the behaviors interact is embodied among the columns of $FM(\mathbb{B})$, indicated as inter-coupling.

Definition 1. Coupled Behaviors Coupled behaviors $\mathbb{B}_c$ refer to behaviors $\mathbb{B}_{i_1 j_1}$ and $\mathbb{B}_{i_2 j_2}$ that are coupled in terms of relationships $f(\theta(\cdot), \eta(\cdot))$, where $(i_1 \neq i_2) \vee (j_1 \neq j_2) \wedge (1 \leq i_1, i_2 \leq I) \wedge (1 \leq j_1, j_2 \leq J_{max})$

$$\mathbb{B}_c = (\mathbb{B}_{i_1 j_1}^\theta)^\eta * (\mathbb{B}_{i_2 j_2}^\theta)^\eta ::= \mathbb{B}_{ij}(\mathscr{E}, \mathscr{O}, \mathscr{C}, \mathscr{R})| \quad (1)$$
$$\sum_{i_1, i_2 = 1}^{I} \sum_{j_1, j_2 = 1}^{J_{max}} f(\theta_{j_1 j_2}(\cdot), \eta_{i_1 i_2}(\cdot)) \odot (\mathbb{B}_{i_1 j_1}, \mathbb{B}_{i_2 j_2})$$

where $f(\theta_{j_1, j_2}(\cdot), \eta_{i_1 i_2}(\cdot))$ is the coupling function denoting the corresponding relationships between $\mathbb{B}_{i_1 j_1}$ and $\mathbb{B}_{i_2 j_2}$, $\sum_{i_1, i_2 = 1}^{I} \sum_{j_1, j_2 = 1}^{J_{max}} \odot$ means the subsequent behaviors of $\mathbb{B}$ are $\mathbb{B}_{i_1 j_1}$ coupled with $f(\theta_{j_1}(\cdot), \eta_{i_1}(\cdot))$, $\mathbb{B}_{i_2 j_2}$ with $f(\theta_{j_2}(\cdot), \eta_{i_2}(\cdot))$.

Definition 2. Coupled Behavior Analysis The analysis of coupled behaviors is to build the objective function $g(\cdot)$ under the condition that behaviors are coupled with each other by coupling function $f(\cdot)$, and satisfy the following conditions.

$$f(\cdot) ::= f(\theta(\cdot), \eta(\cdot)), and \quad (2)$$
$$g(\cdot)|(f(\cdot) \geq f_0) \geq g_0 \quad (3)$$

C. Coupled Hidden Markov Model

CHMM [15] is a model that was proposed to model multiple processes with coupling relationships. CHMM consists of more than one chain of HMMs representing different processes, in which the state of any chain of HMM at time t depends on not only the states of its own chain but also the states of other chains of HMMs at time $t - 1$, namely interaction between modeled processes. Fig. 1 is a standard CHMM with two chains. The hidden variables X_t are assumed to interact locally with their neighbors and each of them has its own observation Y_t.

Suppose there are C coupled HMMs, N is the number of hidden states, the elements of a CHMM are as follows [22]:

- prior probability $\pi = \{\pi_j^{(c)}\}, 1 \leq c \leq C, 1 \leq j \leq N^{(c)}$ $\sum_{j=1}^{N^{(c)}} \pi_j^{(c)} = 1$
- transitional probability $A = \{a_{ij}^{(c', c)}\}, 1 \leq c', c \leq C, 1 \leq i \leq N^{(c')}, 1 \leq j \leq N^{(c)}$ $\sum_{j=1}^{N^{(c)}} a_{ij}^{(c', c)} = 1$
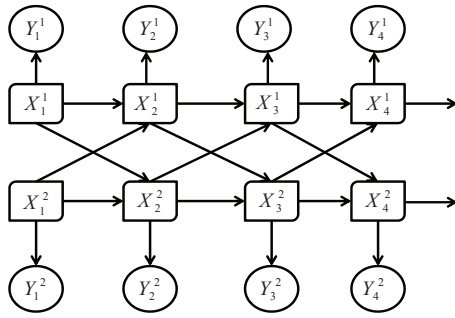
Fig. 1.   A CHMM with Two Chains

- observation probability $B = \{b_j^{(c)}(k)\}, 1 \le c \le C, 1 \le j \le N^{(c)}, 1 \le k \le M$
  $\sum_{k=1}^{M} B_J^{(c)}(k) = 1$
- coupling coefficient $\Theta = r_{c',c}$

III. PROBLEM STATEMENT

A. A Case Study

During the 2008 global financial crisis, we can find some interesting phenomena in different financial markets. In commodity markets, for crude oil price, the 2008 calendar year was one of the most volatile periods in the history, the price reached its record high of 147 dollar per barrel in July and dropped to 60 dollar in November in the same year. Similarly, the equity market also suffered a big decline with high volatility, the S&P 500 index dropped from 1267.38 in July to 896.24 in November. In addition to that, with the fear of global recession led by the troubled US economy, interest markets were also accordingly changed in the financial crisis period; interest in many countries reached its record low in that period.

