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AN EARLY WARNING SYSTEM FOR FINANCIAL CRISES: A TEMPORAL CONVOLUTIONAL NETWORK APPROACH

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Abstract. The widespread and substantial effect of the global financial crisis in history underlines the importance of forecasting financial crisis effectively. In this paper, we propose temporal convolutional network (TCN), which based on a convolutional neural network, to construct an early warning system for financial crises. The proposed TCN is compared with logit model and other deep learning models. The Shapley value decomposition is calculated for the interpretability of the early warning system. Experimental results show that the proposed TCN outperforms other models, and the stock price and the real GDP growth have the largest contributions in the crises prediction.

Keywords: financial crisis, deep learning, TCN, the Shapley value.

JEL Classification: G01, C45, C53.

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1. Introduction

Financial crises can have far-reaching economic and social consequences that reverberate across various sectors, impacting individuals, businesses, and governments alike (Demirgüç-Kunt & Detragiache, 1998; Hoggarth et al., 2002). The consequences of these crises often lead to increased unemployment, lower living standards, and social unrest. These adverse effects can extend beyond the financial realm, destabilizing society, altering political landscapes, and undermining public faith in financial institutions and the broader economy (Ollivaud & Turner, 2014). Therefore, a crucial task for policymakers is to recognize the financial crises in a timely manner. This allows them to take proactive measures, such as deploying counter-cyclical macroprudential policies, to tackle rising risks before they become full-blown crises (Giese et al., 2014; Cerutti et al., 2017). However, there are several challenges in identifying financial crises. Firstly, financial crises are intricate and multifaceted events that are typically driven by a combination of financial factors, which makes it difficult to identify their occurrence. Secondly, financial markets are inherently dynamic and the relationships among various economies can change over time, making traditional indicators less effective in predicting crises. Thirdly, there is often a lack of comprehensive and timely data, making it challenging for policymakers to make informed and pre-emptive decisions on potential financial crises. Furthermore, external shocks, such as geopolitical events, technological advancements, and global economic trends, can have a significant impact on the stability of financial systems, making it difficult to analyse their effects on financial crises. Lastly, investor behaviours and regulatory responses can all influence the likelihood of financial crises, making it challenging to create a purely objective early warning system. Despite these challenges, researchers continue to explore better early warning systems using macroeconomic indicators, financial market data, and qualitative assessments. By incorporating multiple indicators, efforts are made to enhance the reliability of early warning predictors in identifying financial crises.

In this paper, our focus revolves around exploring the capabilities of the temporal convolutional network (TCN) as the early warning model for financial crises. TCN is a deep learning architecture that has gained plenty of attention in recent years due to its ability to effectively capture temporal dependencies and patterns in sequential data (Bai et al., 2018), making it a promising model for financial crises early warning. By applying the TCN model, we aim to assess its performance in identifying the early warning signals preceding financial crises. The performance is compared with other sequential models commonly used in the financial domain to assess its superiority in predicting financial crises. Recent years, neural networks are widely recognized as universal function approximators, offering a solution to the problem of model misspecification commonly found in parametric models in economic studies (Kuan & White, 1994). This is particularly relevant in the financial crisis prediction problem, since crises are inherently nonlinear phenomena. By exploring different models, we aim to provide a better early warning system (TCN) for financial crises. By benchmarking TCN models against these standard early warning systems, we can assess their early warning performance and interpretability, shedding light on the suitability of TCN for applications in financial crisis prediction.

We will defer the discussion of existing early warning literature to focus on exploring the topic in greater detail in the subsequent section. For now, it is sufficient to understand that these early warning models typically generate predictions by analyzing a combination of financial variables, which makes this problem to be a multivariate time series sequence problem. When it comes to choosing a model for a multivariate time series prediction problem, there exist many candidates. For neural network candidates, the multilayer perceptron (MLP) is considered as a basic form that offers the ability to do the multivariate time series prediction (Barron, 1993). The main advantage of the MLP is that it is able to achieve a noteworthy prediction performance with a relatively lower number of components compared to alternative methods (Pinkus, 1999), which means that it can effectively capture complex relationships using fewer parameters. This ability makes it an attractive choice for various applications. By leveraging its capabilities, researchers can employ MLPs to tackle a wide range of tasks, including financial analysis, forecasting, and decision-making. By analyzing a range of observations, Holopainen and Sarlin (2017) indicate that MLPs have the ability to provide precise predictions of financial crises. At the same time, in the modeling sequence problems, recurrent neural networks (RNN) are designed to handle sequential data and capture temporal behavior effectively. Elman (1990) and Binner et al. (2004) have shown that simple RNNs can generate comparable forecasts on sequential problem with traditional models. There exist two widely used variations of RNNs: Long-Short Term Memory (LSTM) networks and Gated Recurrent Units (GRU) networks. The LSTM networks, introduced by Hochreiter and Schmidhuber (1997), can capture long-term dependencies effectively. The GRU networks, proposed by Cho et al. (2014), improve computational efficiency by utilizing gating mechanisms that control the flow of information. While these advanced RNN models have proven their effectiveness in various domains, where they can capture long-term dependencies and retain important information from past time steps, the TCN was proposed by Bai et al. (2018) to further modeling time series data with better performance. This is achieved by utilizing convolutional neural networks in capturing spatial relationships and extend them to handle sequential data. Unlike RNNs which rely on memory cells, TCNs utilize one-dimensional dilated convolutions which allow TCNs to effectively capture temporal dependencies within a sequence. One notable advantage of TCNs is the parallelization capability with dilated convolution which leads to efficient computation, making TCNs applicable for long sequences. To determine whether those sequential prediction models are beneficial in predicting systemic financial crises and whether TCN model can show better prediction results, it is necessary to empirically analyze the problem using data. We construct different early warning models for comparisons on the Jórda-Schularick-Taylor macro-history database (Jordà et al., 2016), which contains the annual financial data of 17 economies during 1870–2016. In this dataset, the systematic financial crisis index is a zero/one dummy, with one indicates the occurrence of a systemic financial crisis at the time t, and zero indicates no financial crisis. The AUC value is then proposed to evaluate the predictive performances of different models, including multilayer perceptron (MLP), long-short term memory (LSTM) and gate recurrent unit (GRU). The results focus on evaluating the early warning capability of TCN in the following task: forecasting financial crisis one year ahead. We set fine-tuning process for each models using appropriate parameters. Then, by examining AUC for each model, we show that TCN model outperforms other traditional models. This superior performance of the TCN highlights their potential use in dealing with financial crises.

