Coupled Market Behavior Based Financial Crisis Detection

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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 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 makes 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 relationship. 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-relationships between behaviors. The problem of coupled behavior analysis is formally defined in [14].

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

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

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

**Definition 1. Coupled Behaviors** Coupled behaviors $\mathcal{B}_c$ refer to behaviors $\mathcal{B}_{11}, \mathcal{B}_{12}$ that are coupled in terms of relationships $f(\theta(\cdot), \eta(\cdot))$, where $(i_1 \neq i_2) \lor (j_1 \neq j_2) \land (1 \leq i_1, i_2 \leq I) \land (1 \leq j_1, j_2 \leq J_{max})$

$$\mathcal{B}_c = (\mathcal{B}_{11})^n \ast (\mathcal{B}_{12})^n \ast \mathcal{B}_{ij}(\mathcal{E}, \theta, \gamma, \kappa) \bigg| \bigg( \sum_{i=1}^{J_{max}} \sum_{j=1}^{J_{max}} f(\theta(i_1 j_1), \eta(i_1 j_1)) \bigg) \bigg)$$

where $f(\theta(i_1 j_1), \eta(i_1 j_1))$ is the coupling function denoting the corresponding relationships between $\mathcal{B}_{11}, \mathcal{B}_{12}$, $\sum_{i=1}^{J_{max}} \sum_{j=1}^{J_{max}} f(\theta(i_1 j_1), \eta(i_1 j_1)) \bigg) \bigg)$

**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

$$g(\cdot)(f(\cdot) \geq f_0) \geq g_0$$

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 $\pi = \{\pi^{(c)}\}, 1 \leq c \leq C, 1 \leq j \leq N^{(c)}$

$$\sum_{j=1}^{N^{(c)}} \pi^{(c)} = 1$$

- transitional probability $A = \{a^{(c, c')}_i\}, 1 \leq c, c' \leq C, 1 \leq i \leq N^{(c')}$

$$\sum_{c'}^{N^{(c')}} a^{(c, c')}_i = 1$$
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 different financial markets.

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.

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.
Whether a crisis appears using the data-driven method. 3) Crisis detection, which determines the couplings between indicators are captured in the crisis period. We explain how the nonlinear characteristics of the coupled market behavior modeling, namely using CHMM knowledge into training and testing sets. 2) CHMM-based data is further partitioned with the involvement of domain structure that better fits the CHMM analysis. The transformed data converts the transactional data into the behavior-oriented data consists of three major parts: 1) Data preprocessing, which is to determine the coupling function \( g \) corresponding to two different periods. Below, \( CM \) describes the characteristics \( f \) of the two indicators. Indicator correlation \( \text{corr}(I_{i1}, I_{i2}) \) is the Pearson correlation coefficient of the two indicators.

### 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 algorithm respectively. Two models are trained on them respectively. 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

\[
g_{CM}(t)(f_{CM}(\cdot)) \geq g_{NM}(t)(f_{NM}(\cdot)),
\]

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.

#### 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 \( CI_{i1,j1} \) refers to the correlations of indicator \( I_{i1} \) with indicators in other markets, where \((i_1 \neq i_2) \land (1 \leq i_1, i_2 \leq m) \land (1 \leq j_1, j_2 \leq n)\). Here \( \text{corr}(\cdot) \) is the Pearson correlation coefficient of the two indicators.

\[
CI_{i1,j1} = \sum_{i_1,i_2=1}^{m} \sum_{j_1,j_2=1}^{n} \text{corr}(I_{i_1,j_1}, I_{i_2,j_2})
\]

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

\[
PI' = (PI - PI_{\text{min}})/(PI_{\text{max}} - PI_{\text{min}})
\]

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

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**TABLE I**

**Correlations of Indicators in Three Markets**

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Baa Spread</th>
<th>TED Spread</th>
<th>DJIA</th>
<th>GOLD</th>
<th>SP500</th>
<th>WTI OIL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pearson Correlation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sig.(2-tailed)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baa Spread</td>
<td>Pearson Correlation</td>
<td>.987**</td>
<td>1</td>
<td>-0.060</td>
<td>.282**</td>
<td>-.129**</td>
</tr>
<tr>
<td></td>
<td>Sig.(2-tailed)</td>
<td>.000</td>
<td>.080</td>
<td>.258**</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>TED Spread</td>
<td>Pearson Correlation</td>
<td>.000</td>
<td>.000</td>
<td>1</td>
<td>.078*</td>
<td>.133*</td>
</tr>
<tr>
<td></td>
<td>Sig.(2-tailed)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DJIA</td>
<td>Pearson Correlation</td>
<td>-.060</td>
<td>-.078*</td>
<td>.024</td>
<td>.234***</td>
<td>-.016</td>
</tr>
<tr>
<td></td>
<td>Sig.(2-tailed)</td>
<td>.080</td>
<td>.000</td>
<td>1</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>GOLD</td>
<td>Pearson Correlation</td>
<td>.582**</td>
<td>0.258**</td>
<td>.000</td>
<td>.000</td>
<td>-.040</td>
</tr>
<tr>
<td></td>
<td>Sig.(2-tailed)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SP500</td>
<td>Pearson Correlation</td>
<td>-.129**</td>
<td>-0.133*</td>
<td>-0.016</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>Sig.(2-tailed)</td>
<td>.000</td>
<td>.000</td>
<td>.647</td>
<td>.242</td>
<td>.000</td>
</tr>
<tr>
<td>WTI OIL</td>
<td>Pearson Correlation</td>
<td>-.250**</td>
<td>-0.255**</td>
<td>-0.018</td>
<td>.049</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>Sig.(2-tailed)</td>
<td>.000</td>
<td>.595</td>
<td>.000</td>
<td>.000</td>
<td></td>
</tr>
</tbody>
</table>
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:

\[
\text{Financial crisis analysis} \rightarrow \text{CHMM modeling} \quad (7)
\]

\[
\Phi(\cdot)|\text{observation} \rightarrow A \quad (8)
\]

\[
\Phi(\cdot)|\text{transition} \rightarrow B \quad (9)
\]

\[
f(\Phi(\cdot)) \rightarrow \Theta \quad (10)
\]

\[
\Phi(\cdot)|\text{prior} \rightarrow \pi \quad (11)
\]