The above examples show that, although all three markets had great change during the financial crisis period, there exists some linkage between commodity, equity and interest markets. Such coupling is more specifically and intuitively demonstrated through Fig. 2 and Table I, and the selected indicators for these three markets are as follows.

- Commodity market: *a. The Gold price (USD per ounce, London PM fix)*. It constitutes the main commodity market and is often used as refuge for asset safety during financial crisis periods. *b. The WTI Crude Oil Futures Price (USD per barrel)*. It has become a major commodity market, not just for commodity producers, but also for investors [16].
- Equity market: *a. The S&P 500 index*. It is a stock market index based on the market capitalizations of 500 leading companies publicly traded in the US stock market. It represents the liquidity of market and recognized as one of the most commonly followed equity indices. *b. Dow Jones Industrial Average (DJIA)*. It is an index that shows how 30 large publicly owned companies based in the US are traded during a standard trading session in the stock market [17].

- Interest market: *a. The TED Spread*. It is the difference between the 3-month interest rates on interbank loans and on 3-month Treasury bill rate. It represents the counterparty risk from one bank lending to another and an indicator of credit risk in the economy [18]. *b. The Baa Spread*. It is the difference between the Baa Corporate bond rate and 10 year Treasury bill rate. It is widely recognized as an assessment of risk for investment.
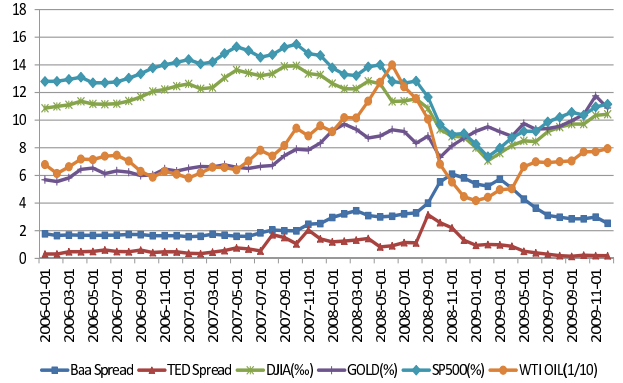

Fig. 2.   Trend of Indicators in Three Markets

The data for Fig. 2 and Table I is from January 2006 to December 2009, including a crisis period and a non-crisis period. Fig. 2 shows that the relationships between these indicators fluctuated during the two periods. The relationships remains much more stable in the non-crisis period (before the late 2007) than the crisis period. Table I further demonstrates that there are strong correlations between the indicators during the whole period, as shown in the Pearson correlations. Based on this, we can come to the conclusion that these three markets are coupled with each other, but the coupled relationships behave differently between the crisis period and non-crisis period.

This typical case study supports our assumption that financial crisis has the transfer effect on multiple indicators, which display different nonlinear and dynamic characteristics. They are coupled in some way; the coupling relationships change with the occurrence of crisis. To effectively detect financial crisis, it is essential to consider the the nonlinear and dynamic factors, and the couplings between indicators. A significant change of the coupling relationships can serve as a strong sign for differentiating the crisis and normal periods. Below, we take these observations to define the problem of coupled market behavior analysis for financial crisis detection, by considering the major difference on multiple indicator coupling relationship between crisis and non-crisis periods.