The advantage in performance can be attributed to three key factors: Firstly, the TCN processes sequential data using time-domain convolutions, making it computationally efficient and faster while RNN processes sequential data by using the output of the previous state as input for the next state. Secondly, the network structure of TCN makes the receptive field (the region of the input that affects the output at a given time) in TCN is larger than that in RNN which only encode the current state of the sequence. Thirdly, the stacked layers of temporal convolutions in TCN can capture long-range dependencies much more efficiently than RNN which capture the long-term dependencies with the expense of computational performance. These advantages motivate us to propose the TCN as the early warning system in financial crisis prediction which also shows better results in this paper. Our main contributions are described as follows: Firstly, we propose TCN model for the financial crisis prediction. Secondly, we consider a cross-country and sequential data as the experimental data, which is because the financial crisis of one country propagate to the crises of other countries. Thirdly, the comparisons between different deep learning models and TCN are constructed based on AUC values, which shows the outperformance of TCN model in the financial crisis prediction. Fourthly, the optimal hyperparameters of deep learning model are constructed to adaptive optimize the models to obtain a stable and reasonable results. Lastly, the Shapley value decomposition is used to interpret the TCN model, which demonstrates the importance and significance of the stock price and the real GDP growth in TCN prediction model.

This paper mainly consists of the following parts: Section 2 reviews the researches on different early warning models on crisis. Section 3 introduces the detail of models in this paper. Section 4 explains the data and the experimental frameworks. Section 5 presents the empirical results. Section 6 concludes the whole paper.

2. Literature review

Although financial crises have occurred throughout history, the use of early warning models is a relatively recent developed in the late 1990s, which was pioneered through the research efforts in Demirgüç-Kunt and Detragiache (1998) and Kaminsky and Reinhart (1999). At first, there were two commonly used methods in the field of financial crisis analysis: the signal method and the logit model. The signal method uses certain signals that could potentially indicate the likelihood of a financial crisis occurring. These signals could include variables such as exchange rate fluctuations, stock market performance, or changes in interest rates, etc (Wheelock & Wilson, 2000; Domaç & Martinez Peria, 2003; Von Hagen & Ho, 2007; Büyükkarabacak & Valev, 2010; Bordo & Meissner, 2012; Duca & Peltonen, 2013; Krishnamurthy & Muir, 2017; Greenwood et al., 2022). Wheelock and Wilson (2000) identifies the factors that contribute to the failure of U.S. banks, finding that the risk of failure increases while probability of acquisition decreases, and that banks with lower equity-to-assets ratios are more likely to be acquired. Domaç and Martinez Peria (2003) investigates the impact of exchange rate regimes on banking crises, finding that adopting a fixed exchange rate regime decreases the likelihood of crises but increases their real costs in developing countries. Von Hagen and Ho (2007) presents an index of money market pressure that helps identify banking crises based on excessive liquidity demand, which reveals that a slowdown in real GDP, low real interest rates, high inflation, large fiscal deficits, and overvalued exchange rates are indicators that precede banking crises, while the impact of monetary base growth on crises probability is minimal. Greenwood et al. (2022) finds that high levels of credit and asset price growth are associated with a significantly increased probability of a financial crisis. Qi et al. (2022) examines the impact of macroprudential policies on house prices and household consumption in China which is one of the main factors that may lead to financial crises. Ionescu et al. (2023) focuses on the need for a regional approach within the European Union in response to multiple crises including financial crises by analyzing socioeconomic indicators. These findings challenge that financial crises as unpredictable events and suggest the importance of implementing policies to maintain the stable indicators for different financial factors. Although those researches point out different signals for financial crises, they rarely consider the earning warning factors for financial crises. Büyükkarabacak and Valev (2010) examines the impact of private credit expansions on banking crises, which suggest that rapid growth in household credit is a strong early warning predictor of banking crises. Duca and Peltonen (2013) introduces a framework that predicts systemic risks. The proposed framework enhances the accuracy of forecasting systemic financial crises and demonstrates good performance in predicting the financial crisis. Krishnamurthy and Muir (2017) finds that crises are characterized by a sudden increase in credit spreads and that the severity of the crisis can be forecasted by credit losses and the fragility of the financial sector, while recessions following crises tend to be severe and lengthy.

On the other hand, the logit model was a statistical technique used to analyse the probability of a binary outcome, such as the occurrence of a financial crisis. This model would incorporate various factors and variables to assess the likelihood of a crisis based on historical data (Demirgüç-Kunt & Detragiache, 1998; Canbas et al., 2005; Bussiere & Fratzscher, 2006; Davis & Karim, 2008a, 2008b; Caggiano et al., 2014, 2016; Filippopoulou et al., 2020). Demirgüç-Kunt and Detragiache (1998) examines the causes of systemic banking crises in various countries between 1980 and 1994 though logit model, which indicate that weak macroeconomic conditions, high real interest rates, vulnerability to balance of payments crises, explicit deposit insurance schemes, and weak law enforcement contribute to these crises. Canbas et al. (2005) introduces an integrated early warning system to identify troubled banks, using financial ratios and logit model, which suggests that implementing the early warning system in bank supervision could lead to significant cost reductions. Bussiere and Fratzscher (2006) presents a novel early warning model based on multinomial logit regression to improve the prediction of financial crises, which demonstrates higher accuracy in forecasting crises in a sample of 20 open emerging markets. Davis and Karim (2008a, 2008b) suggests that a combination of logit and signal extraction approaches can be valuable for global and country-specific early warning system in bank crises prediction, emphasizing the importance of considering policy objectives and striking a balance between accurate crisis predictions and false alarms. While the aforementioned literatures focus on basic logit model, the following researches consider using multinomial logit models for financial crises to better analyse the financial crises problem. Caggiano et al. (2014) develops a multinomial logit model to improve the predictive accuracy for banking crises in Sub-Saharan Africa, which highlight the association of crises with low economic growth, liquidity reduction in the banking system, and widening foreign exchange net open positions. Caggiano et al. (2016) compares binomial and multinomial logit models to build early warning systems for systemic banking crises, finding that the multinomial logit model performs better. Filippopoulou et al. (2020) evaluates the predictive validity of risk indicators for systemic banking crises using a multivariate binary logit early warning model, which show that the specific banking variables and financial stress indicators, are important in forecasting crises up to four years in advance. Truong et al. (2022) develops an early warning system for financial crises with a focus on small open economies with logit models, which indicates that the extracted factors have better predictivity than the long history indicators. Both the signal method and the logit model were considered standard approaches and were widely used by researchers and analysts to understand and predict financial crises. These methods lead to further the development of more robust and sophisticated models in the subsequent years.

