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DIAGNOSING THE PATH OF FINANCIAL STABILITY INDEX: A NEW PERSPECTIVE FOR ARTIFICIAL INTELLIGENCE APPLICATIONS

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ABSTRACT

The study highlights the critical challenge of assessing and maintaining financial stability, given its importance for economic growth and also in the face of financial crises. However, it remains vulnerable to internal and external shocks. Traditional methods for assessing financial stability, such as the IMF's Financial Stability Index (FSI) often rely on fixed–weight models that may not adapt well to changing economic conditions. This gap motivates the exploration of Artificial Intelligence applications to enhance the accuracy and predictive power of the FSI. It aims to design an AI-based financial stability index that accurately measures the resilience of the banking sector to crises. The study proposes new algorithm that integrate deep learning models (DLM) outputs to create a fitness function in a proposed genetic algorithm framework. The study used a multi-method AI approach, using machine learning (ML), DLM, and genetic algorithms (GA), to diagnose and correct the FSI Path. GA aims to optimize the component variables of the FSI across various scenarios. The results concluded that AI techniques outperform traditional methods in predicting FSI trends. Also, GA provided scenario-based optimizations, highlighting the FSI's sensitivity to external shocks. The study's contribution lies in its innovative integration of AI into financial stability analysis, providing policymakers with a dynamic tool for crisis response. The study recommends adopting an AI-enhanced financial stability index for early warning systems for shocks and designing macroprudential policies aligned with economic cycles. It also provides a comprehensive framework for developing countries to mitigate financial instability in the face of overlapping crises.

KEYWORDS: Artificial Intelligence Applications – Machine Learning Models – Deep Learning Models – Genetic Algorithm – Financial Stability Index.

1. INTRODUCTION

Managing the domestic financial system is a major challenge for policymakers in developing countries. Macroeconomic performance in such economies critically depends on the state of the financial system, which strongly affects long–term economic performance and short–term macroeconomic stability. Financial sector distortions pose serious obstacles to long-term growth by harming capital accumulation and total factor productivity growth (Ahir et al., 2023). Financial sector weaknesses may themselves be a source of macroeconomic instability or cause the spread and amplification of macroeconomic shocks emanating from other directions. Accordingly, addressing the fragility of the financial system, reducing transaction costs that represent an additional burden on foreign investments, strengthening financial soundness indicators, and enhancing fiscal discipline are all important steps to address the problem (Phan et al., 2021).

It contributes positively to achieving a state of monetary and financial stability, particularly economic stability in general, which leads to increased savings rates and the spread of positive sentiment that supports foreign investors' confidence in these markets (Romer & Romer, 2017). The focus on financial stability stems from both academic and political perspectives. This topic has been the subject of academic discussion since the crisis (Creel et al., 2015). The main reason for addressing the issue of financial stability is its nature as a public good: it is a nonrival good because its use does not prevent someone else from using it, and it is a non–excludable good because no one can be deprived of its use (Bassett & Rappoport, 2022).

Perhaps the observer of sustainability in its two aspects, external and financial–the two primary aspects of economic sustainability–will find that they are goals that economic authorities deal with apart from general economic goals through sustainable economic policies, due to their impact on the design, implementation, and effectiveness of macroeconomic policies in different time frames (Zelka, 2022 ;Illing & Liu, 2006). The stability of the financial sector–the thermometer that measures the strength of an economy and its ability to absorb various economic shocks–is considered the nominal stabilizer and the ultimate goal of macroprudential policies in the economy, in addition to being the main indicator of the financial stress test results.

The phenomenon of financial soundness has received considerable attention from both researchers and policymakers due to its significant theoretical and empirical implications. This issue is of major importance because it influences the design, implementation, and effectiveness of macroeconomic policies across different timeframes, as well as their capacity to absorb economic shocks. (Karanovic & Karanovic, 2015) constructed an aggregate Financial Stability Index (FSI) for nine Balkan countries from 1995 to 2011, integrating financial soundness, vulnerability, development, and global economic climate indicators to assess regional stability. Using normalized and weighted data–such as credit/GDP ratios, inflation rates, and non– performing loans–the index reveals persistently low financial stability (values below 0.5), with significant declines during the 2001 and 2007 crises.

