Louvain School of Management

Predicting Currency Crises: A comparative analysis of static and dynamic models across time horizons

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During the preparation of this master’s thesis, the author utilized ChatGPT for the following purpose:

1. When I found an interesting scientific paper, but it was written with a very difficult vocabulary, I introduced the text in ChatGPT, to understand the text better, in simpler terms. Then, ChatGPT also helped me to find a good structure for my literature review (table of contents), to better know how I could structure my thesis.

2. After using ChatGPT, the author diligently reviewed and edited the content produced by the tool. We take full responsibility for the final content presented in this thesis.

By signing this declaration, we affirm that the content of this master’s thesis reflects our original work, augmented by the responsible use of AI.

25/05/2024

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1. Introduction

In the evolving field of economic forecasting, it is important to understand and predict financial crises, in this case currency crises, to avoid a maximum of damage. This thesis aims to do a critical evaluation of static and dynamic models used to predict such crises, focusing on their performance across various time horizons and ten emerging countries. The goal is to find which model better forecasts currency crises, for each of the countries, therefore provide insights for policymakers.

The theoretical framework of this thesis is based on a literature review of financial and currency crises as well as the different prediction models. This part of the thesis provides the theoretical basis for the empirical analysis and helps to identify which model, threshold, variables, … to use.

The empirical part of this thesis is a detailed analysis using data from 10 emerging countries (Argentina, Brazil, Ecuador, Egypt, Indonesia, Malaysia, Nigeria, Philippines, South Africa, and Turkey) that have experienced currency crises between 1995 and 2022. This analysis is based on a Logit Early Warning System used in a static and dynamic model to evaluate their predictive power.

The findings of this study are expected to offer significant implications for economic policy and decision-making, particularly in the area of financial stability and crisis prevention. This thesis aims to enhance the understanding of financial crises and improving the ability to predict them and to mitigate their effects.

2. Literature Review

A. Understanding financial crisis

Definition of financial crisis

According to Singh (2010), a financial crisis is defined as a disturbance in financial markets that disrupts the market's capacity to allocate capital, which slows down investment's activities (Portes, 1999).

Singh (2010) uses the term financial crisis to a range of scenarios where certain financial institutions or assets suffer from a significant loss of their value. During a financial crisis, an immediate decrease of paper wealth occurs, which represents the wealth measured in monetary terms. This is as a direct consequence of the financial crisis.

A financial crisis is characterized by the fact that financial institutions no longer want to provide credits to households and businesses. This worsens the disturbance in capital allocation and investment activity (Onopriienko, 2016).

In Perera's article (2016), the distinction between an economic and financial crisis is emphasized. The main distinction lies in the scope and the triggers of each crisis. The financial crises focus on market disruptions whereas the economic crises include wider economic downturns.

Financial crisis

A financial crisis arises from a significant decrease in the value of financial assets, which impacts the financial and investments markets. This crisis is often triggered by unsustainable asset price inflations and credit expansions. A financial crisis may create an economic crisis if no corrective actions are taken when there is a market failure in the financial sector. The financial crises can be classified into currency, debt and banking crisis (G.Perera, 2016).

Economic crisis

An economic crisis refers to a broad decline in the economy and affects all economic activities. The economic crisis is triggered by various factors including financial crises, characterized by declining GDP, inflation, higher unemployment, etc. These crises affect the general public, increasing unemployment and worsening living conditions. The economic crisis can be classified into credit, financial, fiscal, currency crises and hyperinflation (G.Perera, 2016).

Classification of financial crisis

Currency crisis

"*A currency crisis may be defined as a speculative attack on the foreign exchange value of a currency that either results in a sharp depreciation or forces the authorities to defend the currency by selling foreign exchange reserves or raising domestic interest rates.*" (Glick, R., & Hutchison, M. M., 2011).

Consequently, a currency crisis occurs when there is a sudden loss of confidence in a country's currency. This leads to a rapid drop in its value or forces the government to use its reserves or to increase interest rates to stabilize the currency.

According to Emin and Aytaç (2016), currency crises can be categorized into two main different definitions, one based on depreciation rates (Reinhart and Rogoff, 2009) and the other based on the Exchange Market Pressure (EMP) Index (Eichengreen et al., 1996).

Dawood (2016) uses the EMP definition and explains that a currency crisis occurs when a country currency faces intense pressure, which is measured by the EMP. This index has been evolved by Eichengreen, Rose, and Wyplosz in the 1990s, as mentioned by Edison (2003). The EMP is computed using the exchange rates, interest rates, and reserves. When the EMP index exceeds a certain level, it is a sign that a currency crisis might be developing.

However, experts do not always agree on which time frequency to use, or whether to use nominal or real interest rates (Dawood, 2016). Some researchers argue that we should only consider the situations where the currency suffers from a substantial devaluation, while others have a more comprehensive approach and consider more indicators.

Laeven and Valencia (2014) use the depreciation-based definition. "[...] *we define a "currency crisis" as a nominal depreciation of the currency of at least 30 percent that is also at least a 10 percent increase in the rate of depreciation compared to the year before.*" (Laeven, L., & Valencia, F., 2014). This definition means that we can identify a currency crisis when a country's currency becomes much less valuable very quickly and that this decrease is significantly sharper than any decrease experienced the year before.

Banking crisis (systematic and unsystematic)

Giving a clear definition of a banking crisis may be challenging, as "*it is the most debatable definition of all three types of financial crisis*" (Dawood, 2016).

Davis and Karim (2008b) suggest that a banking crisis can be characterized as a situation where banks encounter serious difficulties in fulfilling their role as intermediaries. However, this definition is considered overly broad, including phenomena such as bank runs, closures or mergers of major financial institutions, etc.

Casu et al. (2012) consider a banking crisis if the capitalization of the banking sector declines by a certain threshold or if the net income of banks falls below a specified level. Simpson (2010) analyses the vulnerability of a country's banking system through the variance of its banking sector stock price index relative to regional or global indices. Singh (2010) suggests building a "bank fragility index" based on variables related to liquidity, credit, and interest rate risks.

Lestano et al. (2003) and Davis and Karim (2008b) summarize various definitions of banking crises, including substantial decreases in bank capital, significant reductions in bank deposits indicating runs, closures or mergers of large banks, government interventions, and increases in non-performing loans. Barrell et al. (2010) criticize the inability to accurately identify the start and end dates of banking crises.

Systematic banking crisis

According to Laeven and Valencia (2014), a systemic banking crisis can be seen as a major problem, which affects the financial and corporate sectors of a country, where there's a big increase in failed repayments and a spike in non-performing loans. This leads to the banking system's capital getting severely reduced. These crises usually come after a period of increase in asset prices. Even if some of these crises start because people suddenly rush to withdraw their money from banks, most of the time they happen because it becomes clear that the big banks are in trouble. A systemic banking risk occurs when it is possible that an event has a negative impact on the entire banking system (Wang et al., 2021).

The systematic banking crisis is caused by systematic factors such as economic growth, which can only be managed after a while. The systematic factors are macroeconomic (Irfany & Ulhaqqi, 2023).

Unsystematic banking crisis

On the other side, an unsystematic banking crisis is due to non-systematic factors, such as banking size, non-performing loans, profitability and capital adequacy. These factors can be managed directly by the bank. The non-systematic factors are bank specific (Irfany & Ulhaqqi, 2023).

Sovereign debt crisis

According to Nguyen et al. (2022), sovereign debt crises are identified when a country cannot pay its debts on time or renegotiates them on less favourable terms. Different definitions for debt crisis exist and I will list some of them.

Manasse et al. (2003) define a debt crisis when a country either receives a rating of default from Standard & Poor's due to failure in meeting external obligations on principal or interest payments, or when it receives a loan from the IMF Finance Department exceeding 100% of its quota as part of an extensive financial rescue effort.

Ciarlone and Trebeschi (2005) expand this definition, considering a country to be in debt crisis if the overdue interest or principal payments exceed 5% of its outstanding external debt, or if it participates in debt restructuring or rescheduling schemes.

Conversely, Lestano et al. (2003) and Lausev et al. (2011) limit the debt crisis scenario to situations where a country requests a rescheduling of its sovereign debt or engages in debt-equity swaps or voluntary buybacks.

Additionally, Pescatori and Sy (2007) propose incorporating turbulence in sovereign bond markets as an indicator of potential debt-servicing difficulties. Their definition of a debt crisis includes the Standard & Poor's sovereign default rating, or a sovereign bond spread exceeding 1000 basis points above the U.S. Treasury bill.

Twin crisis

Ari and Dagtekin (2007) develop a composite twin crisis indicator, consisting of components from the Exchange Market Pressure index and vulnerability of the banking system. This indicator aims to model an early warning system for financial crises.

As explained by Laeven and Valencia (2014), a twin crisis is a combination of banking and currency crisis. More precisely, a twin crisis during the year t occurs, when during the year t a banking crisis happens and a currency crisis happens during the period [t-1, t+1].

Triple crisis

As explained by Laeven and Valencia (2014), a triple crisis is a combination of banking, currency and debt crisis. More precisely, a triple crisis during the year t occurs, when during the year t a banking crisis happens and both a currency and debt crises happen during the period [t-1, t+1].

Historical context

In the article of Nguyen et al. (2022), it has been showed that between 1970 and 2019, in the whole world, there have been:

- 263 currency crises
- 123 debt crises
- 88 bank crises

In this paper, I will mostly concentrate on Asian and American countries, and so go into more detail of the crises that happened in those countries.

Mexican Peso crisis (1994)

The Mexican Peso Crisis happened in December 1994, as analysed by Griffith-Jones (1998). This crisis was characterized by a sudden financial collapse following a devaluation of the Mexican peso. The crisis was attributed to a combination of factors, including a large current account deficit, heavy reliance on short-term capital inflows, a fixed exchange rate regime, overvalued peso, lax monetary policies, and political uncertainties.

Briefly, what happened, was that in 1994, the Mexican central bank devalued the peso by 13 to 15 percent. To prevent the excessive capital flight, the central bank increased the interest rates (by 32 percent). The result was that the borrowing expenses were very high and were a threat to the stability of the economy (Chen, 2020).

The Mexican Peso crisis caused other currencies in Latin America to decline as well (Chen, 2020). Other South American nations experienced a rapid currency depreciation and a loss of reserves. This crisis has also been called the "Tequilla shock".

The Asian Financial crisis (1997-1998)

The Asian Financial Crisis has been defined as "*a major financial crisis triggered by a sequence of currency devaluations that destabilized the Asian economy in 1997 and 1998.*" (Investopedia Team, 2022). As explained by Spiegel (2002), in 1997, the Asian financial crisis happened and therefore, a lot of Asian countries experienced a currency crisis between 1997 and 1998/1999. After the 1997 financial crisis, the Asian monetary policy changed.

Five Asian countries experienced a big currency (and banking) crisis, during 1997 – 1998. These countries were Indonesia, Malaysia, South Korea, the Philippines and Thailand (Barro, 2001). They "*experienced nominal currency depreciations of more than 50% from July 1997 to early 1998*" (Barro, 2001). Moreover, the interest rates of these countries reached at least 25% at a moment between July 1997 and January 1998.

The Asian Financial crisis started with the floating of the Thai baht in July 1997, because the Thai baht collapsed and, as the Thai government lacked foreign currency, it was forced to abandon the US Dollar peg (Kenton, 2023). In fact, as explained by Investopedia Team (2022b) in Investopedia, the Thai government exhausted much of the country's foreign exchange reserves when it tried to defend against speculative pressure.

The Philippine peso and the Malaysian ringgit were also impacted (Barro, 2001). The next month, the Indonesian rupiah devalued a lot and had the largest fall among Asian currencies. All of these countries had to let their currencies fall after being under speculative pressure. This means that the governments of those countries stopped intervening to maintain their currency's value against the US dollar. Consequently, the Asian Financial crisis is also called "Asian Contagion" as it was a sequence of currency devaluations (Kenton, 2023).

More context to the Asian Financial crisis has been explained by Patnaik et al. (2011). Before the 1997 crisis, most Asian currencies were pegged to the US Dollar, which created stable exchange rates to facilitate the trade and investment with the United-States. So, the exchange rate was very inflexible at that point. During the financial crisis, the flexibility of the exchange rate increased but it decreased just when the crisis ended. There was a "fear of floating" (Patnaik et al., 2011). The exchange rate flexibility kept increasing and the Asian currencies relied always less on the US Dollar.

When a currency is pegged, it means that the national government or central bank sets a fixed exchange rate for its currency with a single or multiple foreign currencies (Banton, 2022). Some countries are free-floating and in this case the rates fluctuate based on supply and demand in the market, or it can be fixed / pegged to another currency.

During the crisis, the real GDP contracted. To give some numbers, Khoon and Hui (2010) showed that, during the crisis, the stock market and the currency market of Malaysia nearly collapsed. The real GDP growth collapsed from 7,3 % (1997) to –7,4% (1998).

The Asian financial crisis initially impacted East Asia and caused currency devaluations and stock market plunges. Then, it extended its impact to the currencies and stock markets of other, non-Asian, countries, including Argentina, Brazil, and Russia (Kaminsky & Reinhart, 1998).

B. Models for financial crisis

Financial crises involve economic changes and market behaviours. There exist several models to analyse the reasons and main causes of these crises. Singh (2010) discussed about three generations of models to understand financial crises.

First generation of crisis models

The first-generation models, as outlined by Singh (2010), attribute the occurrence of financial crises to weak economic fundamentals. In this first generation, vulnerable economic conditions are susceptible to speculative attacks.

Fluctuations in economic health are considered a key factor in triggering financial crises according to this model. So, when an economy experiences instability, vulnerability, or weakness in its fundamental economic indicators, it becomes more susceptible to suffer from a financial crisis.

In order to mitigate the risk of financial crisis, according to the first-generation model, authorities should focus and stabilize these fundamental economic factors.