Recently, other research articles have explored the application of machine learning methods in financial crisis prediction. These methods include decision trees, neural networks, random forests, support vector machines, and various deep learning models (Tam & Kiang, 1990; Tam, 1991; Olmeda & Fernández, 1997; Huang et al., 2004; Ravi & Pramodh, 2008; Boyacioglu et al., 2009; Duttagupta & Cashin, 2011; Davis et al., 2011; Manasse et al., 2013; Joy et al., 2017; Ward, 2017; Holopainen & Sarlin, 2017; Alessi & Detken, 2018; Ristolainen, 2018; Casabianca et al., 2019; Beutel et al., 2019; Tölö, 2020; Bluwstein et al., 2023). Tam and Kiang (1990) and Tam (1991) introduce a simple neural network approach for predicting bank failures and compares it with other existing prediction methods, which highlight that neural networks are a competitive tool for assessing the financial condition of banks. To further investigate whether the machine learning models can outperform the basic statistical models. Olmeda and Fernández (1997) compares parametric and nonparametric classifiers for bankruptcy prediction and finds that neural networks outperform other individual classifiers, suggesting the use of multiple techniques for accurate risk rating systems. Moreover, Huang et al. (2004) explores the use of support vector machines for corporate credit rating analysis, achieving comparable prediction accuracy with a benchmark neural network model. As the growing literatures on neural networks, more researches try to use neural network models to improve the accuracy of the financial crisis prediction. Ravi and Pramodh (2008) presents a novel principal component neural network architecture and a feature subset selection algorithm for bankruptcy prediction in commercial banks. Boyacioglu et al. (2009) investigates the prediction of bank financial failures in a Turkish case using a comprehensive approach of neural network techniques, support vector machines, and multivariate statistical methods. Ristolainen (2018) presents an early warning system for banking crises using a regional-specific artificial neural network model which outperforms traditional logit regression models and successfully predicts all banking crises in a 24-month horizon, especially when considering regional data. Despite the development in neural network structure, there also comes some classification models in early warning models. Duttagupta and Cashin (2011) examines the factors that contribute to banking crises in emerging market and developing countries using a binary classification tree. Joy et al. (2017) utilizes the classification and regression tree methodology to identify key indicators preceding banking and currency crises in advanced economies. Ward (2017) presents the use of classification tree ensembles to enhance the forecasting of banking crises. Alessi and Detken (2018) proposes an early warning system using a random forest ensemble technique to predict banking crises and identify excessive credit growth and aggregate leverage. Since the fast developments on the statistical and machine learning models in the crises prediction, Holopainen and Sarlin (2017) compares statistical and machine learning methods for crisis prediction and finds that advanced machine learning methods, such as k-nearest neighbours and neural networks, outperform conventional statistical approaches. The study also highlights the effectiveness of ensemble learning techniques in improving predictive performance for early-warning systems. Casabianca et al. (2019) presents an early warning system to predict systemic banking crises which demonstrates that machine algorithms outperform traditional logit models in terms of predictive accuracy, highlighting the build-up of pre-crisis macroeconomic imbalances in advanced countries. To further improve the forecasting accuracy on the financial crises using deep learning techniques, Tölö (2020) explores the recurrent neural networks to predict systemic financial crises which demonstrate that these models outperform traditional logistic regression models. Antulov-Fantulin et al. (2021) examines the predictability of municipal bankruptcies in Italy from 2009 to 2016 using machine learning techniques based on financial, institutional, socio-demographic, and economic data. Liu et al. (2022) constructs early warning systems for financial crises based on the logistic model and seven machine learning methods. This study shows a better performance in out-of-sample tests with machine learning methods. Bluwstein et al. (2023) employs machine learning techniques to develop early warning models for financial crisis prediction, which demonstrates the superiority of nonlinear machine learning models over logistic regression in out-of-sample predictions.

To summarize the above discussions, Table 1 is given to simplify the research papers, the methods and main contributions of those literatures.

Table 1. Summary of the literatures

Research Papers	Methods	Main Contributions
Wheelock and Wilson (2000), Domaç and Martinez Peria (2003), Von Hagen and Ho (2007), Büyükkarabacak and Valev (2010), Bordo and Meissner (2012), Duca and Peltonen (2013), Krishnamurthy and Muir (2017), Greenwood et al. (2022)	Signals	Equity-to-assets ratios Money market pressure index Credit and asset price growth Private credit expansions Credit losses
Demirgüç-Kunt and Detragiache (1998), Canbas et al. (2005), Bussiere and Fratzscher (2006), Davis and Karim (2008a, 2008b), Caggiano et al. (2014), Caggiano et al. (2016), Filippopoulou et al. (2020), Truong et al. (2022)	Logit model	Logit model Binomial logit model Multinomial logit regression Logit and signal extraction Multivariate binary logit model
Tam and Kiang (1990), Tam (1991), Olmeda and Fernández (1997), Huang et al. (2004), Ravi and Pramodh (2008), Boyacioglu et al. (2009), Duttagupta and Cashin (2011), Davis et al. (2011), Manasse et al. (2013), Joy et al. (2017), Ward (2017), Holopainen and Sarlin (2017), Alessi and Detken (2018), Ristolainen (2018), Casabianca et al. (2019), Beutel et al. (2019), Tölö (2020), Antulov-Fantulin et al. (2021), Liu et al. (2022), Bluwstein et al. (2023)	Machine learning model	Decision trees Random forests Support vector machines Ensemble learning techniques Neural networks Recurrent neural networks

3. Materials and methods

In this section, we first simply discuss the theory of MLP, RNN, LSTM, GRU. Then, we further introduce the theory of the TCN model. The MLP is a feedforward neural network which is used for non-sequential data that does not have any temporal connections or memory. RNN, LSTM, and GRU are recurrent neural networks to process sequential data. RNN suffers from the vanishing gradient problem, while LSTM and GRU address this issue by using gating mechanisms. LSTM and GRU are both variants of RNN, in which, LSTM has separate input, output, and forget gates, while GRU has a reset and an update gate. TCN is a temporal convolutional network that uses convolutions to process sequential data which uses dilated convolutions to capture temporal dependencies. All these architectures are can handle sequential data. RNN, LSTM, GRU, and TCN address the limitations of MLP by incorporating memory or convolutions to capture temporal dependencies. LSTM and GRU are both improvements, allowing better long-term memory retention. TCN approaches sequence modeling from a different perspective by leveraging convolutions, which enables parallel processing of multiple points in the sequence.

3.1. MLP

The MLP is a simple feed forward structured artificial neural network, which consists of an input layer, an output layer and multiple hidden layers. As shown in the Figure 1, neurons are fully connected between different layers, and except for the input layer, each layer has several units with a non-linear activation function.

3.2. RNN

The RNN is a special type of an artificial neural network adapted to ordinal or temporal problems, such as natural language processing, language translation, speech recognition and sentiment analysis. The "memory" in RNN could influence the current inputs by the information from prior inputs and then affect outputs, while traditional deep neural networks just suppose the inputs and outputs are independent. As presented in Figure 2, RNN can make use of information in long sequences, but in practice, the standard RNN can only review a few steps due to the problem of gradient vanishing or explosive.

3.3. LSTM

The LSTM network is a special kind of RNN, which is proposed by Hochreiter and Schmidhuber (1997) as a solution to the vanishing gradient and the learning long-term dependencies problems. In standard RNN, the recurrent module normally has a simple structure. However, as shown in Figure 3, the structure of LSTM is more complicated and includes three gates with the forget gate, the input gate, the output gate and a memory storage (cell).