B. Coupled Market Behavior Based Financial Crisis Detection

The problem of coupled behavior based financial crisis detection can be formalized as follows. Let function $f(\cdot)$ capture the coupling relationships between the three markets in the above case, $g(\cdot)$ be the corresponding objective

		Baa Spread	TED Spread	DJIA	GOLD	SP500	WTI OIL
Baa Spread	Pearson Correlation	1	.987**	-.060	.282**	-.129**	-.250**
	Sig.(2-tailed)		.000	.080	.000	.000	.000
TED Spread	Pearson Correlation	.987**	1	-.078*	0.258**	-.133**	-.255**
	Sig.(2-tailed)	.000		.024	.000	.000	.000
DJIA	Pearson Correlation	-.060	-.078*	1	0.234**	-.016	-.018
	Sig.(2-tailed)	.080	.024		.000	.647	.595
GOLD	Pearson Correlation	.282**	0.258**	0.234**	1	-.040	-.068*
	Sig.(2-tailed)	.000	.000	.000		.242	.049
SP500	Pearson Correlation	-.129**	-.133*	-.016	-.040	1	.258**
	Sig.(2-tailed)	.000	.000	.647	.242		.000
WTI OIL	Pearson Correlation	-.250**	-.255**	-.018	-.068*	258**	1
	Sig.(2-tailed)	.000	.000	.595	.049	.000	

function determining whether a crisis exists. Two models are built separately for the crisis and non-crisis periods: Model CM with the coupling function $f_{CM}(\cdot)$ characterizes the coupled market behaviors during the crisis, while Model NM with the coupling $f_{NM}(\cdot)$ describes the characteristics and coupling relationship between indicators from the non-crisis period. If

$$g_{CM}(t)(f_{CM}(\cdot)) \geq g_{NM}(t)(f_{NM}(\cdot)), \qquad (4)$$

time t is in the crisis set, and otherwise in the non-crisis set.

Correspondingly, our key task in financial crisis detection is to determine the coupling function $f(\cdot)$ and the objective function $g(\cdot)$ corresponding to two different periods. Below, the Coupled Hidden Markov Model (CHMM) is explored to capture the coupling relationship and nonlinear dynamics of multiple indicators, with an objective function built to check the major difference in the CHMM outputs.

IV. THE CHMM-BASED CRISIS DETECTION MODEL

This section introduces the system framework for financial crisis detection, the data structure and conversion from business data to behavioral data, the CHMM model and the detection algorithm respectively.

A. System Framework

Based on the case study and corresponding problem definition in Section III, we propose a CHMM based financial crisis detection framework, which is depicted in Fig.3. It consists of three major parts: 1) Data preprocessing, which converts the transactional data into the behavior-oriented data structure that better fits the CHMM analysis. The transformed data is further partitioned with the involvement of domain knowledge into training and testing sets. 2) CHMM-based coupled market behavior modeling, namely using CHMM to model the coupled market behaviors in the two different periods. We explain how the nonlinear characteristics of the indicators and the couplings between indicators are captured in the CHMM models. 3) Crisis detection, which determines whether a crisis appears using the data-driven method.

B. Data Preprocessing

To better fit the model, in this stage we will focus on three parts: indicator selection, data normalization, and data partition.

1. Indicator selection. In CHMM, we use one Markov chain to represent one financial market, so we need to find one indicator for each market. In the real world, there are more than one indicator that can represent the market. For example, in Section III, each of the three markets owns two major indicators. Here we select one indicator for each market which has higher correlations with other markets. This is because our focus is on the coupling relationships among various markets, the indicator more relevant with other markets encloses strong discriminative power.

Definition 3. Indicator Correlation Suppose there are m markets, each market owns n indicators. Indicator correlation CI_{i_1,j_1} refers to the correlations of indicator I_{i_1,j_1} with indicators in other markets, where $(i_1 \neq i_2) \wedge (1 \leq i_1, i_2 \leq m) \wedge (1 \leq j_1, j_2 \leq n)$. Here $corr(\cdot)$ is the Pearson correlation coefficient of the two indicators.

$$CI_{i_1 j_1} = \sum_{i_1,i_2=1}^{m} \sum_{j_1,j_2=1}^{n} corr(I_{i_1 j_1}, I_{i_2 j_2}) \qquad (5)$$

2. Data normalization. The data we choose includes the closing prices of indicators in each market. The data types are different among the various markets, thus we normalize the original price series into $[0, 1]$ to better fit the model. The price of indicator PI is normalized to PI' by