When focusing on currency crisis, Glick and Hutchison (2011) give more insights. The first-generation model of currency crises focuses on inconsistencies between domestic macroeconomic policies. The contradiction is between the government's commitment to an exchange rate and the government budget deficit. The problem here is that the government has pegged to maintain a fixed exchange rate, but at the same time, the government budget is showing a deficit. To manage this deficit, the governments can either use their assets (foreign exchange reserves for example) or borrow money. However, the issue here is that the government cannot exhaust its foreign reserves or borrow indefinitely without facing financial consequences. And so, the solution would be to print more money, which leads to inflation. Inflation is not compatible with a fixed exchange rate.

To conclude, the first-generation model of currency crises, show that a fixed exchange rate and a government budget deficit are fundamentally incompatible.

Second generation of crisis models

According to Singh (2010), the second-generation models provide an alternative perspective on the main cause of financial crises. In these models, weak economic fundamentals are still significant, but the second-generation models introduce the concept of self-fulfilling expectations as a main cause for financial crises.

In this context, the concept of self-fulfilling prophecy assumes a central role. According to Jussim (1986), a self-fulfilling prophecy happens when one person's expectations about another person influence the second person's behaviour that aligns with the initial expectations. Regarding financial crises, this means that if investors and market actors anticipate a crisis, their actions based on these expectations can contribute to the actual occurrence of the crisis, which we call a self-fulfilling prophecy.

Singh (2010) highlights the role of expectations and beliefs that the market participants have. Their expectations and beliefs may lead to financial instability, according to these models. Within this framework, the psychological aspect is an important factor that may influence crisis dynamics. This aspect rises the complexity of forecasting financial crisis, as we not only address tangible economic fundamentals, but also we have to take into account subjective expectations of market participants.

When focusing on currency crisis, Glick and Hutchison (2011) give more insights on the second-generation model. This model has been mainly developed by Obstfeld and explains the impact of the decision-making of policymakers on the occurrence of currency crises. This generation focuses on the strategic choices of governments facing trade-offs between the choice of keeping the fixed exchange rate and the consequences of this (as explained in the first-generation model).

In this generation model, the private sector (investors for example) plays a role. If they think that maintaining the fixed exchange rate could compromise the financial stability of the country, their doubts can lead to a speculative attack (Glick, R., & Hutchison, M. M., 2011).

The challenge of the second-generation model is that it is more uncertain than the first-generation model. Nevertheless, the first 2 generation models are not mutually exclusive but complementary in understanding how currency crises occur. The first-generation model explains on the inherent vulnerabilities of a country, whereas the second-generation model shows that the shift in the investor's sentiment can also trigger a crisis (Glick, R., & Hutchison, M. M., 2011).

Third generation of crisis models

Singh's (2010) third-generation models represent a combination of the first and second generations, by joining the weaknesses in economic fundamentals with vulnerabilities in the banking sector. Hence, these models are also called twin crisis models. This approach provides a more comprehensive understanding of the varied nature of financial crises.

The third-generation model of currency crises show the complexities of financial markets and banking systems, as explained by Glick, R., & Hutchison, M. M. (2011). Different third generation crisis models have been explained in that paper.

For instance, Aghion, Bacchetta, and Banerjee (2001), focus on how currency depreciation can cause financial vulnerabilities. An initial depreciation makes it more expensive for firms with debts in foreign currencies to meet their obligations, which reduces their profits and their ability to borrow. This can lead to reduced investment and reduced demand for the domestic currency and can potentially trigger a crisis.

Another model is the one of Dooley (2000) and Burnside, Eichenbaum, and Rebelo (2004), who discuss how government guarantees can incentivize banks to take on excessive foreign debt. This makes the banking system vulnerable to speculative attacks, making it harder to defend the fixed exchange rate.

C. Early warning systems

Kelman et Glantz (2014) suggest a definition of early warning systems in their book, that comes from the United Nations International Strategy for Disaster Reduction (UNISDR, 2012). UNISDR (2012) defines an early warning system as "*The set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities and organizations threatened by a hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss*" (Kelman & Glantz, 2014).

In simpler terms, an early warning system, abbreviated by EWS, is a proactive alarm that helps people, organizations and governments to get ready for potential dangers. There is a need for the right tools and processes to be able to share important information about the threat. Such knowledge will enable individuals and organizations to take the necessary actions in advance to reduce the risk of harm as much as possible when the hazard actually occurs.

According to Candelon and al. (2012), the early-warning systems emerge as a tool when considering the financial stability. These systems serve as a critical instrument for authorities to allow them to strategically implement optimal policies which aim to prevent, in the best-case scenario, or to mitigate at least the impact of expected financial turbulence.

Connecting UNISDR's definition to the financial context, an early warning system is an alert that makes it possible to avoid potential financial difficulties. This proactive tool is a way to foresee possible financial troubles, so that policymakers, individuals and companies can take action steps to avoid financial crisis.

Different types of early warning systems exist, each one with its own way of predicting financial crises. A few of these systems are presented below to see how they work to help predicting economic challenges.

Different types of EWS

Signal extraction approach

As explained by Dawood (2016), the signal extraction approach is a non-parametric method that has been developed by Kaminsky et al. (1998). The signal extraction approach, as outlined by Dawood (2016), involves monitoring specific macroeconomic and financial indicators for unusual behaviour before crises. It signals a crisis when indicators cross a threshold, which can be set low to prevent missed crises or high to minimize false alarms.

Ari and Dagtekin (2007) argue about the effectiveness of fixed thresholds for indicators in early warning systems. They discuss that once an indicator exceeds the threshold, it is impossible to know whether the deviation is minor or substantial. Another problem that they highlighted is that the method does not send a signal if the indicator remains below the threshold, even if it has an unusual behaviour.

To address these issues, Kaminsky (1999) and Lin et al. (2008) proposed a solution by developing EWS with two threshold levels for each indicator. These thresholds include a mild value to detect moderate deviations and a drastic value to identify strong deviations. However, the choice of these threshold levels is arbitrary.

The solution proposed by Casu et al. (2012) introduces a dynamic approach to set thresholds. In this approach, a warning signal is issued when an indicator goes beyond a certain multiple of standard deviations from its long-run average. The early warning system becomes more adaptive to changing economic conditions. The implementation of this dynamic threshold approach showed better results by reducing the percentage of missed crises from 30-40% to only 3%.

Discrete-dependent-variable approach

According to Dawood (2016), the discrete-dependent-variable approach is a parametric approach that has been developed by Frankel and Rose (1996). To estimate the probability of the occurrence of a crisis, a **logit** or a **probit** regression model is used.

The main difference with the signal extraction approach is that the discrete-dependent-variable approach uses regression analysis to understand how changes in indicators predict the probability of occurrence of a crisis. The indicators are seen as explanatory variables in the regression models.

The advantage of this approach, as argued by Ari and Dagtekin (2007), is that it allows for statistical tests on estimated coefficients, providing a more systematic framework for analysis. However, even if it can accurately predict the absence of a crisis in many cases, its ability to forecast crisis episodes accurately varies. For example, Barrell et al. (2010) found that a logit model correctly identified 66% of crisis episodes but generated 29% of false alarms.

In their papers, Demirgüç-Kunt and Detragiache (1998) along with Davis and Karim (2008) have shown that the **logit-probit** models reduce the 2 types of errors (missed alters and false alarms) better than other early warning systems (Wang et al., 2021).

Logit vs probit model

In my regression model, the dependent variable (crisis happening or not) is dichotomous and takes either the value 0 or 1. However, the explanatory variables (the GDP growth, the inflation, etc) are continuous variables and are not 0 or 1. To be able to have a value of 1 or 0 at the end, we need a logit or probit model. Both of these models (probit and logit) predict the binary dependent outcome based on a set of independent variables.

Now, we should differentiate the logit from the probit model.

As explained by Vasisht, A. K. (2007), the logit and probit models use the so called ‘Cumulative Distribution Function’ (CDF) to explain the behaviour of the dependent variable that is binary. The main difference between the 2 models, is the kind of CDF that they use. The logit model uses the ‘cumulative **logistic** distribution’ function. The probit model (also known as Normit model) uses the ‘cumulative **normal** distribution’ function.

On one hand, the logit model uses the logistic distribution which gives an S-shaped curve and has flatter tails compared to a probit model. So, the logistic curve approaches 0 or 1 more gradually (Vasisht, A. K., 2007).

On the other hand, the probit model is based on the normal (Gaussian) distribution. In this case, the tails approach the axes more quickly than the logistic curve. This means that there is a bigger tendency to have extreme values (0 and 1) (Vasisht, A. K., 2007).

In this paper, I am studying the occurrence of financial crises, which are extreme events, so the logit model is preferred, as explained by Candelon et al. (2014).

Dynamic vs Static model

When using EWS, there is also a difference made between dynamic and static models. Three different types of dynamic EWS models have been explained in the paper by Candelon et al. (2014). In the model, we can include either

- A lagged binary dependent variable
- The lagged index
- Both a lagged binary dependent variable and the lagged index

To conclude the analysis, Candelon et al. (2014) have found that the dynamic EWS, which included the lagged binary crisis indicator, showed better results than the static EWS.

Multinomial approach

A criticism of the discrete-dependent-variable models, highlighted by Bussiere and Fratzscher (2006), is the "post-crisis bias". This bias happens when observations from tranquil times and post-crisis periods are combined. To address this issue, Bussiere and Fratzscher proposed multinomial models with more than two outcomes. This allows to distinguish more than only 2 states (crisis or no crisis). It does a separate analysis of tranquil periods, pre-crisis periods, and crisis/post-crisis periods. Hence, the multinomial approach goes further than the traditional binary regression models as it can predict multiple states, as described by Dawood (2016).

In their paper, Caggiano et al. (2016) show that the multinomial logit outperformed the binominal logit model when predicting systemic banking crises. The binominal logit models are constrained by the “crisis duration bias”.

Machine Learning Algorithms

This approach, that has been used by Son et al. (2009), uses machine learning algorithms to forecast the behaviour of global institutional investors in Asian local markets.

When discussing the effectiveness of the Machine Learning algorithms versus the logit early warning systems, the opinion is mixed. For instance, Alessi and Detken (2018) argued that tree-based Machine Learning models have a higher predictive result compared to logit regression. Holopainen and Sarlin (2017) had similar results and argued that the new machine learning techniques outperformed traditional statistical methods in accuracy.

On the other hand, Beutel, List, and von Schweinitz (2019) showed that the machine learning model tends to overfit, so they might have very good results on the data where they are trained but not good on new data.

What has been noticed, is that the problem of overfitting primarily affects non-linear models. It is rare in linear estimations (logit EWS for example) (Wang et al., 2021).

CRAGGING Algorithm (Regression Tree Models)

This approach has been introduced by Savona and Vezzoli (2015). They made a special algorithm for tree models that considers differences between countries, and then they used the average predictions to make a final tree. The algorithm creates different prediction trees, and in each tree the information from a country is left out at a time. This method showed better forecasting results than the signal extraction approach and had similar results to the logit models (Dawood, 2016).

Markov Regime Switching Models

These models, which have emerged in studies of Mariano et al. (2002) and of Arias and Erlandsson (2005), are based on the volatility of the nominal exchange rate. However, this model isn't the best model when predicting financial crisis, because it works well when there are extended fluctuations in the data (Engel, 1994) but the financial crises happen suddenly and don't last long enough.

The paper of Abiad (2007) talks about the Markov-switching model which is different from the other models as it endogenously identifies and characterizes periods of crisis. This means, that the model determines the periods based on internal dynamics of the data and not on a predefined criterion, which is external. An advantage of this model is that it is able to incorporate information from exchange rate fluctuation.

In his paper, Abiad (2007) showed that this model outperformed the traditional early warning system models. It was more effective to signal the incoming crises as well as minimized the occurrence of false alarms.

Data Mining Classifiers (Artificial Neural Network Model)

This approach has been developed by Kim et al. (2004) to predict the 1997 financial crisis in Korea. It came out that the model was really good at predicting crisis and calm periods. This model outperformed the probit regression when it came to debt crises. The disadvantage of this model is that it doesn't explain how each indicator affects the crisis prediction and so it not very helpful for the policy aspect (Dawood, 2016).

Types of Error

Early warning systems cannot predict everything perfectly and errors occur. In this part, I am going to look at the different types of errors that can happen and what they mean.

The model can determine the probability of a crisis to happen. The reality will be that a crisis actually happens or does not happen!

This leads to 4 different scenarios; that I will summarize in the table below.

	Forecast crisis	**Forecasts no crisis**
Crisis occurs	OK	Missed crisis
No crisis occurs	False alarm	OK

2 of the 4 scenarios are mentioned as "OK" as they are favourable. Either, the crisis is correctly forecasted when a crisis happens, and so the EWS successfully detects and predicts a crisis before it happens. The other favourable case is when no crisis is forecasted when no crisis occurs, and so the EWS accurately predicts that there is no potential crisis. These two scenarios represent the ideal outcomes as it detects real crises and avoids false alarms.

However, there are 2 scenarios that are unfavourable, which are the "missed crisis" and "false alarms". The "missed crisis" is also called Type I error, which means that no crisis has been predicted even if one occurs. Then, the "false alarms" is also called Type II error, which means that a crisis has been forecasted if no crisis really occurs.

As mentioned by Dawood (2016), the sensitivity can be expressed as 1 - Type I error, whereas the specificity can be expressed as 1 - Type II error. The sensitivity and specificity are metrics used to evaluate the performance of diagnostic tests, in this case of the EWS.

The sensitivity measures the system ability to correctly identify periods of a potential financial crisis. This means that a high sensitivity (1 - Type I error) implies that the EWS effectively forecasts an approaching crisis, and so can send alerts to stakeholders to take preventive measures.