3.4. GRU

The GRU is an improvement over the standard RNN, which is introduced by Cho et al. (2014) with similar purpose as the LSTM but fewer paraments. The GRU includes a hidden state and two gates with the reset gate and the update gate to control the flow of information. The reset gate is used to decide what past information to forget. The update gate controls to determine what extent information needs to be passed along to the future. Figure 4 shows an example of GRU.

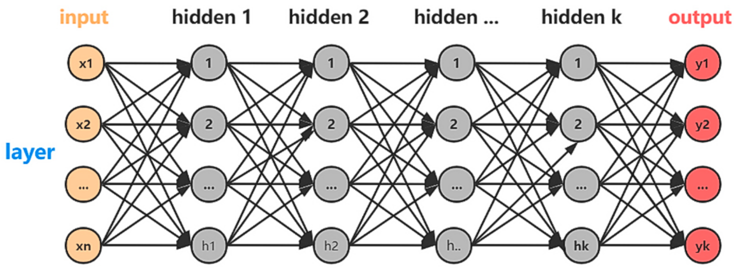

Figure 1. An example of multilayer perceptron

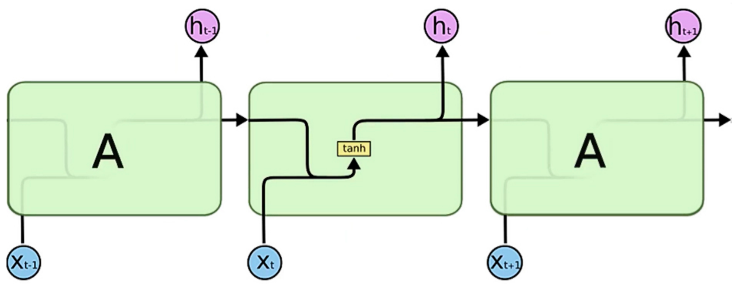

Figure 2. A basic recurrent neural network (Colah's blog, 2015)

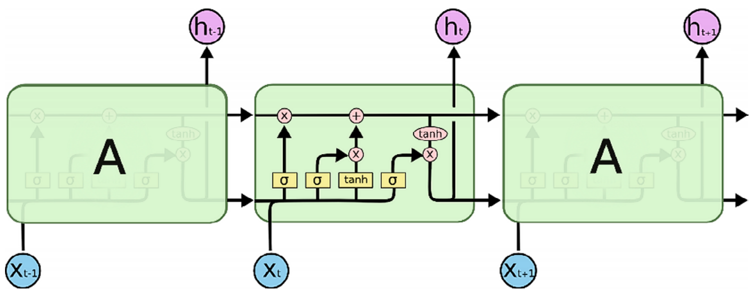

Figure 3. A basic long short term memory networks (Colah's blog, 2015)

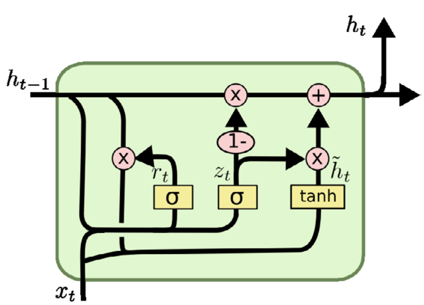

Figure 4. A gated recurrent unit cell (Colah's blog, 2015)

3.5. TCN

The TCN is a convolutional neural network (CNN) structure, which is proposed by Bai, Kolter, and Koltun (2018) for sequence modeling. Different from the process of RNN, the TCN uses causal convolutions where the output at time *t*, is only influenced by present and past inputs. And the model also uses a 1D fully-convolutional network architecture to take each layer with the same length as the input layer by adding spatial pooling (Figure 5). This equation shown below.

$$\left(F * X\right)_{\left(x_t\right)} = \sum_{k=1}^{K} f_t x_{t-K+k}. \tag{1}$$

Then, the TCN adapts the dilated convolutions which has a hyperparameter dilation rate, which refers to the number of kernel intervals (dilatation rate equals 1 in standard CNN). Formally, for an input sequence $X = (x_1, x_2, ..., x_T)$, a filter $F = (f_1, f_2, ..., f_K)$ and the dilated convolution at x_t with the dilatation rate d, the definition of the dilated convolution is:

$$\left(F *_d X\right)_{\left(x_t\right)} = \sum_{k=1}^{K} f_k x_{t-\left(K-k\right)d}. \tag{2}$$

Specifically, when using dilated causal convolution, it usually expands the receptive filed by increasing the dilation rate d in network depth (i.e., $d = O(2^i)$ at level i of the network) and the filter sizes k, since the receptive filed in one layer is $(k - 1)d$. A direct TCN structure can be seen in Figure 6 with kernel size = 2 and dilations rate = [1, 2, 4, 8]:

Moreover, TCN applies a generic residual block to add a branch which leads out to a series of transformations $\mathcal{F}\left(x\right)$ and the input x with the activation functions added on residual blocks as the final output.

$$\text{o} = \text{Activation}\left(x + \mathcal{F}\left(x\right)\right). \tag{3}$$

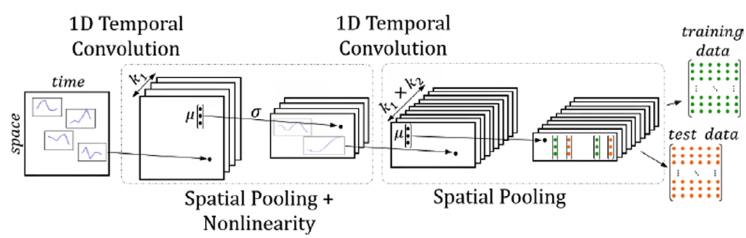

Figure 5. A basic temporal convolutional network with spatial pooling units (Firat et al., 2015)

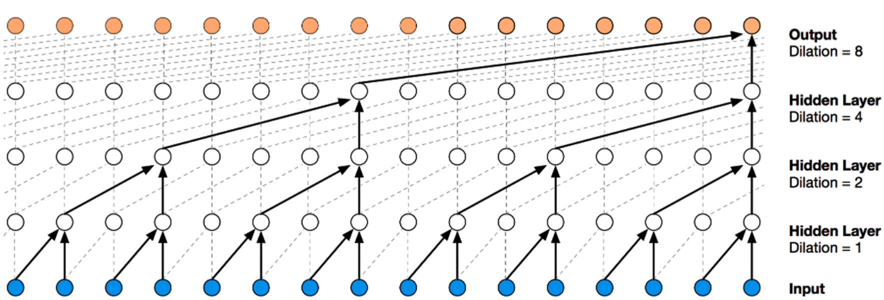

Figure 6. A dilated causal convolution with dilation factors d = 1, 2, 4, 8 and filter size k = 2