EU–member Balkan countries demonstrated stronger stability post–2006, benefiting from robust macroprudential frameworks, while non–EU nations experienced delayed shocks due to weaker integration. A Chanut–Laroque volatility analysis identified financial development and global economic conditions as key drivers of instability. The findings underscore the importance of regional policy coordination and enhanced data systems to mitigate risks, particularly for non–EU Balkan economies exposed to external vulnerabilities.

(Denis Negotei Ioana-Alina, 2018) constructed a Composite Financial Stability Index (CFSI) for the Euro Area (1998–2012) using 25 indicators across four sectors: external, real, financial, and global economic climate. The index, normalized and weighted, successfully identified periods of financial instability, including the 2008 crisis, and revealed a general stability improvement post-1990s. A Chanut–Laroque volatility analysis highlighted the financial sector's dominant role in driving instability, while global economic indicators amplified turbulence during crises. The findings underscore the need for enhanced supervisory frameworks and stress the index's utility in complementing traditional macroprudential analyses for Euro Area policymakers. (Modise et al., 2023) examined the potential advantages of implementing an Aggregate Financial Stability Index (AFSI) as a supplementary tool for monitoring Botswana's financial system.

In response to recurring financial disturbances since the early 2000s, the study emphasizes the need for effective mechanisms to detect systemic stress. The AFSI is constructed using sub–indices that represent financial development, vulnerability, soundness, and external factors, with the ARDL model applied to assess the influence of macroeconomic variables. The results show that the AFSI is a reliable indicator, offering policymakers a clearer understanding of financial stress and enabling more informed responses.

Over the past few decades, artificial intelligence (AI) applications have become a primary tool for analyzing economic fluctuations, policy impacts, and welfare levels. Unlike traditional macroeconomic models with reduced form equations–which merely describe the behavior of aggregate variables–AI applications more accurately capture the economic structure by modeling the motivations and constraints of individual actors, their interactions within institutional frameworks, and the resulting decision–making processes (Damasevicius, 2023). They also assess how these decisions influence macroeconomic variables. Additionally, AI facilitates the seamless integration of external shocks without relying on reduced–form residual analysis. Among its key advantages is the ability to handle nonlinear models, which are common in real–world scenarios, as well as complex, nonstationary, noisy, and incomplete data. AI can process vast amounts of variables and identify relationships that lack fixed forms, unlike linear regression models. Most importantly, these applications provide highly predictive solutions (e.g., Rahmani et al., 2023 ; Kumar, 2024 ; Jiao et al., 2025).

Based on the foregoing, we do not argue in this paper about the effectiveness of AI applications in constructing the FSI. Rather, we seek to answer two fundamental questions. First, "How, and under what circumstances can AI applications contribute to the design of the Egyptian FSI?". Second, "To what extent can extent does the adoption of these applications contribute to enhancing financial discipline processes by predicting the directional behavior pattern of the Egyptian FSI and correcting its path under the umbrella of contemporary economic crises?". The question of constructing and forecasting an FSI's path has traditionally been an important test of credibility economic models for FSI design.

Our new proposed algorithm is based on a central hypothesis stating: "FSI that the study aims to design can serve as a thermometer to measure the resilience and soundness of the Egyptian banking sector. Additionally, AI applications can be relied upon to adjust and correct the index's directional path". Unlike the IMF's approach–used by many central banks worldwide–this proposed FSI construction method differs both in the number of variables selected for its core components, and in how their relative weights are determined. Previous approaches rely on fixed relative weights when constructing the index. In contrast, this proposed approach argues that such static weighting is insufficient to build an index capable of serving as a reliable 'thermometer' for financial fragility.

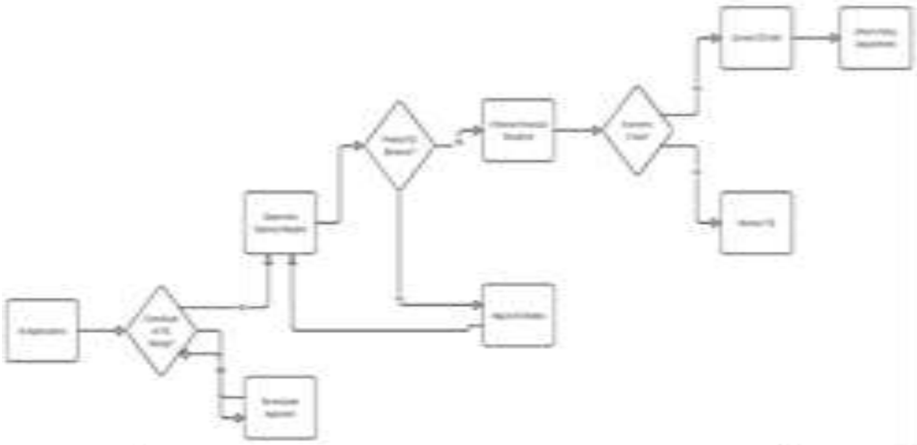

Figure 1: The Current, And Future Analytical Scenario Diagram.