On the other hand, the specificity measures the system ability to correctly identify periods of no potential financial crisis. A high specificity (1 - Type II error) shows that the EWS can correctly distinguish normal market conditions from those that are threatening a crisis. It is important to have a high specificity, to maintain confidence in the system and prevent unnecessary measures, that can be very costly.

Therefore, a balance between sensitivity and specificity is essential to ensure that the system can correctly identify true crises while minimizing false alarms and missing crisis.

While both types of errors are matters of concern, the missing crisis (false negatives) are often considered more dangerous in the context of forecasting financial crisis. As no crisis has been predicted, the policymakers and financial institutions had no opportunity to take measures to mitigate the impact of a crisis.

Optimal cut-off

The choice of the cut-off has a direct impact to the type I error and type II error, which means that finding the best cut-off is also a challenge. If the threshold is high, the probability of Type I errors is higher, and the Type II errors are lower. In their article, Davis & Karim (2008) confirm this. They compare a threshold of 0.05 and of 0.5. The model with a cut-off of probability of 0.5 is better at identifying non-crisis periods and the 0.05-probability model better predicts the crisis periods.

To establish this threshold, various methodologies have been developed. I will talk about some of them.

Arbitrary cut-off method

As explained by Ferdous et al. (2022), to determine which threshold better signals an incoming crisis, several potential alternative thresholds (0.5, 0.25, 0.1, ...) have been established and the predictive power compared. However, this method is arbitrary and is not very effective because it has a high value for Type I and Type II errors (Bussiere and Fratzscher 2006).

Noise-to-signal ratio

Kaminsky et al. (1998) introduced a model based on the Noise-to-signal ratio, abbreviated by NSR. This method aims to reduce the NSR to its lowest point. It involves calculating the proportion of incorrect warnings to accurate signals. This method prioritizes the reduction of Type II errors but doesn't count the Type I errors (Ferdous et al., 2022).

Credit scoring approach

Candelon et al. (2012) recommended the credit scoring approach and precision metrics over the NSR model for selecting precise cut-off points. This approach takes into account both types of error (I and II) whereas the NSR cut-off only takes into account the type II error (occurrence of false alarms). This method aims to reduce the absolute value difference between crisis occurrence and no crisis occurrence. This approach uses sensitivity and specificity to identify the cut-off threshold. The optimal cut-off threshold is the intersection of sensitivity and specificity (Ferdous et al., 2022).

Mathematically, it can be said that the optimal cut-off, under the scoring approach, is the threshold that minimizes the absolute value of the difference between the sensitivity and the specificity (Candelon et al., 2012).

$$c^*_{CSA} = \arg min_{c\,\in[0,1]}\ |Se(c_{CSA}) - Sp(c_{CSA})|$$

where Se is the sensitivity, Sp is the specificity and c is the cut-off.

Accuracy Measures

Another approach to find the optimal cut-off, is the Accuracy measure. The optimal cut-off is obtained by maximizing the Youden Index, which is defined as follows in the paper by Candelon et al. (2012).

$$c^*_{AM} = \arg max_{c\,\in[0,1]} J(c)$$

Where J(c) is the Youden Index and is defined as J(c) = Se(c) + Sp(c) -1.

We want to keep the cut-off, which has the highest Youden index, because it means that it would have the highest proportion of calm and crisis periods correctly identified in the model.

3. Empirical Part

My thesis will concentrate on emerging countries, and I did the choice of taking Argentina, Brazil, Ecuador, Egypt, Indonesia, Malaysia, Nigeria, Philippines, South Africa and Turkey. This choice was made based on the dates when the currency crises happened in these countries and based on the availability of the data.

The following table shows during which years a currency crisis happened in these countries (Nguyen et al., 2022). I only listed in this table the crises date after 1995, as I only had data available starting in 1995. As explained in the article of Nguyen et al., (2022), the dates end in 2019. I did my research to find in which countries there was a currency crisis after 2019.

Country	Year of currency crisis
Argentina	2002, 2013-2016, 2018-2021
Brazil	1999, 2002, 2008, 2015
Ecuador	1998-1999
Egypt	2003, 2016-2017
Indonesia	1997-1998, 2000
Malaysia	1997-1998
Nigeria	1999, 2016
Philippines	1997-1998
South Africa	2001, 2008, 2015
Turkey	1996-1997, 1999, 2001, 2008, 2018, 2021-2022

The currency crisis dates, after 2019, for Argentina came from Bird (2023) and Bourgeois (2023). For the dates of Turkey, I got it from Strohecker, K. (2022).

A. Methodology

The core of the empirical analysis is the Logit EWS model, that will be applied in a **static and dynamic** variation. In the dynamic model, I will extend the static approach by including the lagged variable of crises to introduce a temporal dimension to the analysis.

In addition to considering 2 different EWS models, I will also consider **5 different time horizons**. I will analyse the predictive power of each model when predicting the occurrence of a crisis in the next month, in the next 3 months, 6, 9 and 12.

As the dependent variable (crisis) is a binary variable (1 if a crisis occurs and 0 if not), I need a **threshold**. If the value of the logit model is above the threshold, the predicted value is 1 and 0 else. This threshold will be computed for each country distinctly and for each time horizon.

Then, an **in-sample analysis** will be conducted using data from 1995 to 2022 to evaluate the models ability to correctly identify historical crisis and non-crisis periods. The primary metric for comparison is the AUC. Based on this, I will already have an idea which of the 2 models (dynamic or static) has a higher AUC.

The AUC, which is the Area Under the ROC (Receiver Operating Characteristics) curve, are important tools to check a model's performance (Agarwal, 2024). The ROC curve measures the performance of a classification model because it compares the True Positive Rate and the False Positive Rate. And so, the AUC measures the probability that the model ranks a positive example higher than a negative one when there are random comparisons (Agarwal, 2024). This means a higher AUC value shows a better model performance in ranking positives about negatives.

The **out-of-sample analysis** is designed to assess the models' predictive power on unseen data. This involves a rolling window approach, where a fixed window of 11 years will be used to train the models, after which they are tasked with predicting the occurrence of a currency crisis in the subsequent time horizon. For each time horizon and both models (static and dynamic), the predictive accuracy is quantified using AUC, True Positive Rate (TPR), and True Negative Rate (TNR).

The final step involves a comparative analysis of the static and dynamic models across all time horizons and metrics. The aim is to identify which model, static or dynamic, and which prediction horizon, offers the best balance of predictive accuracy for each of the ten emerging countries studied.

B. Variable choice

To be able to conduct my analysis, I need to find the explanatory variables that could explain the occurrence of a currency crisis. All the data I retrieved for this analysis was obtained from World Bank Open Data and Trading Economics. After reading various results in the literature, I kept the following set of explanatory variables for the analysis:

Gross domestic product (GDP) growth rate

Investopedia Team (2024) defined the GDP per capita as a metric that measures the country economic output per person. It is used to analyse the prosperity of a country based on its economic growth. When the GDP growth rate is low or negative, it can signal economies distress and so a country is more susceptible to a currency crisis. (Ferdous et al., 2022)

Real interest rate

As defined by Investopedia Team (2022), "*the real interest rate is the interest rate that has been adjusted to remove the effects of inflation*". So, the real interest rate is the difference between the nominal interest rate and the rate of inflation. It represents the change in purchasing power that comes from an investment. When the real interest rates are extremely high or low, it indicates economic imbalances that might precede a currency crisis (IMF, 2000).

Exchange rate

The real exchange rate is part of the current-account indicators and real appreciations of the domestic currency show potential problems in the current account (Kaminsky and Reinhart, 1998). The exchange rate can have a huge impact on the occurrence of a currency crisis. In fact, if a country has a fixed exchange rate system, when the country is pressured to abandon the current exchange rate peg (or fixed rate), then a currency crisis is likely to happen (Glick and Hutchison, 2011).

There might be 2 different outcomes when the peg is challenged, the one of a successful attack and of an unsuccessful attack, as described by Glick and Hutchison (2011). If there is a successful attack, then the country must allow its currency to devalue and so it loses value compared to the currency it was pegged to. If there is an unsuccessful attack, the country is able to maintain the pegged exchange rate, but the country probably needs to use a large portion of its foreign currency reserves to buy back its own currency to support its value. It might also need to raise domestic interest rates, which might slow economic growth.

International reserves over M2

As defined by Kagan (2020) in Investopedia, "*international reserves are any kind of reserve funds, which central banks can pass among themselves, internationally*". These reserves can be gold or specific currency. The international reserves are also called exchange reserves. In my analysis, I took the value of international reserves excluding gold.

The foreign exchange reserves have been included in the analysis to evaluate the degree to which the banking system's liabilities are supported by international reserves. The foreign exchange reserves are part of the capital account indicators (Kaminsky & Reinhart, 1998).

In the article *What Are Foreign Currency Reserves and Can They Help Combat the Global Economic Crisis?* (Hellenic Shipping News Worlwide, n.d.), the main reasons of the existence of foreign currency reserves are explained. First, the foreign currency reserves help to keep the value of a domestic currency at a fixed rate. If a country has a floating exchange rate, the foreign currency reserves can keep the domestic currency lower than the dollar. In case, there is an economic crisis, a central bank can take action and exchange its foreign currency for the local currency to ensure the competitiveness of its companies. There exist many more reasons to the existence of these reserves.

And so, the international reserves can act as dissuasive against speculative attacks on the country's currency. Moreover, the international reserves can also be used to provide liquidity in the foreign exchange market in case of a currency crisis, to stabilize the currency's value.

The M2 (broad money) includes all the components of M1 (currency in circulation, traveler's checks, demand deposits, and other checkable deposits) plus savings deposits, time deposits under $100,000, and retail money market mutual funds. The M2 is a measure that reflects the money supply available in an economy that can be spent and invested (Wall Street Mojo, n.d.).

In my analysis, I will rather use the ratio of international reserves to broad money (M2), which will measure the potential demand for foreign assets from domestic sources (Arslan & Cantú, 2019)

Imports (% GDP)

As defined by Global economy, the imports represent the value of all goods and other market services received from the rest of the world. Imports are part of the current-account indicators and increases in imports show potential problems in the current account (Kaminsky & Reinhart, 1998).

Exports (% GDP)

As defined by Global economy, the exports represent the value of all goods and other market services provided to the rest of the world. Exports are part of the current-account indicators and declines in exports show potential problems in the current account (Kaminsky & Reinhart, 1998).

Terms of trade

Terms of trade are part of the current-account indicators and declines in terms of trade show potential problems in the current account (Kaminsky & Reinhart, 1998). As defined by Global economy, the terms of trade are calculated as the percentage ratio of the export unit value indexes to the import unit value indexes. The balance of trade indicates whether a country is exporting more than it imports or vice versa (IMF, 2000).

Inflation

Another variable used to forecast financial crisis, is the inflation. The inflation can be defined as the rate at which priced of goods and services rise (Fernando, 2024). This said, it means that in times of inflation, the purchasing power declines. In terms of currency, it means that a unit of currency buys less than it did in prior periods. In case of extreme situations, we can talk about hyperinflation when the inflation is above 50% per month (Fischer et al., 2002).

Financial system deposits of GDP

As defined by Global economy, the financial system deposits are the demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP. This indicator shows the size of a country's financial sector relative to its GDP. If there is a big growth in financial sector deposits, it can signal a potential bubble in asset prices which could precipitate a currency crisis (IMF, 2000).

Current account (% of GDP)

The current account represents the country's transactions with the rest of the world (Tuovila, 2023). A positive balance means that the nation is a lender globally. When it is negative, it means that it is a net borrower (Wikipedia contributors, 2023b). So, when the current account is deficit, it indicates that the country is having problems to repay external debt, which might lead to a currency crisis.

Variable	**Abbreviation**
Financial system deposits of GDP	FinDep
Gross domestic product (GDP) growth rate	GDP
Current account (% of GDP)	CurrAcc
Inflation	Inf
Terms of trade	Trade
Exports (% GDP)	Exp
Imports (% GDP)	Imp
Real interest rate	RealInt
Exchange rate	Exch
International reserves / M2	IntRes

C. Pre-analysis steps

Before being able to start the model and the analysis, there are a few pre-analysis steps and transformations that need to be done. The pre-analysis steps that will be done are: Transform the data into monthly data, test for stationarity, calculate the correlation, test the significance of the explanatory variables and calculate the Exchange Market Pressure indexes.

Transform into monthly data

The data of the different variables that I needed, were provided in different frequencies (annually, quarterly and monthly). To be able to conduct my analysis in the best way, I needed to standardize all datasets to a monthly frequency. Another problem that I had, was that sometimes I did not have the data starting in 1995 or ending in 2022, so I needed to extrapolate and interpolate my database to be able to find these values.

Among the several interpolation methods available, I chose cubic spline interpolation for its ability to produce a smooth curve that passes through the known data points, providing a more realistic estimation of the variables. As explained by McKinley and Levine (1998), the cubic spline interpolation is a method to construct a smooth, continuous curve that passes through a set of data points. This method fits piecewise cubic polynomials between each pair of data points. It ensures that the overall curve is smooth and that the first and second derivates are continuous across the entire interval.

Stationarity

After having the data monthly and from January 1995 until December 2022, I now needed to check for stationarity. To do so, I relied on the Augmented Dickey unique root test (ADF). I used the ADF test to determine if any of the time series had a unit root, which would mean that the data was non-stationarity.

Having stationary data is important to perform time series analysis. The ADF test is a statistical significance test and so there is a hypothesis testing with a null and alternate hypothesis. The ADF tests for a unit root which makes the times series non-stationary. If more unit roots are contained in the series, more differencing operations need to be done to make the data stationary (Prabhakaran, 2022).