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 \( S_t^{(c)} \) is the hidden state of model \( c \) at time \( t \). The number of parameters is \( N^C \) when the number of hidden states 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 focuses 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

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

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:

\[
P(\{y|x_1, x_2, \ldots, x_C\}) = P(\{y|x_1, x_2, \ldots, x_C\}) = \frac{P(x_1, y|x_1, x_2, \ldots, x_C)}{P(x_1, x_2, \ldots, x_C)}
\]

\[
= \omega_1 P(y|x_1)
\]

here for simplicity, \( y \) represents the current state and \( x \) refers to for previous states, \( \omega_1 = \frac{P(x_1, \ldots, y|x_1, y_2, \ldots, y_C)}{P(x_1, x_2, \ldots, x_C)} \).

Similarly, we can obtain

\[
P(\{y|x_1, x_2, \ldots, x_C\}) = \omega_1 P(y|x_1) = \omega_2 P(y|x_2) = \cdots = \omega_C P(y|x_C)
\]

Then the joint conditional probability can be rewritten as

\[
P(\{y|x_1, x_2, \ldots, x_C\}) = \sum_{c=1}^{C} \theta_{c} P(y|x_C)
\]

\(^1\)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 focuses on the type of CHMM that the state of one chain at time \( t \) depends on the states of all chains (including itself).
The coupled market behaviors in the testing set can be seen are deployed on the testing set to detect the financial crisis. Crises and non-crisis period, separately. The trained models for the two parts. Models are trained on the training set to period, the time period associated with the crisis is labeled considering the financial events and performance at that time.

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.

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A. The Data Sets

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

V. EXPERIMENTS

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 \( X_j^{(i)}(1 \leq j \leq n) \) is said to signal a financial crisis at time \( t \) when it crosses an ‘optimal threshold’ \( \overline{X} \),

\[
\begin{align*}
\{ S_i^j = 1 \} &= \{ S_i^j, |X_i^j| > |\overline{X}_i| \} \quad (18) \\
\{ S_i^j = 0 \} &= \{ S_i^j, |X_i^j| < |\overline{X}_i| \} \quad (19)
\end{align*}
\]

where \( S_i^j = 1 \) represents indicator \( j \) used in signaling the crisis at time \( t \), and \( S_i^j = 0 \) 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],

\[
I_t = \sum_{j=1}^{n} S_i^j \quad (20)
\]

here \( I_t \) 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 \( t \),

\[
P_t = P(Y_t = 1) = E(Y_t|X) = \frac{1}{1 + e^{-b_0 + b_1 x_1 + \ldots + b_n x_n + \epsilon}} \quad (21)
\]

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

\[
\text{Compute the likelihood of } b^k \text{ given the models } \{b^1, b^2, \ldots, b^M\}, \text{ and } \{b^1, b^2, \ldots, b^N\}; \text{ if } CL(b^k | CM) \geq CL(b^k | NM) \text{ then } b^k \rightarrow CS; \text{ else } b^k \rightarrow NS;
\]

<table>
<thead>
<tr>
<th>Market</th>
<th>Indicator 1</th>
<th>Indicator 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commodity Market</td>
<td>Gold price</td>
<td>WTI Crude Oil Price</td>
</tr>
<tr>
<td>Equity Market</td>
<td>S&amp;P 500</td>
<td>DJIA</td>
</tr>
<tr>
<td>Interest Market</td>
<td>The TED Spread</td>
<td>The Baa Spread</td>
</tr>
</tbody>
</table>

B. Baseline Approaches

\[
I_t = \sum_{j=1}^{n} S_i^j \quad (20)
\]

here \( I_t \) 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.

\[
P_t = P(Y_t = 1) = E(Y_t|X) = \frac{1}{1 + e^{-b_0 + b_1 x_1 + \ldots + b_n x_n + \epsilon}} \quad (21)
\]

\[
\text{here } x_i(1 \leq i \leq n) \text{ is explanatory variable, } \epsilon \text{ is the error term. Then the log-likelihood function can be written as}
\]
follows:

\[ l(\theta) = \sum_{t=1}^{T} Y_t (\ln(P_t)) + (1 - Y_t) (\ln(1 - P_t)) \]  \hspace{1cm} (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.

\[ \text{Overall Accuracy} = \frac{TN + TP}{TP + FP + FN + TN} \]  \hspace{1cm} (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.

\[ \text{Precision} = \frac{TP}{TP + FP} \]  \hspace{1cm} (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>
<thead>
<tr>
<th>Approach</th>
<th>Overall Accuracy</th>
<th>Precision</th>
<th>Type I error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal</td>
<td>0.5714</td>
<td>0.9057</td>
<td>0.3962</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.7895</td>
<td>0.6585</td>
<td>0.3415</td>
</tr>
<tr>
<td>ANN</td>
<td>0.6857</td>
<td>0.7170</td>
<td>0.2830</td>
</tr>
<tr>
<td>CHMM</td>
<td>0.8571</td>
<td>0.6038</td>
<td>0.0943</td>
</tr>
</tbody>
</table>

![Fig. 4. Overall Accuracy of Four Approaches](image)

![Fig. 5. Precision of Four Approaches](image)

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 a 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.

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