$$PI' = (PI - PI_{min})/(PI_{max} - PI_{min}) \qquad (6)$$

3. Data partition. In our system, the training data would be divided into two parts: crisis set and non-crisis set. Two models are trained on them respectively. Model CM represents the complex coupled market behaviors in the crisis period, Model NM indicates the relationships in the non-crisis stage. Domain knowledge from the National Bureau of Economic Research (NBER) Business Cycle Dating
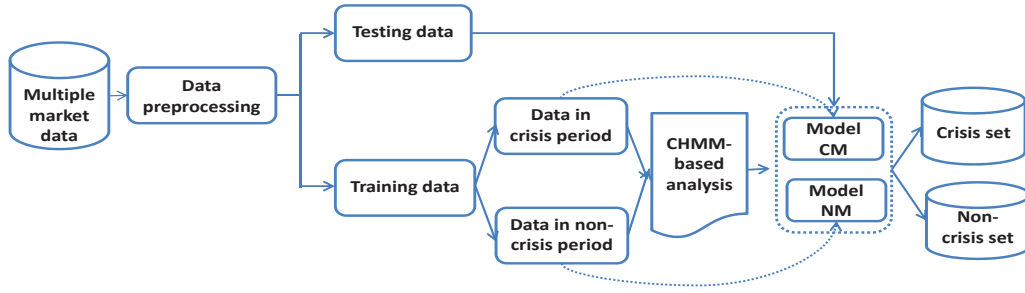
Fig. 3.   The Proposed Crisis Detection Framework

Committee[1] is involved in this data splitting. The following economic cycles occurred in our selected data: Q3-1990 to Q1-1991 (led by the Gulf war), Q1-2001 to Q4-2001 (triggered by the dot-com bubble) and Q4-2007 to Q2-2009 (caused by the subprime crisis). The former two cycles are used for training, with the last for testing.

C. CHMM-based Market Behavior Modeling

In the CHMM-based financial crisis detection system, three HMM chains, namely HMM-C capturing the commodity market sequence $\Phi(C)$, HMM-E enclosing the equity market sequence $\Phi(E)$, and HMM-I for the interest market sequence $\Phi(I)$, are built. Accordingly, a CHMM is built to incorporate all three sequences, which maps the financial crisis problem represented by coupled market behaviors of three markets into the CHMM. This mapping works as follows:

$$Financial\ crisis\ analysis \rightarrow CHMM\ modeling \quad (7)$$
$$\Phi(\cdot)|observation \rightarrow A \quad (8)$$
$$\Phi(\cdot)|transition \rightarrow B \quad (9)$$
$$f(\Phi(\cdot)) \rightarrow \Theta \quad (10)$$
$$\Phi(\cdot)|prior \rightarrow \pi \quad (11)$$

where $f(\cdot)$ is the coupling function.

Two CHMM models are trained on the Q3-1990 to Q1-1991 and Q1-2001 to Q4-2001 data sets respectively. Below, we discuss the calculation of the parameters in the CHMM.

Assume there are C coupled chains, the hidden state is denoted by S, the state transitional probability is [2]

$$P(S_t^{(c)}|S_{t-1}^{(1)}, S_{t-1}^{(2)}, \ldots, S_{t-1}^{(C)}) \quad (12)$$

where the $S_t^{(c)}$ is the hidden state of model c at time t. The number of parameters is N^C when the number of hidden state is N for each chain. To learn the parameters, many researchers proposed several variations of CHMM. For instance, in [14][19], the state transition probability is counted as the product of all marginal conditional probabilities:

$$P(S_t^{(c)}|S_{t-1}^{(1)}, S_{t-1}^{(2)}, \ldots, S_{t-1}^{(C)}) = \prod_{c'} P(S_t^{(c)}|S_{t-1}^{(c')}) \quad (13)$$

[1]The NBER's Business Cycle Dating Committee maintains a chronology of the U.S. business cycle. Available at http://www.nber.org/cycles.html
[2]This paper focus on the type of CHMM that the state of one chain at time t depends on the states of all chains (including itself).

The above method reflects an approximation, which is not a properly defined probability density, namely the right hand side does not sum up to one [20].

In our paper, we will use the method illustrated in [21], in which new parameters are introduced to capture the interaction and model the joint transition probability as

$$P(S_t^{(c)}|S_{t-1}^{(1)}, S_{t-1}^{(2)}, \ldots, S_{t-1}^{(C)}) = \sum_{c'=1}^{C} (\theta_{c'c} P(S_t^{(c)}|S_{t-1}^{(c')})) \quad (14)$$

where $\theta_{c'c}$ is the coupling weights which measure the coupling weights from chain c' to c, namely how $S_{t-1}^{(c')}$ affects $S_t^{(c)}$. The joint dependency is modeled as a linear combination of all marginal dependencies. An simple interpretation is as follows:

$$P(y|x_1, x_2, \ldots, x_C) = \frac{P(y, x_1, x_2, \ldots, x_C)}{P(x_1, x_2, \ldots, x_C)}$$
$$= \frac{P(x_1), P(y|x_1), \ldots, P(x_C|P(y, x_1, x_2, \ldots, x_C))}{P(x_1, x_2, \ldots, x_C)} \quad (15)$$
$$= \omega_1 P(y|x_1)$$

here for simplicity, y represents the current state and x refers to for previous states, $\omega_1 = \frac{P(x_1), \ldots, P(x_C|P(y, x_1, x_2, \ldots, x_C))}{P(x_1, x_2, \ldots, x_C)}$. Similarly, we can obtain

$$P(y|x_1, x_2, \ldots, x_C) = \omega_1 P(y|x_1) = \omega_2 P(y|x_2)$$
$$= \cdots = \omega_C P(y|x_C) \quad (16)$$

Then the joint conditional probability can be rewritten as

$$P(y|x_1, x_2, \ldots, x_C) = \sum_{c=1}^{C} \theta_c P(y|x_C) \quad (17)$$

where $\theta_c = \frac{1}{C}\omega_c, 1 \leq c \leq C$ are the parameters used to represent the interactions among different markets in our work. Then the corresponding algorithm in [21] is used to learn the model.

D. Financial Crisis Detection

In the above, we have got two models: models CM and NM capturing the coupled market behaviors for the crisis and non-crisis stages respectively. Here these models are used to determine whether the coming coupled market behavior b^k appears to be in crisis or not. To this end, the conditional likelihood (CL) is calculated for the two models CM and NM corresponding to the given coupled market behavior b^k. The algorithm for detecting financial crisis is described

in Algorithm 1. Steps 1 to 2 train the crisis model CM and non-crisis model NM. Steps 3 to 11 form a loop process to compute the likelihood of new coupled market behavior b^k in the testing set based on the two models. The output of the algorithm includes two sets: crisis set CS and non-crisis set NS.

Algorithm 1: Financial Crisis Detection

Input: A training set T_1 of financial crisis data $\{b^1, b^2, \ldots, b^M\}$; A training set T_2 of non-financial crisis data $\{b^1, b^2, \ldots, b^N\}$; A testing set $\{b^1, b^2, \ldots, b^O\}$

Output: A financial crisis set CS; A non-financial crisis set NS

1 Train the model CM on the training set T_1;
2 Train the model NM on the training set T_2;
3 **forall the** b^k *in the Testing set* **do**
4   Compute the likelihood of b^k given the models CM and NM, respectively:
5     $CL(b^k \mid CM)$ and $CL(b^k \mid NM)$;
6   **if** $CL(b^k \mid CM) \geq CL(b^k \mid NM)$ **then**
7 | $b^k \to CS$;
8   **else**
9 | $b^k \to NS$;
10   **end**
11 **end**

V. EXPERIMENTS

In this section, we discuss the data sets, baseline methods, experimental settings as well as evaluation metrics and experimental outcomes.

A. The Data Sets

The data from three financial markets: commodity market, equity market and interest market are extracted for the experiments. As shown in Table II, two typical indicators are chosen for each market. According to the discussions in the data preprocessing stage in Section IV, only one indicator is selected to represent each market based on their correlations with other markets. The selected indicators are: the WTI Crude Oil Price, DJIA and the TED Spread.

The data is obtained from the Economic Research [3]. The data includes weekly prices from January 1990 to December 2009, and have been divided into two parts considering the domain knowledge: the training set consists of the data from 1990 to 2005, the testing set from 2006 to 2009. By considering the financial events and performance at that time period, the time period associated with the crisis is labeled for the two parts. Models are trained on the training set to capture the characteristics of coupled market behaviors in crisis and non-crisis period, separately. The trained models are deployed on the testing set to detect the financial crisis. The coupled market behaviors in the testing set can be seen

as $b^k (1 \leq k \leq O)$ in Algorithm 1. Because indicators in different markets may appear on different trading days, we delete those days that some markets are missing and only choose the trading days that all markets have trading.