The Levin, Lin, Chu (LLC) test, as explored in the article by Hlouskova & Wagner (2006), is a first-generation panel unit root test designed to determine the stationarity of panel data. This test is notable for its capacity to handle heterogeneous panels where each unit may exhibit its own autoregressive process. The LLC test formulates the null hypothesis that each unit in the panel has a unit root against the alternative that all units are stationary. One of the key aspects of the LLC test is the selection of a significance level, often set at 5%. This significance level determines the critical values used to compare the test statistic. If the test statistic falls beyond these critical values, the null hypothesis of non-stationarity is rejected, suggesting stationarity.

I used RStudio to test for stationarity with the LLC test. The exact results are shown in the **Annexe 1**. In summary, 6 of the 10 variables were stationary, so I needed to transform 4 of the 10 variables. For this, I calculated the growth rate for each variable. These variables where the financial system deposit to GDP, the exchange rate, the imports (% GDP) and exports (% GDP).

In the following table, I show the p-value of the first LLC test and if needed, of the second test. In **Annexe 2**, the exact results of this second test are shown.

Variable	**First LLC test**	**Second LLC test (after differencing)**
FinDep	0.863	2.267e-14
GDP	0.0009851	
CurrAcc	3.721e-06	
Inf	1.945e-08	
Trade	< 2.2e-16	
Exp	0.5441	< 2.2e-16
Imp	0.8413	< 2.2e-16
RealInt	0.04536	
Exch	0.9987	1.317e-07
IntRes	< 2.2e-16	

Correlation

The Pearson correlation coefficient shows the linear relationship between two variables (Jagdeesh, 2023). To interpret the strength of the relationship, we can use the rule of thumb where we say, that if the correlation coefficient is below 0.25 (in absolute values), there is no relationship (Zach, 2021). This pre-analysis needed to be done, because if 2 variables are highly correlated, they transmit similar information and so it would be better to delete one of the 2 variables (Hassan, 2023).

After having done the correlation matrix, shown in the **Annexe 3**, I could conclude that none of the variables showed a correlation, in absolute terms, above 0.25 and so I kept all the variables.

Significance

It is important to consider which variables may be significant and which ones are not. For this I did a significance test and I found that only 7 of the 10 variables listed where significant (at a significance level of 5%) to predict the occurrence or not of a currency crisis in my panel (**Annexe 4**).

- Significant variables: Financial system deposits of GDP, Exports (% of GDP) growth rate, Gross domestic product (GDP) growth rate, Real interest rate, Current account (% of GDP), Inflation, Exchange rate
- Non-significant variables: Terms of trade, Imports (% of GDP) growth, International reserves / M2

Afterwards, I did an Akaike's information criterion (AIC) and a Bayesian information criterion (BIC). This is the most common approach to compare and select statistical models (Kuha, 2004). I used this to compare 2 models in terms of their fitting to data that penalizes at the same time too complex models.

As shown in **Annexe 5**, I found lower AIC and BIC values for the model with only 7 variables, which is better. I chose to keep the panel with only 7 variables as it is supported by both AIC and BIC criteria, indicating that it provides a good balance of simplicity and performance.

Exchange Market pressure (EMP) index

As seen in the literature review, to define a currency crisis, there was the depreciation and EMP index-based approach. In my analysis, I will use the EMP approach. For this part, I chose 2 different EMP indexes and I would only retain the best of the 2 for my final panel.

KLR-index

First, I calculated the EMP index developed by Kaminsky, Lizondo and Reinhart (1998). The KLR index, coming from the initials of the authors, is a measure to identify currency crises by analysing exchange market pressure (Kaminsky et al., 1998).

The KLR index is calculated by taking the weighted average of monthly percentage changes in the exchange rate and monthly percentage changes in a country's foreign reserves. The weights are adjusted so that both components have the same conditional variance. A high KLR index value means that there is a stronger selling pressure on the domestic currency, as the currency is depreciating or that there is a loss of international reserves (Kaminsky et al., 1998).

In the paper by Lestano & Jacobs (2004), the mathematical expression of the modified KLR index was shown like this:

$$KLR_{i,t} = \frac{\Delta\, e_{i,t}}{e_{i,t}} - \frac{\sigma_e}{\sigma_r}\frac{\Delta\, r_{i,t}}{r_{i,t}} + \frac{\sigma_e}{\sigma_i}\Delta\, i_{i,t}$$

In this formula,

- $e_{i,t}$ is the units of country i's currency per US dollars in period t
- $r_{i,t}$ is the gross foreign reserves of country i in period t
- σ_e is the standard deviation of the relative exchange change $\Delta\, e_{i,t}/e_{i,t}$
- σ_r is the standard deviation of the relative change in the reserves $\Delta\, r_{i,t}/r_{i,t}$
- $i_{i,t}$ is for the nominal interest rate for country i in period t
- σ_i is the standard deviation of the change in the nominal interest $\Delta\, i_{i,t}$

To be able to calculate this index, I need to calculate the standard deviations for the 3 variables mentioned above. The standard deviations are calculated, as defined by Candelon et al. (2014), as follows:

$$\Delta\, X_{i,t} = X_{i,t} - X_{i,t-6}$$

This approach is used to capture medium-term trends and smooth out short-term volatility.

EMP index

I also calculated another EMP index, which was presented in the paper by Klutse et al. (2022). This EMP index uses the exchange rate, the international reserves but also the imports.

The formula is the following:

$$EMP_{i,t} = \frac{e_{i,t} - e_{i,t-1}}{e_{i,t-1}} - \frac{RES_{i,t} - RES_{i,t-1}}{IMP_{i,t-1}}$$

In this formula, we have that:

- $EMP_{i,t}$ is the exchange rate market pressure for country i in period t
- $\frac{e_{i,t} - e_{i,t-1}}{e_{i,t-1}}$ is the change in the exchange rate.

- $\frac{RES_{i,t} - RES_{i,t-1}}{IMP_{i,t-1}}$ is the change in the international exchange reserves scaled by one-period-lagged value of imports of goods and services.

Comparison

I did a comparative analysis with a logistic regression model trained with predictors derived from the EMP index and the KLR index, which exact results are shown in **Annexe 6**. The model with the EMP index outperformed and I found a better AUC criterion for that one, so I will continue my analysis with keeping the EMP index.

D. Analysis

After having done all the pre-analysis steps, I am now finally able to do the models and analyse the results.

Threshold

To calculate the optimal cut-off, I used the accuracy measure approach. For this, I did a loop, where I varied the threshold from 0 to 1 with 0.001 steps. For each value of the threshold, the Youden index was calculated and the threshold with the greatest Youden index has been kept. I repeated this methodology for each country and each time horizon. The optimal thresholds found are shown in the table below, and the Python output in **Annexe 7**.

THRESHOLD	C1	C3	C6	C9	C12	
Argentina	0.178	0.284	0.237	0.249	0.122	
Brazil	0.063	0.118	0.14	0.307	0.168	
Ecuador	0.01	0.001	0.001	0.946	0.002	*4 times minimum*
Egypt	0.085	0.129	0.132	0.12	0.218	
Indonesia	0.614	0.121	0.209	0.289	0.502	
Malaysia	0.101	0.031	0.043	0.232	0.03	*3 times second minimum*
Nigeria	0.145	0.111	0.275	0.399	0.447	
Philippines	0.176	0.229	0.411	0.567	0.646	*3 times maximum and once second maximum*
South Africa	0.225	0.062	0.501	0.481	0.412	
Turkey	0.295	0.106	0.219	0.174	0.507	

First, I looked at the different thresholds and I immediately noticed that Ecuador had 4 out of 5 times the lowest threshold, Malaysia 3 out of 5 times the second lowest and Philippines had 3 times the highest and once the second highest threshold.

Comparison in sample

For the in-sample analysis, I decided to compare the in-sample AUC for the dynamic vs the static model. So, I can later compare this conclusion with the out of sample model and see if the preference is kept. For the in-sample model I kept the data of all the years available (1995-2022). The exact outcome is in **Annexe 8**.

In the tables below, the results are shown:

	C1		C3		C6		C9		C12	
	AUC static	AUC dynamic	AUC static	AUC dynamic	AUC static	AUC dynamic	AUC static	AUC dynamic	AUC static	AUC dynamic
Argentina	0.971952	**0.996952**	0.958802	**0.99262**	0.936968	**0.992718**	0.917022	**0.993971**	0.913605	**0.994628**
Brazil	0.772497	**0.966146**	0.770727	**0.972577**	0.758835	**0.976624**	0.754492	**0.984229**	0.758999	**0.989442**
Ecuador	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Egypt	0.867963	**0.993333**	0.859628	**0.988936**	0.834783	**0.983508**	0.824689	**0.991265**	0.811213	**0.989519**
Indonesia	**0.999866**	0.999599	**0.999536**	0.999304	0.999513	**0.999708**	0.99772	**0.99924**	**0.99955**	0.996402
Malaysia	0.953659	**0.997997**	0.955335	**0.998015**	0.956644	**0.998091**	0.958059	**0.998355**	0.954343	**0.998196**
Nigeria	0.972623	**0.998397**	0.982955	**0.999304**	0.993085	**0.999708**	0.996537	**0.999747**	0.995277	**0.998876**
Philippines	0.999466	**0.999866**	0.999504	**0.999752**	0.997417	**0.999551**	0.996197	**0.999383**	0.997817	**0.99962**
South Africa	0.643796	**0.97037**	0.659054	**0.979268**	0.687994	**0.983626**	0.697162	**0.984118**	0.694295	**0.983716**
Turkey	0.898741	**0.985981**	0.899426	**0.984495**	0.871728	**0.973592**	0.847757	**0.976728**	0.856918	**0.976231**

For each of the 5 different time frames and for each country, the dynamic model nearly always had a better AUC than the static one (which is shown in bold). The only exception is Indonesia for C1, C3 and C12. So, the dynamic model consistently outperforms the static model across all time horizons and for 9 of the countries. So, the dynamic model is better suited to capture the nuances of economic trends and risks that can lead to currency crises.

To be able to test if the AUC of the dynamic model is statistically different from the static model, I performed the test of DeLong and Clarke-Pearson (1988), as described in the paper of Candelon et al. (2012).

The null hypothesis of this test is $H_0 : AUC_1 = AUC_2$ which means that there is no difference in the performance of the two EWS models. The test statistic W_{AUC} is calculated as follows:

$$W_{AUC} = \frac{(AUC_1 - AUC_2)^2}{V(AUC_1 - AUC_2)} \qquad \text{where}$$

- AUC_1 and AUC_2 are the AUC values for the 2 models (dynamic and static)
- $V(AUC_1 - AUC_2)$ is the variance of the difference between the two AUC values.

Under the null hypothesis, this test statistic follows an asymptotic chi-square distribution with one degree of freedom, when the sample size T approaches infinity.

I did this test for each time horizon and each country and found the following results:

	C1		C3		C6		C9		C12	
	W_AUC	p_value	W_AUC	p_value	W_AUC	p_value	W_AUC	p_value	W_AUC	p_value
Argentina	6.91	0.01	8.18	0.00	15.71	0.00	24.16	0.00	26.10	0.00
Brazil	60.27	0.00	67.11	0.00	77.20	0.00	88.07	0.00	92.00	0.00
Ecuador	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Egypt	43.43	0.00	42.56	0.00	48.07	0.00	60.66	0.00	65.13	0.00
Indonesia	0.04	0.83	0.02	0.90	0.02	0.90	0.26	0.61	0.82	0.36
Malaysia	14.26	0.00	13.67	0.00	13.27	0.00	13.01	0.00	14.20	0.00
Nigeria	7.88	0.00	5.13	0.02	2.05	0.15	0.93	0.33	0.75	0.39
Philippines	0.08	0.78	0.03	0.87	0.50	0.48	0.77	0.38	0.43	0.51
South Africa	138.44	0.00	140.20	0.00	126.88	0.00	121.65	0.00	122.93	0.00
Turkey	24.32	0.00	22.93	0.00	25.28	0.00	36.71	0.00	32.71	0.00

I can conclude that for 3 out of the 10 countries and sometimes 4, the difference in AUC is not significant. The dynamic model still outperforms the static one but for Ecuador, Indonesia, Philippines and sometimes Nigeria it is not significantly different.

Then, I looked at the maximum AUC per country (of course it is mostly from the dynamic model), but I wanted to look if there is a trend in the time horizons.

	C1	C3	C6	C9	C12
Argentina	0.996952	0.99262	0.992718	0.993971	0.994628
Brazil	0.966146	0.972577	0.976624	0.984229	0.989442
Ecuador	1	1	1	1	1
Egypt	0.993333	0.988936	0.983508	0.991265	0.989519
Indonesia	0.999866	0.999536	0.999708	0.99924	0.996402
Malaysia	0.997997	0.998015	0.998091	0.998355	0.998196
Nigeria	0.998397	0.999304	0.999708	0.999747	0.998876
Philippines	0.999866	0.999752	0.999551	0.999383	0.99962
South Africa	0.97037	0.979268	0.983626	0.984118	0.983716
Turkey	0.985981	0.984495	0.973592	0.976728	0.976231

For 4 out of 10 countries, the AUC of the dynamic model at the C1 time horizon is the highest, which could mean that the dynamic model is particularly adapted at short-term crisis prediction. For Indonesia, the AUC of the static model at the C1 time horizon is the highest. On the other hand, for 3 countries, the AUC of the dynamic model of C9 time horizon is the highest. And for Brazil, the best one was for C12 time horizon.