Our approach believes in the ability of machine learning models (MLM) to determine the optimal relative weights for the main sub–indices comprising this index. Deep learning models (DLM) constitute a core component of this proposed approach, given their fundamental role in predicting the FSI's behavioral path. As a key pillar in designing and implementing macroprudential policies, DLM offer high explanatory and predictive power. This capability enables economic authorities to identify deviation patterns from current policies, thereby informing more effective policy adjustments. The application of artificial intelligence in this approach extends further. The study proposes new algorithm that integrate DLM outputs to create a fitness function in a proposed genetic algorithm (GA) framework. GA aims to optimize the component variables of the FSI across various scenarios. This will enable policymakers to formulate policies and strategies to make appropriate decisions under the circumstances and conditions that the Egyptian economy is experiencing.

2. LITERATURE REVIEW

A considerable amount of literature has been published on financial stability. Karanovic and Karanovic (2015) constructed an aggregate Financial Stability Index (FSI) for nine Balkan countries from 1995 to 2011, integrating financial soundness, vulnerability, development, and global economic climate indicators to assess regional stability. Using normalized and weighted data–such as credit/GDP ratios, inflation rates, and non– performing loans–the index reveals persistently low financial stability (values below 0.5), with significant declines during the 2001 and 2007 crises.

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The origins of genetic algorithms date back to Turing's concept of a "learning machine" that mimics evolutionary processes. By the 1960s, researchers began actively developing computer simulations of biological evolution, with Holland's work playing a pivotal role. These algorithms are inspired by natural systems, where gene reproduction, crossover, and mutation enhance adaptability, allowing complex structures to emerge from simpler components. While traditionally rooted in Darwinian evolution and Mendelian genetics, the approach can also incorporate Lamarckian or Baldwinian principles.

Booker, Goldberg, and Holland (1989) highlighted the probabilistic nature of genetic algorithms, setting them apart from earlier optimization techniques that relied on deterministic, enumerative, or purely computational methods. The standard genetic algorithm, as described by Koza (1992) and Kim and Han (2000), follows a structured process beginning with the initialization of a randomly generated population of fixed–length character strings. This is followed by an iterative cycle of mutation, where individuals may undergo minor random changes, and crossover, where pairs of individuals exchange segments to produce new offspring. The population evolves through these operations until the newly formed individuals are evaluated for fitness, with only the fittest advancing to the next iteration. The algorithm terminates once an individual meets the predefined fitness criteria or another stopping condition is satisfied (Hassanat et al., 2019).

Udom and Doguwa (2015) constructed the Nigerian Financial System Stability Index (FSSI), expanding the Banking Sector Stability Index (BSI) to include indicators from the banking, insurance, and capital markets sectors, to provide a comprehensive measure of financial stability during the global financial crisis. The study concluded that the FSSI represents an accurate tool for policymakers to monitor systemic risks and implement targeted interventions through the interconnectedness of banks and capital markets.

Similarly, Akosah, Loloh, Lawson, and Kumah (2018) created an Aggregate Financial Stability Index (AFSI) for Ghana to assess the performance of its financial system after the adoption of inflation targeting in 2017. This index is derived from four sub-indices: the Financial Development Index (FDI), the Financial Soundness Index (FSI), the Financial Vulnerability Index (FVI), and the World Economic Climate Index (WECI). The study concluded that the Ghana Financial Stability Index (AFSI) is an effective tool for policymakers to measure systemic risks and guide monetary policy to achieve and enhance financial stability.