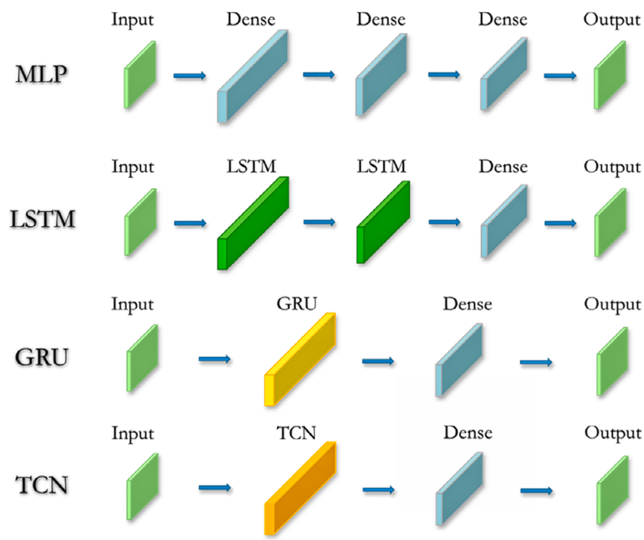

Figure 7. The designed model structure: MLP, LSTM, GRU, TCN

So far, we have learned the principle of the models used in this paper in previous subsections. The design of our employed research methods is given by Figure 7 to illustrate the basic structures of MLP, LSTM, GRU, TCN which are used in this paper.

4. Data analysis

4.1. Crisis variable

This paper uses Jórda-Schularick-Taylor macro crisis database (Jordà et al., 2016), which covers 17 countries from 1870 to 2016: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the USA and the UK. The dataset defines systemic financial crises as "events during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions" (Schularick & Taylor, 2009).

In this dataset, the dependent variable (the systemic financial crisis) is a dummy variable which is set to be 1 when one country starts a systemic financial crisis at a particular year. The specific dependent variable is defined as follows specifically. For a crisis database, $C_{t,n}$ is 1 if the crisis occurs in country N at time t + 1, otherwise 0. Since financial crisis is long-lasting, the variables relevant to crisis after one year is still in a state of crisis, which is called the crisis duration bias (Caggiano et al., 2014). Hence, we remove the relevant indicators corresponding to the post-crisis period in the dataset in order to alleviate the crisis duration bias. Furthermore, the prediction of a crisis at time t is conducted at time t – 1, wherein a one-year ahead forecast is made utilizing the available predictor variables at time t – 1. This demonstrates the early warning capability of the suggested model, which holds practical utility.

Overall, the data lists a total of 83 financial crises. The financial crises trending over time is shown in Figure 8, which also shows that the financial crises were common between World War II (1870–1939), with 56 crises. After the World War II, the financial sector was relatively stable and there was no financial crisis for a long time until it broke out again in the 1980s. It's probably relevant to the end of the Bretton Woods era in 1973, which widened the external imbalances. After 1980s, the global financial system has become increasingly complex and widely fluctuated with the opening of financial market. And in recent 40 years, there exist three financial crises which also has been shown in Figure 8: (i) Savings and loan crisis (1987–1991); (ii) The Asian financial crisis (1997–1998); (iii) The Subprime Mortgage Crisis (2007–2009). In addition, we can also find that Italy, Denmark and Spain have the greatest number of financial crises, larger than seven, and Canada and Australia have the least, less than two (see Figure 9).

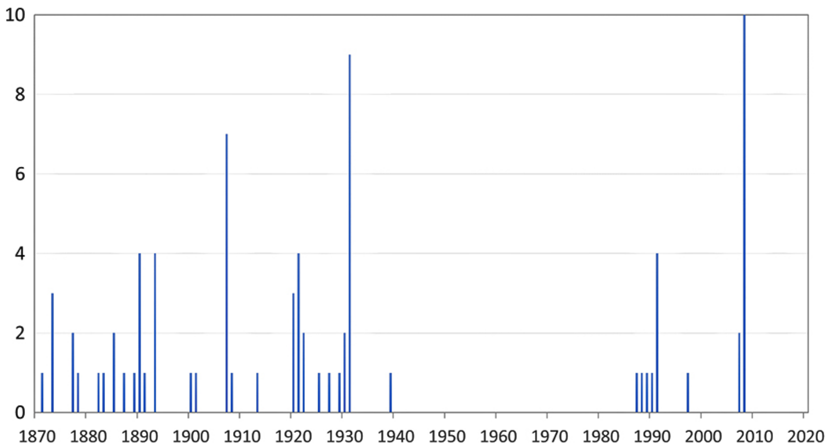

Figure 8. The financial crises in all countries over time. The figure shows that financial crises were mainly concentrated before 1930 and after 1980

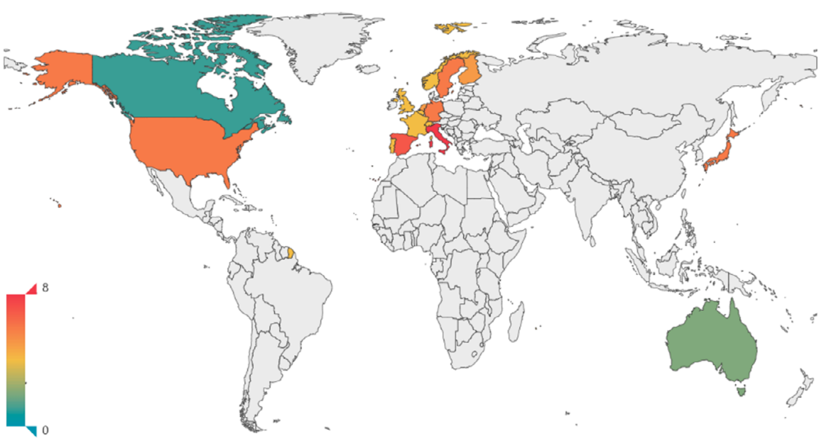

Figure 9. The number of financial crises in each country. It shows the financial crises in 17 countries with other countries marked as grey color. The number of crises that occur increase as the color deepens

4.2. Early warning indicators

A financial crisis is often an amalgam of events, which includes substantial changes in credit volume and asset prices, the external finance supply, the macroeconomic environment notably and others. Our data cover a range of macro financial indicators and we clarify five fundamental factors diving crises. There are five variables used in this study: There are five variables used in this study: (i) Credit volume (loans to non-financial private sector divided by GDP (addr. loans/GDP)). As the level of private loans increase, the ability of an individual to repay the loans is reduced and more risk is involved; (ii) Asset prices (the real stock prices (addr. rsp) and real house prices (addr. rhp)). The rapid run-ups in stock and house price would statistically increase the financial crisis probability; (iii) Indicators of external or global imbalances (current account balances relative to GDP (addr. ca/GDP)). The United States and the euro area countries experienced the severe crises with large current account deficits; (iv) Macroeconomic environment (the annual growth in real GDP (addr. GDP)). These indicators are selected based on their generality and as the key economic channels that affect the likelihood of systemic financial crises. It should be noted that in order to keep the data stable and comparable between countries, we use the growth rate for all explanatory variables. Table 2 gives descriptive statistics of these indicators. And to display the correlation between crisis events and indicators, we take the UK data as an example and visualize the dynamic changes of these five indicators surrounding the systemic financial crisis in Figure 10. From the Figure 10, it can be found that these variables have obvious changes before and after the crisis. Indeed, in order to get more information from sequential series, we consider five lags structure of these five indicators (Schularick & Taylor, 2009; Fricke, 2017).