When I examined the minimum AUC values, I observed the following:

	C1	C3	C6	C9	C12
Argentina	0.971952	0.958802	0.936968	0.917022	0.913605
Brazil	0.772497	0.770727	0.758835	0.754492	0.758999
Ecuador	1	1	1	1	1
Egypt	0.867963	0.859628	0.834783	0.824689	0.811213
Indonesia	0.999599	0.999304	0.999513	0.99772	0.996402
Malaysia	0.953659	0.955335	0.956644	0.958059	0.954343
Nigeria	0.972623	0.982955	0.993085	0.996537	0.995277
Philippines	0.999466	0.999504	0.997417	0.996197	0.997817
South Africa	0.643796	0.659054	0.687994	0.697162	0.694295
Turkey	0.898741	0.899426	0.871728	0.847757	0.856918

The static model at C12 time horizon is the lowest for 3 out of 10 countries and for 3 out of 10 countries the C1 static model horizon had the lowest AUC. This indicates that the static model probably struggles with short-term and long-term crisis prediction. The lower performance at C1 could be due to a lack of responsiveness to recent developments that a dynamic model might capture. And the lower performance at C12 could be due to the inability to accurately account for economic changes over an extended time period.

To conclude this part, the results seem logical to me and match my expectations, that the dynamic model does better than the static model one and that the AUC is higher for short term predictions than long term.

Comparison out-of-sample

AUC dynamic and static

For the out-of-sample prediction, I want to determine whether the dynamic model maintains its superior performance in forecasting the currency crises. For this, I will compare again the AUC of each model. Moreover, I will compare the True Positive Rate (TPR) and the True Negative Rate (TNR).

As I am dealing with crises, the most important ratio is the TPR as I want to make sure that I correctly identify the crises incurring, as the goal is to prevent or mitigate the detrimental effects of such events. It is more important to correctly identify the occurrence of a currency crisis than the non-occurrence of a crisis.

Nevertheless, it is also important to consider the TNR, as a high rate of false alarms, where crises are predicted but do not occur, could weaken citizen's confidence. The public's anticipation of a crisis could inadvertently lead to financial instability. Therefore, while my focus is primarily on maximizing the TPR, maintaining a good TNR is also crucial, which shows the importance of balance in predictive accuracy.

All the results are shown in **Annexe 9**.

For the first time horizon analysis, which was <u>**C1**</u>, I found the following results:

C1	Static Model			Dynamic Model		
	AUC	TPR	TNR	AUC	TPR	TNR
Argentina	96%	95%	86%	**98%**	**98%**	**91%**
Brazil	81%	79%	63%	**91%**	**88%**	**79%**
Ecuador			**100%**			**100%**
Egypt	95%	88%	**98%**	**96%**	**92%**	**98%**
Indonesia			**100%**			**100%**
Malaysia			89%			**94%**
Nigeria	**93%**	**92%**	97%	**93%**	**92%**	**98%**
Philippines			**100%**			**100%**
South Africa	82%	79%	67%	**91%**	**92%**	**86%**
Turkey	92%	75%	90%	**95%**	**92%**	**95%**

For 5 out of 6 countries, the AUC of the dynamic model was still better than the static one (for Nigeria the AUC was exactly the same). The TPR was better in the dynamic model for 5 out of 6 countries and the exact same for 1 out of 6 countries. The TNR was better in the dynamic model for 7 countries out of 10 and exact the same for 3 countries between the static and dynamic model. When I only look at the TPR, I see that the difference between the greatest and smallest TPR is 20% for the static model and 10% for the dynamic model.

So here I can see that the dynamic model still outperforms the static for the majority of the countries and metrics but does not always outperform it.

Now, for the **C3**, I concluded that:

C3	Static Model			Dynamic Model		
	AUC	TPR	TNR	AUC	TPR	TNR
Argentina	93%	90%	86%	**97%**	**97%**	**91%**
Brazil	79%	68%	72%	**95%**	**93%**	**86%**
Ecuador			**100%**			**100%**
Egypt	88%	73%	**99%**	**96%**	**88%**	**99%**
Indonesia			99%			**100%**
Malaysia			**88%**			**88%**
Nigeria	81%	79%	95%	**94%**	**93%**	**97%**
Philippines			**100%**			**100%**
South Africa	72%	75%	60%	**91%**	**89%**	**64%**
Turkey	84%	73%	86%	**95%**	**92%**	**90%**

The AUC of the dynamic model was better for all of the 6 countries compared to the static one. The TPR was also better for all the 6 countries in the dynamic model. For the TNR, the dynamic model scored better for 6 out of 10 countries and equally than the static one for the 4 remaining countries. So, I can conclude that the dynamic model still outperforms the static one, even more than in C1 analysis. When I only look at the TPR, I see that the difference between the greatest and smallest TPR is 22% for the static model and 9% for the dynamic model.

Now, for the **C6** analysis, I concluded that:

C6	Static Model			Dynamic Model		
	AUC	TPR	TNR	AUC	TPR	TNR
Argentina	88%	88%	**86%**	**90%**	**91%**	**86%**
Brazil	75%	65%	76%	**94%**	**88%**	**92%**
Ecuador			**100%**			**100%**
Egypt	**79%**	66%	**99%**	**79%**	**69%**	**99%**
Indonesia			**100%**			**100%**
Malaysia			**88%**			**88%**
Nigeria	**70%**	**65%**	**98%**	**70%**	**65%**	96%
Philippines			**100%**			**100%**
South Africa	60%	53%	**78%**	**67%**	**65%**	66%
Turkey	73%	59%	86%	**79%**	**69%**	**88%**

The AUC of the dynamic model was better for 4 of 6 countries and equally for 2. For the TPR, the dynamic model was better for 5 out of 6 countries and equally for 1 country (Nigeria). For the TNR, the dynamic model was better for 2 out of 10 countries, equally for 6 countries and less good for the last 2 (Nigeria and South Africa). When I only look at the TPR, I see that the difference between the greatest and smallest TPR is 35% for the static model and 26% for the dynamic model.

I can conclude that even if the dynamic model still outperforms, in most cases, the static, it is more and more equally to the static one.

Now, for the **C9** analysis, I can conclude that:

C9	Static Model			Dynamic Model		
	AUC	TPR	TNR	AUC	TPR	TNR
Argentina	84%	85%	**85%**	**85%**	**88%**	**85%**
Brazil	73%	33%	89%	**92%**	**48%**	**98%**
Ecuador			**100%**			**100%**
Egypt	**72%**	**63%**	**99%**	**72%**	**63%**	**99%**
Indonesia			**100%**			**100%**
Malaysia			94%			**96%**
Nigeria	**61%**	**55%**	98%	**61%**	**55%**	**99%**
Philippines			**100%**			**100%**
South Africa	52%	**45%**	77%	**61%**	**45%**	**95%**
Turkey	67%	48%	81%	**74%**	**50%**	**87%**

The AUC of the dynamic model is better for 4 countries out of 6 and equally for 2. The dynamic model has a better TPR for 3 countries and equal for the remaining 3. The TNR of the dynamic model scores better for 5 countries and equally for 5. When I only look at the TPR, I see that the difference between the greatest and smallest TPR is 52% for the static model and 43% for the dynamic model.

Now for **C12**, I conclude that:

C12	Static Model			Dynamic Model		
	AUC	TPR	TNR	AUC	TPR	TNR
Argentina	**81%**	87%	**85%**	**81%**	**89%**	**85%**
Brazil	71%	41%	78%	**91%**	**65%**	**91%**
Ecuador			**100%**			**100%**
Egypt	65%	46%	**99%**	**66%**	**51%**	**99%**
Indonesia			**100%**			**100%**
Malaysia			**88%**			**88%**
Nigeria	**55%**	**48%**	**99%**	**55%**	**48%**	**99%**
Philippines			**100%**			**100%**
South Africa	46%	**39%**	72%	**56%**	**39%**	**91%**
Turkey	62%	**34%**	84%	**70%**	30%	**90%**

The AUC of the dynamic model is better for 4 countries out of 6 and equally for 2. The dynamic model also has a better TPR for 3 countries, a worse for 1 and equal for 2. The TNR of the dynamic model is better for 3 countries and equally for 7 countries. When I only look at the TPR, I see that the difference between the greatest and smallest TPR is 53% for the static model and 59% for the dynamic model.

I did 2 other tables that summarized the best performances of the 2 different models. These 2 tables show, in percentage, how much the dynamic or static model outperformed for each metric and each time horizon, on the left and how many times they scored equally.

Superiorty	Static Model			Dynamic Model		
	AUC	TPR	TNR	AUC	TPR	TNR
C1	0%	0%	0%	83%	83%	70%
C3	0%	0%	0%	100%	100%	70%
C6	0%	0%	20%	67%	83%	20%
C9	0%	0%	0%	67%	50%	50%
C12	0%	17%	0%	67%	50%	30%

	Equal		
	AUC	TPR	TNR
C1	17%	17%	30%
C3	0%	0%	30%
C6	33%	17%	60%
C9	33%	50%	50%
C12	33%	33%	70%

What I notice immediately here, and is very clear, is that the static model never outperformed the dynamic model, when talking about the AUC. This means that the dynamic model has a better overall performance as it distinguishes better between the occurrences and non-occurrences of crises, regardless of the countries and the time horizons. As this is consistent, I can conclude a strong generalizability, as it can adapt to different countries and time horizons.

For the TPR, the dynamic model still outperforms in general the static model, even if it is less consistent for the AUC. However, what is interesting, is that the dynamic model scores, in average, for 48% of the countries better than the static one and for 48% of the countries they score equally in terms of TNR. This means that the difference between a static and dynamic model isn't as great anymore when considering the TNR.

I also saw that the difference between the greatest and smallest TPR in the static model was always (expect for C12) greater than the same difference in the dynamic model. This could mean that the static model's performance is more sensitive and less stable across countries.

Time horizon with the best AUC, TPR & TNR

In this part, I decided to focus on the different time horizons and to concentrate how these performed in terms of AUC, TPR and TNR.

For the best AUC value, TPR and TNR I did the following table:

Best	Static Model			Dynamic Model		
	AUC	TPR	TNR	AUC	TPR	TNR
C1	100%	100%	10%	67%	67%	20%
C3	0%	0%	0%	33%	33%	0%
C6	0%	0%	10%	0%	0%	0%
C9	0%	0%	20%	0%	0%	40%
C12	0%	0%	10%	0%	0%	0%
Equally	0%	0%	50%	0%	0%	40%

This table means that 6 out of 6 countries (100%), had the best AUC in the C1 time horizon in the static model. In the dynamic model, 4 countries (67%) scored the best AUC in C1 and 2 countries (33%) scored the best AUC for the C3 time horizon.

When examining the best TPR, the static model again had all 6 countries (100%) achieving their best results in C1. The dynamic model, however, had a different distribution: 4 countries (67%) recorded its highest TPR in C1, and 2 countries (33%) achieved their top TPR scores in C3.

Looking at the best TNR, the static model had a more spread-out performance with 1 country (10%) having its best value in C1, 1 country (10%) in C6, 2 countries (20%) in C9, 1 country (10%) in C12, and 3 countries where performance was equal across all the time horizons. The dynamic model showed similar variability, with 2 countries (20%) achieving its best TNR in C1, 4 (40%) in C9 and 4 countries of equal performance across different time horizons.

I did an identical table, shown below, which presents the results of the time horizon with the worst AUC, TPR and TNR.

Worst	Static Model			Dynamic Model		
	AUC	TPR	TNR	AUC	TPR	TNR
C1	0%	0%	20%	0%	0%	20%
C3	0%	0%	30%	0%	0%	10%
C6	0%	0%	0%	0%	0%	10%
C9	0%	33%	10%	0%	33%	10%
C12	100%	67%	0%	100%	67%	10%
Equally	0%	0%	40%	0%	0%	40%

For the worst AUC, all 6 countries (100%) scored their lowest with both the static and dynamic models in the C12 time horizon.

In terms of the worst TPR, the conclusion is identical in the static and dynamic model, with 4 countries (67%) having their lowest scores in the C12 time horizon and 2 countries (33%) in C9.

Finally, for the worst TNR, I see again a very spread-out performance. The static model had 2 countries (20%) scoring the lowest in C1, 3 countries (30%) in C3 and 1 (10%) in C9 and with 4 countries of equally worst performance. The dynamic model has 2 countries (20%) with their lowest TNR in C1, 1 (10%) in C3, 1 (10%) in C6, 1 (10%) in C9, and 1 in C12, and 4 countries where the performance was equally the worst.

To conclude this part, it is evident that the static model shows a strong preference for the C1 time horizon, where it achieved its best AUC and TPR across all 6 countries (100%). This suggests a robustness in the static model's ability to predict outcomes effectively in the short term.

In contrast, the dynamic model displays a broader distribution of its best performances across time horizons, particularly favouring the C1 and C3 horizon for AUC and TPR, with 67% resp. 33% of countries achieving their best scores in these time frames, respectively. This indicates the dynamic model's adaptability and potential in capturing evolving patterns over slightly longer durations.

For TNR, both models exhibit a more diverse performance across different time horizons, though with a slight preference for later horizon, C9, and worse performance in short term.

The results here show that, while the static model may be preferable for immediate predictions, the dynamic model offers valuable insights for slightly longer-term forecasting.

Best model and time horizon per country

In this part, I want to present, for each country, which would be the best model (static or dynamic) and best time horizon (C1, C3, C6, C9, C12) to consider when wanting to predict the currency crises.

The most important metric in prediction of currency crises is the TPR, as we want to make sure that we correctly predict the crisis that will occur. So, for each country, the best model and respective time horizon is summarized in the table below.

	Best model	Time horizon	TPR
Argentina	dynamic	C1	98%
Brazil	dynamic	C3	93%
Egypt	dynamic	C1	92%
Nigeria	dynamic	C3	93%
South Africa	dynamic	C1	92%
Turkey	dynamic	C1 & C3	92%

In general, the best TPR has come from the dynamic model and from the C1 and c3 time horizon. And so, I can conclude that the short term is preferred to correctly predict the crises. The best TPR value is for Argentina with 98%, which means that with 98% accuracy we can predict a currency crisis happening in the following month, using a dynamic model. Also, the C3 time horizon scores very well. For example, for Brazil it was able to predict in 93% of the cases, that a currency crisis is happening in the next 3 months. The worst TPR recorded, was for Turkey, where the accuracy was only 30% when using the dynamic C12 model.