TABLE II
TRADING INDICATORS

Market	Indicator 1	Indicator 2
Commodity Market	Gold price	WTI Crude Oil Price
Equity Market	S&P 500	DJIA
Interest Market	The TED Spread	The Baa Spread

B. Baseline Approaches

In order to evaluate the performance of our approach in analyzing financial crisis, we compare it with the following approaches:

- *Signal approach*. This approach [3] believes that the indicators behave differently at the moment when the financial crisis occurs when compared with a relatively normal period. Suppose there are n possible indicators, the change of an indicator $X^j (1 \leq j \leq n)$ is said to signal a financial crisis at time t when it crosses an 'optimal threshold' $\overline{X}^j$,

$$\{S_t^j = 1\} = \{S_t^j, |X_t^j| > |\overline{X}_t^j|\} \tag{18}$$

$$\{S_t^j = 0\} = \{S_t^j, |X_t^j| < |\overline{X}_t^j|\} \tag{19}$$

here $S_t^j = 1$ represents indicator j used in signaling the crisis at time t, and $S_t^j = 0$ otherwise. Usually the threshold value can be located between the 10th percentile and 20th percentile [4]. However, different indicators often produce different prediction outcomes for financial crisis. To obtain a more stable prediction outcome, multiple indicators are used and combined for the signaling [22],

$$I_t = \sum_{j=1}^{n} S_t^j \tag{20}$$

I_t is then recognized as an indicator that combines all the information. The threshold for this indicator is determined in the same way as in the case of other indicators.

- *Logistic approach*. The Logistic regression is used for predicting the outcome of a categorical dependent variable based on one or more predictor variables. Suppose $Y_t = 1$ represents that there is a financial crisis at time t, and $Y_t = 0$ otherwise. P_t is the probability of having a financial crisis at time t,

$$P_t = P(Y_t = 1) = E(Y_t|X)$$
$$= \frac{1}{1 + e^{-b_0 + b_1 x_1 + \cdots + b_n x_n + \varepsilon}} \tag{21}$$

here $x_i (1 \leq i \leq n)$ is explanatory variable, ε is the error term. Then the log-likelihood function can be written as

follows:

$$l(\theta) = \sum_{t=1}^{T} Y_t(ln(P_t)) + (1-Y_t)(ln(1-P_t)) \quad (22)$$

where T is the number of periods. The parameters can be obtained through estimating the maximum likelihood.

- *ANN approach.* An ANN network consists of an interconnected group of artificial neurons and processes information using a connectionist approach, with functions to map input values into output values. Using ANN to analyze financial crisis is the process of learning to separate the testing set into different classes (crisis set and non-crisis set) by finding common features between samples in the training set. Here we will use the most popular ANN learning algorithm, the back-propagation algorithm [8], to conduct the learning process.

C. Experimental Settings

All the comparison approaches use the same indicators as our proposed CHMM approach. Also, the training data and testing data are the same for the Logistic approach, ANN and CHMM. Since the signal approach only considers the simple calculation of the number of indicators in signaling, no relationships among the indicators are considered. The Logistic approach only captures the linear relationships between indicators, while ANN captures the non-linear relationships without considering the coupling relationships between indicators.

D. Performance Evaluation

In this paper, to compare the performance of our approach with other ones, the following evaluation metrics are used:

- *Overall Accuracy.* Overall Accuracy is the percentage of correctly classified instances.

$$Overall\ Accuracy = \frac{TN + TP}{TP + FP + FN + TN} \quad (23)$$

where TP, TN, FP and FN represent true positive, true negative, false positive and false negative, respectively. We treat financial crisis cases as the positive class here.

- *Precision.* Precision is the percentage of correctly classified positive instances.

$$Precision = \frac{TP}{TP + FP} \quad (24)$$

- *Type I error.* The percentage of the number of times with no signal fired when there is a crisis against the times that there is a crisis.
- *AUC.* AUC is the area under the ROC curve, where ROC is created by plotting the TP rate (true positive out of the positives) and FP rate (false positive out of the negatives). The AUC represents the classification accuracy, the larger the better.

E. Experimental Results

1) Technical Performance: Here we compare the technical performance of our approach against other three approaches on the testing data. Overall accuracy, precision and type I error listed in the former part are calculated. The results are reported in Table III, Fig. 4 and Fig. 5. The horizontal axis (P-Num) in Fig. 4 and Fig. 5 stands for the number of detected financial crisis (i.e., the number of trading weeks with abnormal coupled market behaviors).