Table 2. Descriptive statistics for predictors for the period 1870–2016

Variable	mean	median	std.	25th percentile	75th percentile	Observations
loans/GDP	2.07	1.84	7.92	–1.65	5.46	1478
rsp	7.85	5.41	22.01	–4.45	17.85	1478
rhp	7.16	5.41	14.71	1.08	10.83	1478
ca/GDP	–0.22	–0.07	4.24	–2.33	1.89	1478
GDP	2.56	2.48	3.88	0.97	4.25	1478

Note: Units are one-year percentage growth except for ca/GDP, which is a percentage level.

4.3. Evaluation of predictions

Considering that financial crisis prediction results can be interpreted as probability estimates, we apply AUC, the area under the ROC curve, to evaluate the prediction models. In fact, AUC is a commonly used measurement in the early warning literatures on predicting systemic financial crises (Alessi et al., 2015). Specifically, each model outputs a value between 0 and 1 which indicates the probability of the financial crisis. If the output is greater than some threshold h, this means that the model predicts a systemic financial crisis in next year. Otherwise, there will be no crisis. To introduce the definition of AUC used in this paper, we set the following variables. Correctly prediction on a crisis is true positive (TP) and correctly

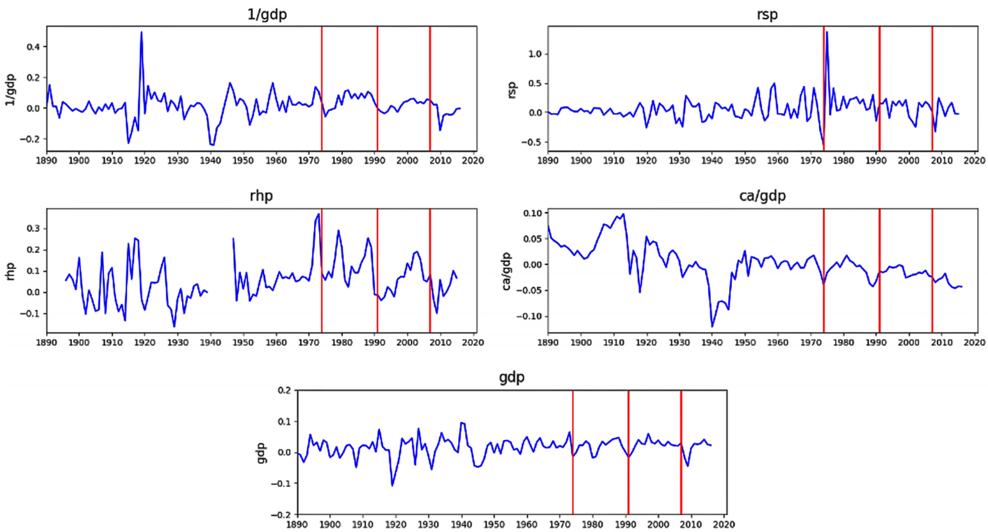

Figure 10. The development of five indicators around the systemic financial crisis in UK. The red lines are financial crises. The horizontal axis only covers data from 1890 to 2016 due to the reason that plenty of data before 1890 are missed

prediction on a normal state is true negative (TN). False alarms are marked as false positives (FP) and missed crises are false negatives (FN). Sensitivity and specificity are defined as TP/(TP+FN) and TN/(TN+FP) respectively. Then, we can plot the ROC curve by using 1-specificity as x-axis and sensitivity as y-axis (see Figure 11).

5. Result

5.1. Description of the problem

The financial crisis prediction problem involves the task of forecasting the likelihood or occurrence of a financial crisis. This challenging problem requires the analysis of the indicators to identify the risk of a crisis. The Jórda-Schularick-Taylor macro-history database is used to analyze the financial crises problem in this paper. Firstly, the factors for early warning financial crises are constructed. Secondly, TCN models are given based on those factors to solve the financial crisis prediction problem. Thirdly, logit model, MLP, LSTM, GRU models are introduced for comparisons. Fourthly, factor drivers are analyzed for the TCN model, which gives detailed explanations help economist in decision-making. In summary, through different parameter tuning technique and prediction AUC values, the empirical results show that the TCN model outperforms the other early warning models.

5.2. Prediction performance

In this paper, we construct TCN, MLP, LSTM and GRU models by using optimal hyperparameters which are given in Table 3. MLP, LSTM and GRU select the hidden layers up to three layers and some other parameters, including optimizers, learning rates and the numbers of units. TCN mainly selects filters and kernel sizes which means that the model has a large enough receptive field and can capture the time series data for financial crisis prediction.

Next, we evaluate the predictive performance of the deep learning model by recalling the parameters of different models summarized in Table 3. During the training of the model, we set the data in 1870–1974 as the train dataset, which used for model fitting and to obtain the weight matrices and bias vectors in section 3. The data from 1975 to 1989 is set as validation dataset which is used to adjust hyperparameters and provide an unbiased estimate of the final tuned model. The validation dataset in the process of training is also used to avoid overfitting by set early stopping strategy. Finally, data from 1990 to 2016 are used as test dataset to evaluate the model's generalization ability. That is, the model is trained in the train dataset and the validation dataset. The actual prediction ability is evaluated by the test dataset. It should be noted that, after we obtain the hyperparameters, we set the train dataset and validation dataset as the new train dataset to fit the model. In the training process, we apply the early-stopping algorithms to avoid overfitting and set the maximum number of epochs to 200. Finally, the test dataset is used to test the actual learning ability of the model. Table 3 shows the selected hyperparameters of each model after the tuning procedure and the corresponding AUC performance. In this study, a maximum of three layers is employed in the neural network architecture. It is well-known that training even a simplistic neural network model can be time-consuming and resource-intensive. In this paper, we utilize multiple factors as inputs, resulting in a multi-dimensional input for the model. Consequently, the training process for the proposed model is more time-consuming. Hence, for the demonstration of the effectiveness of the TCN model, we restrict the number of layers to no more than three with the consideration on time, resource limitations, and the requirement for prediction accuracy.

From Table 4, it can be concluded that the MLP performs better than the logit model with the AUC of 0.64 and the LSTM and GRU outperform MLP, with a prediction accuracy of 0.65 and 0.67. And the TCN shows the best performance and the AUC is 0.76, which is about over 10% higher than LSTM and GRU.