When I look at the TNR, the best model and time horizon is summarized below.

	Best model	Time horizon	TNR
Argentina	dynamic	C1 & C3	91%
Brazil	dynamic	C9	98%
Ecuador	both	all	100%
Egypt	both	C3, C6, C9, C12	99%
Indonesia	both	all	100%
Malaysia	dynamic	C9	96%
Nigeria	both	C12	99%
Philippines	both	all	100%
South Africa	dynamic	C9	95%
Turkey	dynamic	C9	95%

The TNR has more varied preferences (very different time horizons and both models are preferred). The country that scored the less good was South Africa with the maximum TNR being at 78%.

Performance of TPR

As shown in the tables above, I can see that gradually the TPR value is going down when moving from C1 to C12 time horizon, which is completely logical, as it is easier to forecast a currency crisis happening in the following month than one happening in the next year.

C6	
Country	**TPR**
Argentina	91%
Brazil	88%
Egypt	69%
Nigeria	65%
South Africa	65%
Turkey	69%

However, I would consider that a 6 month's horizon, would be a good for policymakers to start acting to mitigate or maybe even trying to avoid the crisis from happening.

I can see, as shown in the table, that in Argentina with 91% accuracy, the policymakers can predict a currency crisis in the next 6 months, which is a good result. For Brazil, having 88% seems also good. For Egypt, Nigeria, South Africa and Turkey, the model doesn't score as good anymore (if I consider 70% as an acceptable threshold).

	TPR				
	C1	**C3**	**C6**	**C9**	**C12**
Argentina	**98%**	**97%**	**91%**	**88%**	**89%**
Brazil	**88%**	**93%**	**88%**	48%	65%
Egypt	**92%**	**88%**	69%	63%	51%
Nigeria	**92%**	**93%**	65%	55%	48%
South Africa	**92%**	**89%**	65%	45%	39%
Turkey	**92%**	**92%**	69%	50%	30%

I summarized here the maximum TPR per country, and, when considering 85% as a threshold, I can see that Argentina is always above (even if the accuracy decreases), but even I want to forecast a currency crisis happening in the next year in Argentina, I can do it with 89% accuracy.

Turkey scores very good in C1 and C3, and then starting in C6 it scores very bad, so I would only consider forecasting 3 months ahead for Turkey, because it seems very unpredictable. South Africa, Nigeria and Egypt have the same pattern as Turkey (very good in C1 and C3 and then bad), but the TPR value is decreasing less drastically.

Brazil has very good accuracies until C6 and in C9 and C12 it is not good anymore, and so I would only consider forecasting until 6 months ahead for Brazil.

Analysis of Turkey

I chose to do an in-depth analysis of my results for Turkey, as it is the country that has the most currency crises happening between 1995 and 2022.

I did the plot for the predicted probabilities of the static and dynamic out of sample model for the time horizon C1 and C3, as it were the ones with the best True Positive Rate. As a reminder, the TPR of C1 of Turkey is 75% for the static model and 92% for the dynamic model. The TPR of C3 of Turkey is 73% of the static model and 92% for the dynamic model.

I will compare the predicted probabilities of crises.

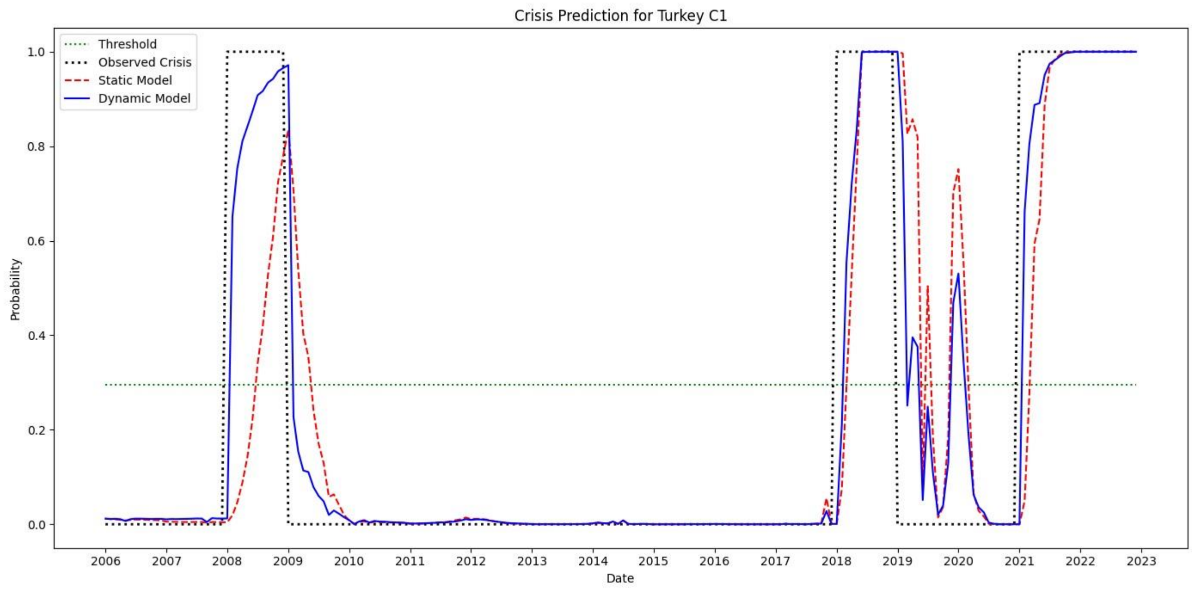

Fig 1

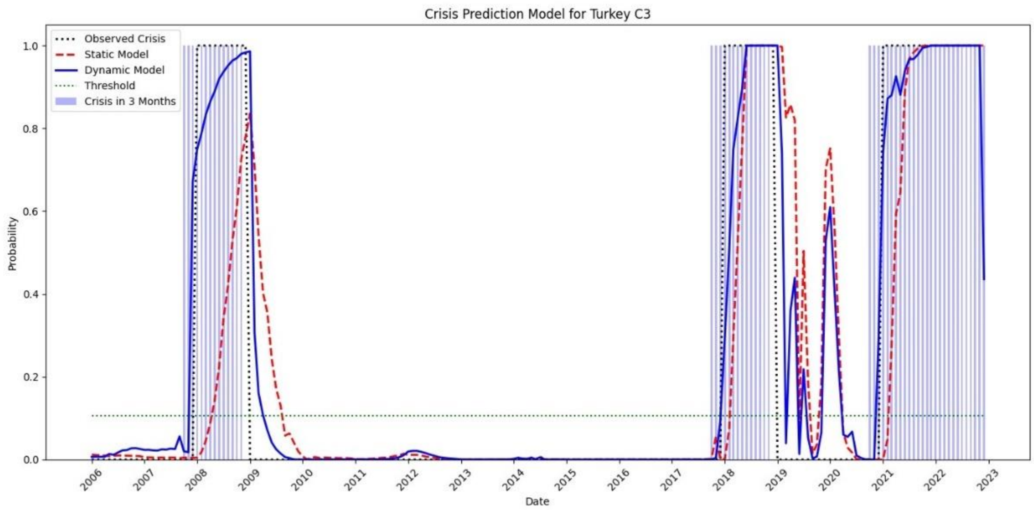

Fig 2

I observe, in Fig 1 and 2, that between 2019 and 2021, for both time horizons and both models, there are a lot of fluctuations in the predicted probabilities and some of them above the threshold (specially for C3 where the threshold is lower). There has been no currency crisis between January 2019 and December 2020 for Turkey. But due to the COVID-19 crisis, the variables fluctuated a lot, which reflects also in the fluctuation of the predicted probability of crises.

When a currency crisis is predicted, but not really happened, it is calculated by the FPR (False Positive Rate). The value of this one is 14% (static C1), 9% (dynamic C1), 14% (static C3) and 9% (dynamic C1). So, I observe that the dynamic model predicted fewer wrong crises, which can also be seen in this plot. The blue curve doesn't go as often above the threshold as the red one between 2019 and 2021.

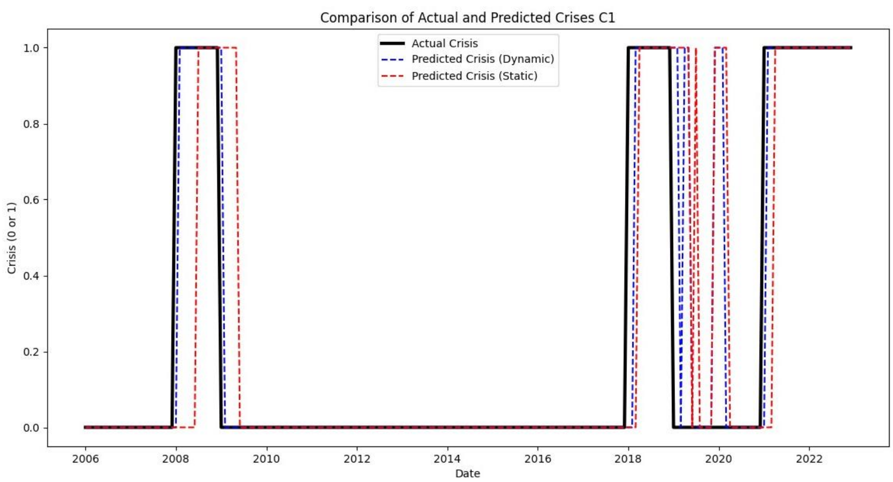

Fig 3

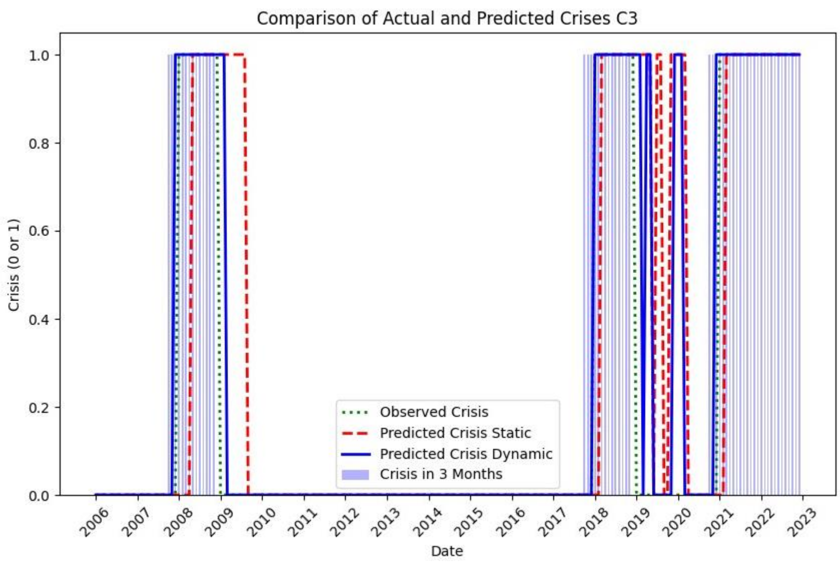

Fig 4

In the graphs of the comparison of Actual and Predicted Crises of C1 and C3, I can see that there have been predicted various crises during that time when there was none (Fig 3 & 4).

What I also observed, is that the dynamic model (in the case of C1 and C3), predicts faster the currency crises, than the static one. The static model still predicts a crisis some months after it happened, whereas the dynamic model reacts very fast (Fig 3 & 4).

Except for the years 2019 and 2020 where the models predicted crises where there were none, it predicted very well the crises of 2008, 2018 and 2021-2022 (with the dynamic model reacting a bit faster).

4. Limitation

In this thesis, I have encountered a notable limitation concerning the availability of data for my analysis. My dataset was from 1995 to 2022, but for four out of the 10 countries studied—Indonesia, Malaysia, Philippines, and Ecuador— the only crises occurred, were in the training set (from 1995 to 2005). This limitation is due to challenges in finding historical economic data predating 1995. As a result, when conducting out-of-sample analysis, I was not able to find the AUC and the TPR for these countries, given that no further crises were recorded in the out-of-sample period for these countries.

Despite this constraint, the thesis still shows significant insights. The methodology and findings for the other countries offer a meaningful understanding of the forecasting of currency crises. However, it remains regrettable that the full extent of the analysis could not be applied to these four countries.

5. Conclusion

The analysis showed the predictive power of static and dynamic models across various time horizons and countries when forecasting currency crises. It highlights the different performance between these 2 models, particularly emphasizing the dynamic model's superior accuracy across most metrics and time horizons.

From an economic point of view, the ability to accurately predict currency crises is important for policymakers and economic analysts. Currency crises can lead to significant economic disruptions, affecting employment and overall economic growth. The results suggest that dynamic models, especially at shorter time horizons (notably C1 and C3), provide a more reliable tool for forecasting these events. My analysis proved that it is, in most cases (often around 80 and 95%), possible to forecast a crisis with some months in advance. This reliability is crucial for policymakers who need to make informed decisions to implement preventive measures, and mitigate, or even avoid, potential negative effects on the population and economy.

Moreover, thanks to the plot of crises prediction of Turkey, I was able to see that the COVID-19 crisis significantly distorted the economic variables that were used in the model. This led the models to wrongly predict currency crises where none occurred.

Furthermore, the models (dynamic and static) scored best for Argentina, where it was able to predict for a 12-month period, at 89% accuracy, a currency crisis happening. This is a result, that I was not expecting and that I am very impressed and surprised by. Policymakers in Argentina are able to predict 1 year in advance, with 89% accuracy, that a currency crisis will happen and can mitigate the effects or, in the best-case scenario, prevent it from happening. This is probably due to the fact that there was a currency crisis between 2019 and 2021, and so the predictions materialized for Argentina and were more controversial for Turkey.

In conclusion, the analysis provided is a valuable insight to the field of economic forecasting, showing how it could guide economic policy and future research directions. The evidence strongly supports the use of dynamic models for predicting currency crises, particularly for short to medium-term forecasts.