TABLE III
TECHNICAL PERFORMANCE OF FOUR APPROACHES

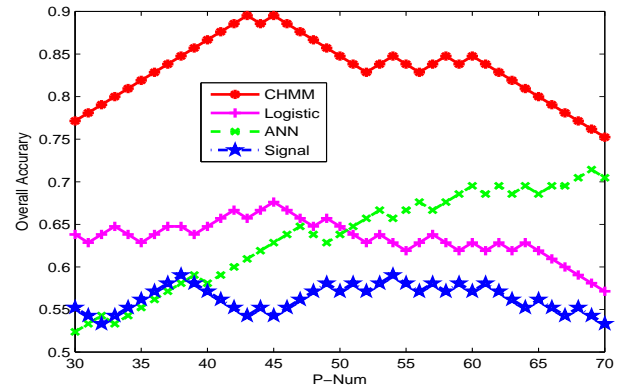| Approach	Overall Accuracy	Precision	Type I error
Signal	0.5714	0.9057	0.3962
Logistic	0.7895	0.6585	0.3415
ANN	0.6857	0.7170	0.2830
CHMM	0.8571	0.6038	0.0943

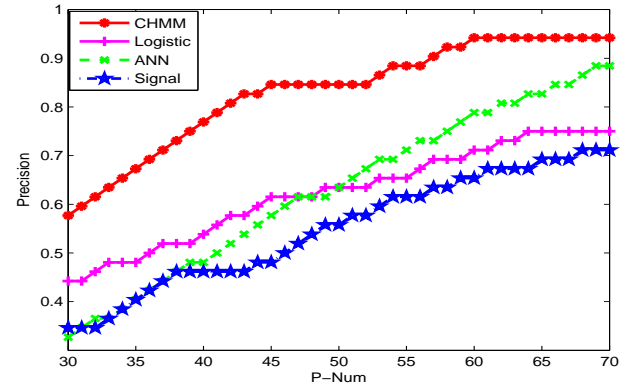Fig. 4.   Overall Accuracy of Four Approaches

Fig. 5.   Precision of Four Approaches

The results in Table III, Fig.4 and Fig.5 come up with the following conclusions: Our CHMM-based coupled market behavior based financial crisis detection approach performs best in terms of all data sets and evaluation metrics. For instance, CHMM outperforms other methods by greatly reducing the Type I Error to about 23.8% to 33.3% of the other methods. CHMM is with the highest overall accuracy increase about 36% compared to the Signal method, and

20% over the best performing Logistic method. The precision improvement could be as high as about 40% against the Signal method, and 20% against the best performing Logistic when P-Num = 45. It clearly shows that the coupled market behavior analysis is a promising approach for financial crisis detection. The main reason lies on that our approach can capture the complex coupling relationships among financial markets in financial crisis and non-crisis periods. In addition, CHMM has been demonstrated to be an useful model to characterize the coupled market behaviors.

Interestingly, the results of the logistic and ANN approaches are conflicting with each other. In the whole testing period, the logistic approach performs better than ANN by accuracy, but the ANN gets a better precision. This may be because, in real financial markets, the relationships among different markets may disclose more stationary and linear characteristics in the non-crisis period, while such a feature becomes more non-linear and dynamics when a crisis takes place. However, both of them overlooks the couplings between market indicators and the coupling changes during crisis. The Signal approach achieves the worst performance, indicating that we cannot detect financial crisis only through observing simple changes of indicators.

2) Exploration of Performance Score: In this section we compare the four approaches in terms of three performance scores, denoted as '1-AUC' '2-Accuracy' and '3-Precision'. The results are depicted in Fig.6. The results show that the CHMM-based method outperforms all the rest on all performance aspects. This further shows the great potential of incorporating couplings between market behaviors in detecting financial crisis.
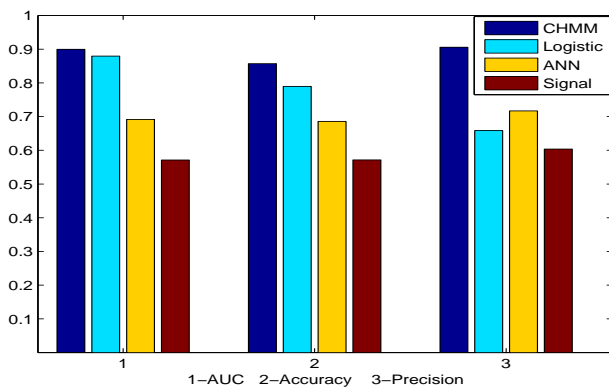

Fig. 6.   Performance Scores of Four Approaches

VI. Conclusions

The effective detection of financial crisis is crucial but very challenging. Many methods have been studied by applying financial and statistical theories. A modern trend is the data-driven learning approach, which incorporates the advanced learning techniques to identify inconsistency caused by crisis on the major market indicators. In this paper, we have proposed a new financial crisis detection approach to consider the nonlinear characteristics in the market, the coupling relationships between different markets' behaviors, and the significant impact caused by crisis occurrence on the indicator dynamics and couplings. A CHMM-based model has been designed to capture the above aspects and deployed to detect the subprime mortgage crisis in the US financial markets by selecting major indicators from the commodity, equity and interest markets. The results show the clear advantage of our approach against the Signal, Logistic and ANN based methods with a significant accuracy improvement.