Table 3. Summary of the prediction models

Abbreviation	Model name	Hyperparameters
LR	Logistic regression model	solver = ['liblinear', 'newton-cg', 'lbfgs', 'sag', 'saga']; C = [0.01,0.1,1,10,100]
MLP	Multilayer perceptron	optimizer = ['adam', 'SGD', 'RMSprop']; units = [2,4,8,16,32,64,128]; lr = [1e-1,1e-2, 1e-3]
GRU	Gated Recurrent Unit	units = [2,4,8,16,32,64,128]; lr = [1e-1,1e-2, 1e-3]
LSTM	Long Short-Term Memory	units = [2,4,8,16,32,64]; lr = [1e-1,1e-2, 1e-3, 1e-4]
TCN	Temporal Convolutional Network	nb filters = [2,4,8,16,32,64]; K = [2,4,8,16,32,64]; lr = [1e-1, 1e-2, 1e-3]

Note: lr means learning rate. K means kernel size. The model's tuning is based on the space of possible hyperparameter values.

Table 4. Performance for one-year ahead crisis prediction

Model	Hyperparameters	Performance
LR	default	0.5
MLP	hidden layers = 2, units1 = 4, units2 = 8, lr = 0.001	0.6388
GRU	hidden layers = 1, units = 32, lr = 0.01	0.6731
LSTM	hidden layers = 2, units1 = 32, units2 = 2, lr = 0.001	0.6522
TCN	nb filters = 4, kernel size = 8, lr = 0.1	0.7621
Training period	1870–1989	
Crisis train	37	
N train	1150	
Test period	1990–2016	
Crisis test	17	
N test	328	

Note: The numbers in the table are AUC. A higher value is better. The dependent variable is the pre- crisis dummy defined in Section 4.1. The details of the model in Figure 10. All the models use up to five lags of the same variables: the real GDP, the real stock price, the real house price, current account balances relative to GDP ratio, and the annual growth in real GDP.

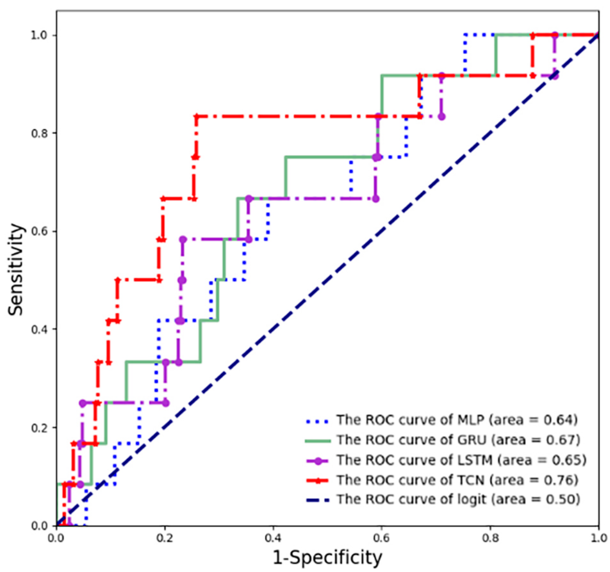

Figure 11. The ROC curve for models. The horizontal axis shows the 1-specificity and the vertical axis shows the sensitivity. AUC is the area under the ROC curve. Well-calibrated probabilities should close the left and upper boundaries of the ROC space

In addition, we also show the ROC curves for all models in Figure 11. These curves illustrate a trade-off between sensitivity and specificity, with increased sensitivity accompanied by decreased specificity. The closer the curve is to the left and upper boundaries of the ROC space, the more accurate the modeling method becomes. It can be seen from the Figure 11 that the ROC curve corresponding to TCN is the closest line to the vertical axis compared to the other models, which means it performs best. And the ROC curves for the LSTM and GRU are almost overlapped and lie approximately in the middle between the ROC curve for the TCN and the logit. Hence, for a given sensitivity level, the TCN generates approximately half the number of false alarms compared to the LSTM and GRU. In particular, at the sensitivity of 0.8, the TCN yields false alarms less than 30% of the time (the horizontal axis corresponds to 0.30), while the LSTM and GRU yield false alarms about 60%. And the MLP and logit produces false alarms nearly 65% and 80% of the time respectively. If we consider a lower and higher sensitivity level, such as the sensitivity level with lower than 0.2 or higher than 0.9, the ROC curves of the TCN, LSTM, GRU and MLP are similar but all are better than logit. Hence, consistent with the high AUC statistics, the TCN has the best performance relative to these models in crises prediction.

5.3. Drivers of TCN predictions

In this subsection, we will try to explore the drivers of the TCN model in the financial crisis prediction. To find the importance of the indicators in TCN models, we train the non-empty subset of the indicators (set loans/GDP, rsp, rhp, ca/GDP, GDP) with the same hyperparameters as given in Table 4. The result is shown in Table 5 and each row presents the model performance with the predictors marked as x. The rows 1–5 in Table 5 show the result with one indicator and the real GDP growth is the most important predictor. The rows 6–15 show the two-indicators models and can conclude that the combination of the stock price and the real GDP growth outperforms the other combinations. The three-indicator combinations (row 16–25) show the same that the combinations with the stock price and the real GDP growth are better than other three-indicator models. The four-indicator models (row 26–30) show the combination without the stock price perform worst. Hence, it can be found that the real GDP growth and the stock price are the essential indicators among the original selected indictors for TCN model in the financial crisis prediction.

To further explain the interpretability of TCN model, we use the Shapley value (Lundberg & Lee, 2017; Shapley, 1952) to calculate the contribution of each additive explanatory variable. The Shapley value is calculated conveniently with the AUC performance measure by a series of subsets in Table 5 and each indicator's Shapley value is presented in Table 6. From Table 6, it can be found that the stock price and the real GDP growth contribute largely in the TCN prediction model and their Shapley value are approximately 0.12. The same conclusion is also obtained from the Table 5. The loans to GDP also contribute, while the house price and the current account to GDP have negligible contributions. And the sum of five indicators' Shapley values measures the difference of actual value (0.7621) and average prediction (0.5). Therefore, we conclude that the stock price and the real GDP growth are the most important predictors in TCN models of crises prediction.