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7. Appendix

Annexe 1: Stationarity (Levin –Lin-Chu Unit-Root Test)

```
> llc_result_Financial_Deposit <- purtest(pdata$Financial.System.Deposits.to.GDP, test = "levinlin")
> print(llc_result_Financial_Deposit)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Financial.System.Deposits.to.GDP
z = 1.0939, p-value = 0.863
alternative hypothesis: stationarity
```

```
> llc_result_Exports <- purtest(pdata$Exports....GDP., test = "levinlin")
> print(llc_result_Exports)

        Levin-Lin-Chu Unit-Root Test (ex. var.:
        None)

data:  pdata$Exports....GDP.
z = 0.11089, p-value = 0.5441
alternative hypothesis: stationarity
```

```
> llc_gdp <- purtest(pdata$GDP.Growth.Rate, test = "levinlin")
> print(llc_gdp)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$GDP.Growth.Rate
z = -3.0947, p-value = 0.0009851
alternative hypothesis: stationarity
```

```
> llc_import <- purtest(pdata$Imports....of.GDP., test = "levinlin")
> print(llc_import)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Imports....of.GDP.
z = 0.99963, p-value = 0.8413
alternative hypothesis: stationarity
```

```
> llc_intreserves <- purtest(pdata$International.Reserves...M2.growth, test = "levinlin")
> print(llc_intreserves)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$International.Reserves...M2.growth
z = -32.809, p-value < 2.2e-16
alternative hypothesis: stationarity
```

```
> llc_interest <- purtest(pdata$Real.interest.rate, test = "levinlin")
> print(llc_interest)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Real.interest.rate
z = -1.6916, p-value = 0.04536
alternative hypothesis: stationarity
```

```
> llc_current <- purtest(pdata$Current.Account, test = "levinlin")
> print(llc_current)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Current.Account
z = -4.4806, p-value = 3.721e-06
alternative hypothesis: stationarity
```

```
> llc_inflat <- purtest(pdata$Inflation.Rate, test = "levinlin")
> print(llc_inflat)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Inflation.Rate
z = -5.4958, p-value = 1.945e-08
alternative hypothesis: stationarity
```

```
> llc_exch <- purtest(pdata$Exchange.Rate, test = "levinlin")
> print(llc_exch)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Exchange.Rate
z = 2.8499, p-value = 0.9978
alternative hypothesis: stationarity
```

```
> llc_import <- purtest(pdata$Imports....of.GDP..growth.rate, test = "levinlin")
> print(llc_import)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Imports....of.GDP..growth.rate
z = -9.8758, p-value < 2.2e-16
alternative hypothesis: stationarity
```

```
> llc_trade <- purtest(pdata$Balance.of.Trade, test = "levinlin")
> print(llc_trade)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Balance.of.Trade
z = -55.361, p-value < 2.2e-16
alternative hypothesis: stationarity
```

Annexe 2: Second Stationarity (Levin –Lin-Chu Unit-Root Test)

```
> llc_result_Financial_Deposit <- purtest(pdata$Financial.Growth.Rate, test = "levinlin")
> print(llc_result_Financial_Deposit)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Financial.Growth.Rate
z = -7.5447, p-value = 2.267e-14
alternative hypothesis: stationarity
```

```
> llc_result_Exports <- purtest(pdata$Exports....GDP..growth.rate, test = "levinlin")
> print(llc_result_Exports)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Exports....GDP..growth.rate
z = -10.297, p-value < 2.2e-16
alternative hypothesis: stationarity
```

```
> llc_exch <- purtest(pdata$Exchange.Rate.Growth.Rate, test = "levinlin")
> print(llc_exch)

        Levin-Lin-Chu Unit-Root Test (ex. var.: None)

data:  pdata$Exchange.Rate.Growth.Rate
z = -5.1479, p-value = 1.317e-07
alternative hypothesis: stationarity
```

Annexe 3 : Correlation matrix

Correlation Matrix

Variable	Financial System Deposits to GDP	Exports Growth Rate	GDP Growth Rate	Imports Growth Rate	International Reserves Growth Rate	Real interest rate	Current Account	Inflation Rate	Exchange Rate	Balance of Trade
Financial System Deposits to GDP	1.00	−0.02	−0.08	−0.01	−0.03	0.00	0.01	−0.03	−0.10	0.00
Exports Growth Rate	−0.02	1.00	0.04	0.14	0.00	−0.01	0.02	0.00	0.00	0.01
GDP Growth Rate	−0.08	0.04	1.00	0.06	0.07	−0.15	0.07	−0.06	−0.08	0.01
Imports Growth Rate	−0.01	0.14	0.06	1.00	−0.01	−0.02	0.02	0.00	−0.01	−0.01
International Reserves Growth Rate	−0.03	0.00	0.07	−0.01	1.00	−0.03	0.05	0.00	−0.04	0.04
Real interest rate	0.00	−0.01	−0.15	−0.02	−0.03	1.00	−0.16	−0.23	0.06	0.00
Current Account	0.01	0.02	0.07	0.02	0.05	−0.16	1.00	−0.05	−0.05	0.00
Inflation Rate	−0.03	0.00	−0.06	0.00	0.00	−0.23	−0.05	1.00	−0.03	0.01
Exchange Rate	−0.10	0.00	−0.08	−0.01	−0.04	0.06	−0.05	−0.03	1.00	0.00
Balance of Trade	0.00	0.01	0.01	−0.01	0.04	0.00	0.00	0.01	0.00	1.00

Annexe 4: Significance test

```
------------------------------------------------------------------------------
                                   Coef.  Std.Err.    z    P>|z| [0.025 0.975]
------------------------------------------------------------------------------
const                               0.174    0.031   5.607 0.000  0.113  0.235
Financial Growth Rate              -2.395    0.494  -4.844 0.000 -3.364 -1.426
Exports Growth Rate                 2.166    0.453   4.783 0.000  1.278  3.053
GDP Growth Rate                    -0.022    0.002 -13.478 0.000 -0.025 -0.019
Imports Growth Rate                -0.707    0.486  -1.455 0.146 -1.660  0.245
International Reserves Growth Rate -0.142    0.084  -1.683 0.092 -0.307  0.023
Real interest rate                 -0.002    0.001  -2.802 0.005 -0.003 -0.000
Current Account                     0.003    0.002   2.281 0.023  0.000  0.006
Inflation Rate                      0.004    0.000  13.578 0.000  0.003  0.004
Exchange Rate                       0.000    0.000   2.548 0.011  0.000  0.000
Balance of Trade                    0.000    0.000   0.173 0.863 -0.000  0.000
Group Var                           0.008    0.014
==============================================================================
```

Annexe 5: Robustness test

```
All Variables Model:
AIC: 3950.580027427478, BIC: 3999.5375974511358

7 Significant Variables Model:
AIC: 2581.787394190545, BIC: 2612.385875455331
```

Annexe 6: EMP Models comparison

```
KLR Index Model Metrics: {'Accuracy': 0.8705357142857143, 'AUC': 0.7838771660761188,
EMP Index Model Metrics: {'Accuracy': 0.872023809523809 5, 'AUC': 0.7938371498580921,
```

Annexe 7: Thresholds and Youden Index

C1 model

```
Argentina: Optimal Threshold = 0.178, Youden Index = 0.8913043478260869
Brazil: Optimal Threshold = 0.063, Youden Index = 0.3500000000000001
Ecuador: Optimal Threshold = 0.01, Youden Index = 1.0
Egypt: Optimal Threshold = 0.085, Youden Index = 0.639344262295082
Indonesia: Optimal Threshold = 0.614, Youden Index = 1.0
Malaysia: Optimal Threshold = 0.101, Youden Index = 0.657142857142857
Nigeria: Optimal Threshold = 0.145, Youden Index = 0.90625
Philippines: Optimal Threshold = 0.176, Youden Index = 1.0
South Africa: Optimal Threshold = 0.225, Youden Index = 0.19999999999999996
Turkey: Optimal Threshold = 0.295, Youden Index = 0.6869300911854102
```

C3 model

```
Argentina: Optimal Threshold = 0.28400000000000003, Youden Index = 0.9302325581395348
Brazil: Optimal Threshold = 0.11800000000000001, Youden Index = 0.5084745762711864
Ecuador: Optimal Threshold = 0.001, Youden Index = 0.9836065573770492
Egypt: Optimal Threshold = 0.129, Youden Index = 0.6238095238095238
Indonesia: Optimal Threshold = 0.121, Youden Index = 0.9333333333333333
Malaysia: Optimal Threshold = 0.031, Youden Index = 0.6129032258064515
Nigeria: Optimal Threshold = 0.111, Youden Index = 0.901639344262295
Philippines: Optimal Threshold = 0.229, Youden Index = 1.0
South Africa: Optimal Threshold = 0.062, Youden Index = 0.3500000000000001
Turkey: Optimal Threshold = 0.106, Youden Index = 0.6259259259259258
```

C6 model

```
Argentina: Optimal Threshold = 0.23700000000000002, Youden Index = 0.9166666666666665
Brazil: Optimal Threshold = 0.14, Youden Index = 0.5
Ecuador: Optimal Threshold = 0.001, Youden Index = 0.9833333333333334
Egypt: Optimal Threshold = 0.132, Youden Index = 0.6499999999999999
Indonesia: Optimal Threshold = 0.209, Youden Index = 0.9827586206896552
Malaysia: Optimal Threshold = 0.043000000000000003, Youden Index = 0.7049180327868854
Nigeria: Optimal Threshold = 0.275, Youden Index = 0.9649122807017543
Philippines: Optimal Threshold = 0.41100000000000003, Youden Index = 1.0
South Africa: Optimal Threshold = 0.501, Youden Index = 0.25
Turkey: Optimal Threshold = 0.219, Youden Index = 0.5441595441595442
```

C9 model

```
Argentina: Optimal Threshold = 0.249, Youden Index = 0.9166666666666665
Brazil: Optimal Threshold = 0.307, Youden Index = 0.46499999999999986
Ecuador: Optimal Threshold = 0.9460000000000001, Youden Index = 1.0
Egypt: Optimal Threshold = 0.12, Youden Index = 0.6203703703703702
Indonesia: Optimal Threshold = 0.289, Youden Index = 0.9824561403508771
Malaysia: Optimal Threshold = 0.232, Youden Index = 0.8688524590163933
Nigeria: Optimal Threshold = 0.399, Youden Index = 0.9642857142857144
Philippines: Optimal Threshold = 0.5670000000000001, Youden Index = 1.0
South Africa: Optimal Threshold = 0.481, Youden Index = 0.28214285714285703
Turkey: Optimal Threshold = 0.17400000000000002, Youden Index = 0.6158088235294117
```

C12 model

```
Argentina: Optimal Threshold = 0.122, Youden Index = 1.0
Brazil: Optimal Threshold = 0.168, Youden Index = 0.3999999999999999
Ecuador: Optimal Threshold = 0.002, Youden Index = 0.9827586206896552
Egypt: Optimal Threshold = 0.218, Youden Index = 0.5404040404040404
Indonesia: Optimal Threshold = 0.502, Youden Index = 0.871031746031746
Malaysia: Optimal Threshold = 0.03, Youden Index = 0.6440677966101696
Nigeria: Optimal Threshold = 0.447, Youden Index = 0.9824561403508771
Philippines: Optimal Threshold = 0.646, Youden Index = 1.0
South Africa: Optimal Threshold = 0.41200000000000003, Youden Index = 0.24649859943977592
Turkey: Optimal Threshold = 0.507, Youden Index = 0.7547348484848486
```

Annexe 8: In sample, AUC comparison

C1 in sample

	Country	AUC_Static	AUC_Dynamic
0	Argentina	0.971952	0.996952
1	Brazil	0.772497	0.966146
2	Ecuador	1.000000	1.000000
3	Egypt	0.867963	0.993333
4	Indonesia	0.999866	0.999599
5	Malaysia	0.953659	0.997997
6	Nigeria	0.972623	0.998397
7	Philippines	0.999466	0.999866
8	South Africa	0.643796	0.970370
9	Turkey	0.898741	0.985981

C3 model

STATIC MODEL

	Country	AUC_Static_C3
0	Argentina	0.958802
1	Brazil	0.770727
2	Ecuador	1.000000
3	Egypt	0.859628
4	Indonesia	0.999536
5	Malaysia	0.955335
6	Nigeria	0.982955
7	Philippines	0.999504
8	South Africa	0.659054
9	Turkey	0.899426

Dynamic Model

	Country	AUC_Dynamic_C3
0	Argentina	0.992620
1	Brazil	0.972577
2	Ecuador	1.000000
3	Egypt	0.988936
4	Indonesia	0.999304
5	Malaysia	0.998015
6	Nigeria	0.999304
7	Philippines	0.999752
8	South Africa	0.979268
9	Turkey	0.984495

C6 model

	Country	AUC_Static_C6
0	Argentina	0.936968
1	Brazil	0.758835
2	Ecuador	1.000000
3	Egypt	0.834783
4	Indonesia	0.999513
5	Malaysia	0.956644
6	Nigeria	0.993085
7	Philippines	0.997417
8	South Africa	0.687994
9	Turkey	0.871728

DYNAMIC MODEL

	Country	AUC_Dynamic_C6
0	Argentina	0.992718
1	Brazil	0.976624
2	Ecuador	1.000000
3	Egypt	0.983508
4	Indonesia	0.999708
5	Malaysia	0.998091
6	Nigeria	0.999708
7	Philippines	0.999551
8	South Africa	0.983626
9	Turkey	0.973592

C9 model

	Country	AUC_Static_C9
0	Argentina	0.917022
1	Brazil	0.754492
2	Ecuador	1.000000
3	Egypt	0.824689
4	Indonesia	0.997720
5	Malaysia	0.958059
6	Nigeria	0.996537
7	Philippines	0.996197
8	South Africa	0.697162
9	Turkey	0.847757