References

[1] F A. Longstaff, "The subprime credit crisis and contagion in financial markets," *Journal of Financial Economics*, vol. 97, pp. 436-450, 2010.

[2] L. Yu, S. Wang, K.K. Lai and F. Wen, "A multiscale neural network learning paradigm for crisis forecasting," *Neurocomputing*, vol. 73, pp. 716-725, 2010.

[3] G.L. Kaminsky and C.M. Reinhart, "The twin crises: the causes of banking and balance-of-payments problems," *American Economic Review*, vol. 89, no. 3, pp. 473-500, 1999.

[4] G.L. Kaminsky, "Currency and banking crises: the early warnings of distress," *IMF Working Papers*, pp. 99-178, 1999.

[5] A. Berg, C. Pattillo, "Predicting currency crises: the indicators approach and an alternative," *Journal of Money and Finance*, vol. 18, pp. 561-581, 1999.

[6] D. Peng, C. Bajona, "China's vulnerability to currency crisis: a KLR signals approach," *China Economic Review*, vol. 19, no. 2, pp. 138-151, 2008.

[7] T.Y. Kim, C. Hwang and J. Lee, "Korean economic condition indicator using a neural network trained on the 1997 crisis," *Journal of Data Science*, vol. 2, pp. 371-381, 2004.

[8] T.Y. Kim, K.J. Oh, I. Sohn and C. Hwang, "Usefulness of artificial neural networks for early warning systems of economic crisis," *Expert Systems with Applications*, vol. 26, pp. 583-590, 2004.

[9] E. N. Ozkan-Gunay and M. Ozkan, "Prediction of bank failures in emerging financial markets: An ANN approach," *The Journal of Risk Finance*, vol. 8, no. 5, pp. 465-480, 2007.

[10] M. Bussiere, M. Fratzscher, "Towards a new early warning system of financial crises," *Journal of International Money and Finance.* vol. 25, no. 6, pp. 953-973, 2006.

[11] G.L. Zacharias and J. MacMillan, *Behavior Modeling and Simulation:From Individual to Societies.* National Academies Press, 2008.

[12] Y.S. Xu, Lee and K.C., *Human Behavior Learning and Transfer.* CRC Press, 2005.

[13] H. Liu, J. Salerno and M.J. Young, *Social Computing, Behavior Modeling, and Prediction.* Springer, 2008.

[14] L.B. Cao, Y.M. Ou, and P. Yu, "Coupled Behavior Analysis with Applications," *IEEE Transactions on Knowledge and Data Engineering*, vol. 24, no. 8, pp. 831-843, 2012.

[15] M. Oliver and A.P. Pentland, "A Bayesian Computer Vision System for Modeling Human Interactions.," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, pp. 1378–1392, 2012.

[16] C. Daskalaki and G. Skiadopoulos, "Should investors include commodities in their portfolios after all? new evidence.," *Journal of Banking & Finance*, vol. 35, pp. 2606-2626, 2011.

[17] A. Sullivan and M. S. Steven, *Economics: Principles in action.* Prentice Hall Publishing, 2003.

[18] M.K. Brunnermeier, "Deciphering the liquidity and credit crunch 2007-2008," *Journal of Economic Perspectives*, vol. 23, pp. 77-100, 2009.

[19] M. Brand, "Coupled hidden markov models for modeling interactive processes," *Technique Report*, MIT Media Lab, 1997.

[20] S. Zhong, and J. Ghosh, "HMMs and coupled HMMs for multi-channel EEG classification," *Proc. IEEE Int. Joint Conf. Neural Networks*, pp. 1154-1159, 2002.

[21] S. Zhong, and J. Ghosh, "A new formulation of coupled hidden markov models," *Technique Report*, University of Texas at Austin, USA, 2001.

[22] C.S. Lin, H.A. Khan R.Y. Chang and Y.C. Wang, "A new approach to modeling early warning systems for currency crises:Can a machine-learning fuzzy expert system predict the currency crises effectively?," *Journal of International Money and Finance*,vol. 27, pp. 1098-1121, 2008.