Table 5. Performance for different variable combinations

loans/GDP	rsp	rhp	ca/GDP	GDP	AUC
X	–	–	–	–	0.5806
–	x	–	–	–	0.5968
–	–	x	–	–	0.5343
–	–	–	x	–	0.6028
–	–	–	–	x	0.7473
X	x	–	–	–	0.6505
X	–	x	–	–	0.5911
X	–	–	x	–	0.5578
X	–	–	–	x	0.6596
–	x	x	–	–	0.5477
–	x	–	x	–	0.6310
–	x	–	–	x	0.7114
–	–	x	x	–	0.5037
–	–	x	–	x	0.6845
–	–	–	x	x	0.6206
X	x	x	–	–	0.6599
X	x	–	x	–	0.5843
X	x	–	–	x	0.7154
X	–	x	x	–	0.5514
X	–	x	–	x	0.6734
X	–	–	x	x	0.6263
–	x	x	x	–	0.3921
–	x	x	–	x	0.6569
–	x	–	x	x	0.6569
–	–	x	x	x	0.6865
X	x	x	x	–	0.5907
X	x	x	–	x	0.6962
X	x	–	x	x	0.6458
X	–	x	x	x	0.2440
–	x	x	x	x	0.4798
X	x	x	x	x	0.7621

Note: The table shows that AUC statistics for TCN models with subset of the indicators set {loans/GDP, rsp, rhp, ca/GDP, GDP}. Higher AUC is better. Variables marked with x are included in the model specification of the corresponding row. The dependent variable is the pre–crisis dummy defined in Section 4.1. loans/GDP – loans to non-financial private sector divided by GDP, rsp – the real stock price, rhp – the real house price, ca/GDP – current account balances relative to GDP ratio, GDP – the annual growth in real GDP.

Table 6. Decomposition of AUC for TCN

	loans/GDP	rsp	rhp	ca/GDP	GDP
TCN	0.0644	0.1221	–0.0156	–0.0224	0.1135

Note: The Shapley value decomposition of AUC is calculated directly from the formula $\phi_{AUC}(k)=\sum_{S\subseteq N-\{k\}}\frac{|S|!\left(|N|-|S|-1\right)!}{|N|!}\left(AUC_{S\cup\{k\}}-AUC_S\right)$, where $S \subseteq N$ is a subset of the set of five predictors and AUC_S are the same as in Table 5 and $AUC\phi$ = 0.5. For example, the sum of the Shapley value is 0.0644 + 0.1221 – 0.0156 – 0.0224 + 0.1135 + 0.5 = 0.762 i.e. it decomposes the AUC of the five variable for TCN into payoff contribution of each variable.

It's well-known that booms in asset prices are signals of the overheating phenomenon in credit market and is related to the positive economic development. In this case, it becomes oblivious and overlook some certain risks when the long-term economic development gets better, which may result in lowering the credit standards and disorder capital expansion. Therefore, the leverage and financial bubbles drive up private investment and the risk of financial crises may increase. In this paper, we use the stock price and house price as the asset price indicators to predict the financial crisis one year ahead. It is concluded that the stock price has the stronger contribution compared with the house price due to that the stock price reflects a shorter-term trend of capital prices than housing price. On the other hand, the financial crises are often accompanied by large contractions in real GDP growth, which is much more pronounced in economic recession. This is because when the real GDP growth rate falls, it will lead to a decrease in output and government revenue, which may lead to an increase in the government deficit ratio and increase the risk of financial crises. It is also reflected in Table 6. In addition, the current account balance to GDP provides an indication of the level of international competitiveness of a country. Generally, countries with a strong current account surplus have a strongly economy dependence on export revenues. These countries may have high savings rates and weak domestic demand. However, in our TCN prediction model we find that the surplus or deficit will not increase the risk of financial crises.

5.4. Discussions

Based on the findings discussed above, the TCN model has demonstrated superior performance. This can be attributed to several key factors. The TCN process different time points in parallel with the help of time-domain convolutions. In addition, the receptive field of TCN is larger than RNNs which makes TCN can capture larger input at a given time. What's more, the temporal convolutions in TCN can capture long-range dependencies more efficient with a low computational cost. Taken together, these unique strengths of the TCN contribute to its superior prediction performance observed in our study. In comparison with existing literature, this study introduces TCN model as a novel approach to predict financial crises. Notably, the TCN model has demonstrated superior performance when compared to other classic prediction models commonly used in the field. This finding highlights the potential of TCN in accurately forecasting crisis events. Furthermore, this study places a significant emphasis on providing detailed explanations of the underlying factors contributing to the occurrence of financial crises through Sharpley value. By thoroughly elucidating these factors, policymakers are equipped with valuable insights to make informed decisions aimed at crisis prevention. The comprehensive analysis conducted in this study enhances our understanding of the complex dynamics and drivers underlying financial crises, ultimately contributing to more effective crisis management strategies.

The financial crisis prediction problem has significant theoretical implications. By developing the early warning TCN model to forecast crises, researchers can gain valuable insights into the drivers of these financial crisis events. Additionally, these implications of TCN model aid in refining existing early warning systems to enhance our overall understanding of financial markets. The practical implications of proposed TCN model are far-reaching. Early warning models generated from the TCN models can serve as valuable tools for crisis management and policy formulation, and can help to allocate resources, implement regulatory measures to enhance financial stability. As the managerial implications of financial crisis early warning, the accurate predictions of TCN can inform risk management strategies and aid in the identification of vulnerable areas within their portfolios. Managers of financial institutions can use the early warning TCN model to identify potential weaknesses in their balance sheets and design and implement more effective regulations and policies aimed at preventing future crises.

6. Conclusions and future work

In this paper, we have focused on analyzing early warning models for financial crises, utilizing the Jórda-Schularick-Taylor macro-history database. By utilizing this comprehensive and reliable database, we were able to analyze a wide range of historical data to verify the superiority of TCN model. The use of this dataset enhances the robustness of our findings, allowing for a more accurate assessment of the early warning power in identifying financial crises. The empirical results of our study demonstrate that the TCN model exhibits superior performance compared to RNNs in the out-of-sample evaluation. Through our experimental analysis, we observed that the TCN model achieved a substantial improvement in precision compared to both LSTM and GRU models, with an increase of over 10%. Furthermore, when compared to the logit model, the TCN model demonstrated an improvement in precision of approximately 50%. These findings emphasize the efficacy of the TCN model in accurately predicting financial crises and highlight its potential as a powerful early warning tool in financial crisis prediction. Subsequently, we further employed the Shapley value decomposition to gain insights into the factors driving the early warning power of the TCN model. Through this approach, we were able to identify the contributions of different indicators in predicting financial crises. Our findings reveal that both stock prices and real GDP growth emerged as strong predictors within the TCN model, which highlight their importance in understanding and forecasting financial crises. This Shapley value decomposition provides valuable insights into the relative contributions of various indicators, shedding light on the key factors of the TCN model. By uncovering these influential variables, policymakers can focus their attention and resources on monitoring and analyzing stock prices and real GDP growth to enhance their crisis prediction capabilities. Our results contribute to the expanding body of research in the field of FinTech, which encompasses the utilization of AI and machine learning techniques in the financial domain. The findings of our study align with the growing interest in exploring the application of advanced technologies to enhance financial analysis and prediction. These findings further support the ongoing efforts to integrate innovative technologies into the financial sector, promoting advancements in FinTech and fostering a more efficient and informed financial ecosystem.

In future work, we would like to further explore new early warning models for financial crisis prediction problem. With the advancements in Generative Pre-trained Transformer (GPT), we are keen on exploring the Transformer technique in our forthcoming research focused on forecasting financial crises.

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