DYNAMIC MODEL

	Country	AUC_Dynamic_C9
0	Argentina	0.993971
1	Brazil	0.984229
2	Ecuador	1.000000
3	Egypt	0.991265
4	Indonesia	0.999240
5	Malaysia	0.998355
6	Nigeria	0.999747
7	Philippines	0.999383
8	South Africa	0.984118
9	Turkey	0.976728

C12 model

STATIC MODEL

	Country	AUC_Static_C12
0	Argentina	0.913605
1	Brazil	0.758999
2	Ecuador	1.000000
3	Egypt	0.811213
4	Indonesia	0.999550
5	Malaysia	0.954343
6	Nigeria	0.995277
7	Philippines	0.997817
8	South Africa	0.694295
9	Turkey	0.856918

DYNAMIC MODEL

	Country	AUC_Dynamic_C12
0	Argentina	0.994628
1	Brazil	0.989442
2	Ecuador	1.000000
3	Egypt	0.989519
4	Indonesia	0.996402
5	Malaysia	0.998196
6	Nigeria	0.998876
7	Philippines	0.999620
8	South Africa	0.983716
9	Turkey	0.976231

Annexe 9: out-of-sample

Model C1

- Static model

```
C1 out of sample static
Argentina: AUC = 0.9640721450617284, TPR = 0.9537037037037037, FNR = 0.046296296296296294, FPR = 0.13541666666666666, TNR = 0.8645833333333334
Brazil: AUC = 0.8064814814814815, TPR = 0.7916666666666666, FNR = 0.20833333333333334, FPR = 0.37222222222222223, TNR = 0.6277777777777778
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.9530092592592593, TPR = 0.875, FNR = 0.125, FPR = 0.022222222222222223, TNR = 0.9777777777777777
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.10784313725490197, TNR = 0.8921568627450981
Nigeria: AUC = 0.9251302083333331, TPR = 0.9166666666666666, FNR = 0.08333333333333333, FPR = 0.03125, TNR = 0.96875
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.004901960784313725, TNR = 0.9950980392156863
South Africa: AUC = 0.8219907407407407, TPR = 0.7916666666666666, FNR = 0.20833333333333334, FPR = 0.3277777777777778, TNR = 0.6722222222222223
Turkey: AUC = 0.9158653846153846, TPR = 0.75, FNR = 0.25, FPR = 0.09615384615384616, TNR = 0.9038461538461539
```

- Dynamic model

```
C1 out of sample dynamic
Argentina: AUC = 0.9783950617283951, TPR = 0.9814814814814815, FNR = 0.018518518518518517, FPR = 0.09375, TNR = 0.90625
Brazil: AUC = 0.9106481481481482, TPR = 0.875, FNR = 0.125, FPR = 0.2111111111111111, TNR = 0.7888888888888889
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.9590277777777777, TPR = 0.9166666666666666, FNR = 0.08333333333333333, FPR = 0.016666666666666666, TNR = 0.9833333333333333
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.058823529411764705, TNR = 0.9411764705882353
Nigeria: AUC = 0.9251302083333331, TPR = 0.9166666666666666, FNR = 0.08333333333333333, FPR = 0.020833333333333332, TNR = 0.9791666666666666
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.004901960784313725, TNR = 0.9950980392156863
South Africa: AUC = 0.9083333333333333, TPR = 0.9166666666666666, FNR = 0.08333333333333333, FPR = 0.1388888888888889, TNR = 0.8611111111111112
Turkey: AUC = 0.9516559829059829, TPR = 0.9166666666666666, FNR = 0.08333333333333333, FPR = 0.05128205128205128, TNR = 0.9487179487179487
```

Model C3

- Static model

```
C3 out of sample static
Argentina: AUC = 0.9302224371373308, TPR = 0.9, FNR = 0.1, FPR = 0.13829787234042554, TNR = 0.8617021276595744
Brazil: AUC = 0.7861201298701298, TPR = 0.6785714285714286, FNR = 0.32142857142857145, FPR = 0.2784090909090909, TNR = 0.7215909090909091
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.881590319792567, TPR = 0.7307692307692307, FNR = 0.2692307692307692, FPR = 0.011235955056179775, TNR = 0.9887640449438202
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.00980392156862745, TNR = 0.9901960784313726
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.11764705882352941, TNR = 0.8823529411764706
Nigeria: AUC = 0.8144736842105263, TPR = 0.7857142857142857, FNR = 0.21428571428571427, FPR = 0.04736842105263158, TNR = 0.9526315789473684
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
South Africa: AUC = 0.7153003246753248, TPR = 0.75, FNR = 0.25, FPR = 0.4034090909090909, TNR = 0.5965909090909091
Turkey: AUC = 0.8402074898785425, TPR = 0.7307692307692307, FNR = 0.2692307692307692, FPR = 0.14473684210526316, TNR = 0.8552631578947368
```

- Dynamic model

```
C3 out of sample dynamic
Argentina: AUC = 0.968568665377176, TPR = 0.9727272727272728, FNR = 0.02727272727272727, FPR = 0.0851063829787234, TNR = 0.9148936170212766
Brazil: AUC = 0.9492694805194806, TPR = 0.9285714285714286, FNR = 0.07142857142857142, FPR = 0.13636363636363635, TNR = 0.8636363636363636
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.9615384615384613, TPR = 0.8846153846153846, FNR = 0.11538461538461539, FPR = 0.011235955056179775, TNR = 0.9887640449438202
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.11764705882352941, TNR = 0.8823529411764706
Nigeria: AUC = 0.9353383458646617, TPR = 0.9285714285714286, FNR = 0.07142857142857142, FPR = 0.02631578947368421, TNR = 0.9736842105263158
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
South Africa: AUC = 0.9119318181818182, TPR = 0.8928571428571429, FNR = 0.10714285714285714, FPR = 0.36363636363636365, TNR = 0.6363636363636364
Turkey: AUC = 0.9493294534412955, TPR = 0.9230769230769231, FNR = 0.07692307692307693, FPR = 0.09868421052631579, TNR = 0.9013157894736842
```

Model C6

- Static model

```
C6 out of sample static
Argentina: AUC = 0.8825245550909268, TPR = 0.8761061946902655, FNR = 0.12389380530973451, FPR = 0.14285714285714285, TNR = 0.8571428571428571
Brazil: AUC = 0.7534602076124568, TPR = 0.6470588235294118, FNR = 0.35294117647058826, FPR = 0.23529411764705882, TNR = 0.7647058823529411
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.7915270935960591, TPR = 0.6551724137931034, FNR = 0.3448275862068966, FPR = 0.011428571428571429, TNR = 0.9885714285714285
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.11764705882352941, TNR = 0.8823529411764706
Nigeria: AUC = 0.6956590122680089, TPR = 0.6470588235294118, FNR = 0.35294117647058826, FPR = 0.016042780748663103, TNR = 0.983957219251337
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
South Africa: AUC = 0.6, TPR = 0.5294117647058824, FNR = 0.47058823529411764, FPR = 0.21764705882352942, TNR = 0.7823529411764706
Turkey: AUC = 0.7336443079829947, TPR = 0.5862068965517241, FNR = 0.41379310344827586, FPR = 0.14383561643835616, TNR = 0.8561643835616438
```

- Dynamic model

```
C6 out of sample dynamic
Argentina: AUC = 0.8958475153165419, TPR = 0.911504424778761, FNR = 0.08849557522123894, FPR = 0.14285714285714285, TNR = 0.8571428571428571
Brazil: AUC = 0.9375432525951556, TPR = 0.8823529411764706, FNR = 0.11764705882352941, FPR = 0.08235294117647059, TNR = 0.9176470588235294
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.7948768472906405, TPR = 0.6896551724137931, FNR = 0.3103448275862069, FPR = 0.005714285714285714, TNR = 0.9942857142857143
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.11764705882352941, TNR = 0.8823529411764706
Nigeria: AUC = 0.6956590122680089, TPR = 0.6470588235294118, FNR = 0.35294117647058826, FPR = 0.0374331550802139, TNR = 0.9625668449197861
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
South Africa: AUC = 0.6717993079584775, TPR = 0.6470588235294118, FNR = 0.35294117647058826, FPR = 0.3352941176470588, TNR = 0.6647058823529411
Turkey: AUC = 0.790151157298063, TPR = 0.6896551724137931, FNR = 0.3103448275862069, FPR = 0.1232876712328767, TNR = 0.8767123287671232
```

Model C9

- Static model

```
C9 out of sample static
Argentina: AUC = 0.8430642633228841, TPR = 0.853448275862069, FNR = 0.14655172413793102, FPR = 0.14772727272727273, TNR = 0.8522727272727273
Brazil: AUC = 0.7275914634146341, TPR = 0.325, FNR = 0.675, FPR = 0.10975609756097561, TNR = 0.8902439024390244
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.716751453488372, TPR = 0.625, FNR = 0.375, FPR = 0.011627906976744186, TNR = 0.9883720930232558
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.058823529411764705, TNR = 0.9411764705882353
Nigeria: AUC = 0.610733695652174, TPR = 0.55, FNR = 0.45, FPR = 0.016304347826086956, TNR = 0.9836956521739131
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
South Africa: AUC = 0.521341463414634, TPR = 0.45, FNR = 0.55, FPR = 0.23170731707317074, TNR = 0.7682926829268293
Turkey: AUC = 0.6669642857142857, TPR = 0.484375, FNR = 0.515625, FPR = 0.18571428571428572, TNR = 0.8142857142857143
```

- Dynamic model

```
C9 out of sample dynamic
Argentina: AUC = 0.850950235109718, TPR = 0.8793103448275862, FNR = 0.1206896551724138, FPR = 0.14772727272727273, TNR = 0.8522727272727273
Brazil: AUC = 0.923780487804878, TPR = 0.475, FNR = 0.525, FPR = 0.024390243902439025, TNR = 0.975609756097561
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.7191133720930233, TPR = 0.625, FNR = 0.375, FPR = 0.005813953488372093, TNR = 0.9941860465116279
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.04411764705882353, TNR = 0.9558823529411765
Nigeria: AUC = 0.610733695652174, TPR = 0.55, FNR = 0.45, FPR = 0.010869565217391304, TNR = 0.9891304347826086
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
South Africa: AUC = 0.6129573170731708, TPR = 0.45, FNR = 0.55, FPR = 0.054878048780487805, TNR = 0.9451219512195121
Turkey: AUC = 0.7393973214285714, TPR = 0.5, FNR = 0.5, FPR = 0.12857142857142856, TNR = 0.8714285714285714
```

Model C12

- Static model

```
C12 out of sample static
Argentina: AUC = 0.81463173504696, TPR = 0.8739495798319328, FNR = 0.12605042016806722, FPR = 0.15294117647058825, TNR = 0.8470588235294118
Brazil: AUC = 0.7058337919647771, TPR = 0.41304347826086957, FNR = 0.5869565217391305, FPR = 0.22151898734177214, TNR = 0.7784810126582279
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.6532544378698225, TPR = 0.45714285714285713, FNR = 0.5428571428571428, FPR = 0.011834319526627219, TNR = 0.9881656804733728
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.11764705882352941, TNR = 0.8823529411764706
Nigeria: AUC = 0.5463607975018017, TPR = 0.4782608695652174, FNR = 0.5217391304347826, FPR = 0.011049723756906077, TNR = 0.988950276243094
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
South Africa: AUC = 0.46078701155751234, TPR = 0.391304347826087, FNR = 0.6086956521739131, FPR = 0.2848101265822785, TNR = 0.7151898734177216
Turkey: AUC = 0.6242004264392323, TPR = 0.34285714285714286, FNR = 0.6571428571428571, FPR = 0.15671641791044777, TNR = 0.8432835820895522
```

- Dynamic model

```
C12 out of sample dynamic
Argentina: AUC = 0.8135442412259021, TPR = 0.8907563025210085, FNR = 0.1092436974789916, FPR = 0.15294117647058825, TNR = 0.8470588235294118
Brazil: AUC = 0.9094661529994496, TPR = 0.6521739130434783, FNR = 0.34782608695652173, FPR = 0.0949367088607595, TNR = 0.9050632911392406
Ecuador: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Egypt: AUC = 0.6551141166525781, TPR = 0.5142857142857142, FNR = 0.4857142857142857, FPR = 0.005917159763313609, TNR = 0.9940828402366864
Indonesia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
Malaysia: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.11764705882352941, TNR = 0.8823529411764706
Nigeria: AUC = 0.5463607975018017, TPR = 0.4782608695652174, FNR = 0.5217391304347826, FPR = 0.011049723756906077, TNR = 0.988950276243094
Philippines: AUC = N/A, TPR = N/A, FNR = N/A, FPR = 0.0, TNR = 1.0
South Africa: AUC = 0.5634287286736379, TPR = 0.391304347826087, FNR = 0.6086956521739131, FPR = 0.0949367088607595, TNR = 0.9050632911392406
Turkey: AUC = 0.6979744136460555, TPR = 0.3, FNR = 0.7, FPR = 0.1044776119402985, TNR = 0.8955223880597015
```

Abstract :

This thesis is a comparative analysis of static and dynamic models to predict currency crises, focusing on their effectiveness across different time horizons in 10 emerging countries. The main findings show that in the short term (1 to 3 months' time horizon), the models can deliver a True Positive Rate of over 88%. However, as the time horizon extends, the effectiveness of the models reduces. Remarkably, in Argentina, the dynamic model continues to show high effectiveness with an 89% True Positive Rate at a 12-month horizon. This analysis also identifies an anomaly in predictive accuracy during the 2019 to 2021 period, which is attributed to the economic disturbances caused by the COVID-19 pandemic. It distorted the models' parameters and led to false predictions of crises. Overall, the dynamic model, which incorporates lagged crisis data, consistently outperforms the static model across most time horizons and countries.

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