Bitetto, Cerchiello, and Mertzanis (2023) presented a new data-driven approach to measuring financial soundness in 119 countries over the period 2010–2017 using the International Monetary Fund's Financial Soundness Indicators (FSIs). An alternative data-driven measure of financial soundness (FSIND) was constructed, which captures cross-sectional and temporal dependencies of data. It demonstrated strong predictive power, providing policymakers and financial institutions with a reliable tool for monitoring financial stability. It also provides a scalable and adaptable framework for analyzing global financial stability, bridging the gap between theory and data-driven policymaking.

Goulet Coulombe (2024) provide a clear empirical framework for integrating machine learning into macroeconomic forecasting, highlighting its most influential aspects. It identifies key features of machine learning (ML) that improve macroeconomic forecasting and goes beyond simply identifying the best-performing machine learning algorithms. It focuses on understanding how these algorithms contribute to forecasting accuracy. The study concludes that machine learning enhances macroeconomic forecasting primarily through nonlinear modeling, which captures complex relationships during uncertain economic periods. Also, Pallathadka et al. (2023) emphasized the application of machine learning (ML) models to predict bankruptcies, leveraging financial data to enhance forecasting accuracy. It also plays a role in identifying early warning signs of financial distress, enabling proactive risk management, and protecting economic stability. By combining advanced machine learning techniques with optimization algorithms, it provides an accurate and scalable approach to bankruptcy prediction, enabling policymakers to integrate these predictive models into regulatory frameworks to monitor systemic risks and ensure financial stability.

Our approach believes in the ability of machine learning models (MLM) to determine the optimal relative weights for the main sub–indices comprising this index. Deep learning models (DLM) constitute a core component of this proposed approach, given their fundamental role in predicting the FSI's behavioral path. As a key pillar in designing and implementing macroprudential policies, DLM offer high explanatory and predictive power. This capability enables economic authorities to identify deviation patterns from current policies, thereby informing more effective policy adjustments. The application of artificial intelligence in this approach extends further. The study proposes new algorithm that integrate DLM outputs to create a fitness function in a proposed genetic algorithm (GA) framework. GA aims to optimize the component variables of the FSI across various scenarios. This will enable policymakers to formulate policies and strategies to make appropriate decisions under the circumstances and conditions that the Egyptian economy is experiencing.

3. HAVE MLM BECOME THE ARTISTIC SCULPTORS OF FSI DESIGN?

In 2002, the International Monetary Fund (IMF) outlined the essential aspects of achieving economic sustainability, dividing them into three categories: external sustainability, financial sustainability, and financial sector stability. Regarding financial sector stability, the IMF defined it as a state in which the financial sector can withstand internal and external crises while continuing to perform its core functions: efficiently allocating financial resources toward investment opportunities and maintaining effective payment systems–even during crises–without disrupting self-correcting mechanisms that mitigate financial risks and imbalances. Additionally, it emphasized the need to align the financial asset values growth rate with the sustainable economic growth rate (IMF, 2002).

This section discusses the design and analysis of FSI in the Egyptian economy. The FSI is a quantitative measure of the banking sector's ability to efficiently allocate economic resources through financial intermediation services while remaining vulnerable to external and internal shocks. Such vulnerabilities can lead to the accumulation of systemic risks, potentially disrupting the financial system’s performance or undermining confidence in its soundness, with negative effects on the real economy. The FSI reflects overall financial stability, helping to detect imbalances in the financial sector at an early stage. However, it is ineffective in predicting periods of financial stress (IMF, 2002 ; GFSR, 2024). The concept of designing and constructing this index–both quantitatively and practically–was not introduced into the Egyptian economy until 2017. Since then, the Egyptian FSI has become a key measure of the economy’s resilience and its ability to absorb economic shocks. It has also emerged as a nominal stabilizer and a central objective of macroprudential policies, in addition to serving as the primary indicator of financial stress test results (Al-Rjoub, 2021).

Once the Egyptian economy began implementing and constructing this index, monetary authorities promptly applied it retrospectively using quarterly historical time series data dating back to March 2011. The IMF's methodology for constructing the index–a composite quantitative measure–relied on a broad set of 21 variables grouped into four sub-indices□: banking sector performance (BPI), macroeconomic performance conditions (MPI), financial market development (FMI), and global economic climate (GEI). This methodology aligns with one of the most widely adopted approaches among countries that have developed similar indices. The index is calculated as an equally weighted average□□ of the selected variables, covering the core dimensions of financial stability. Like many such indices, it employs empirical normalization□□□–a technique also used in this study. However, this study modifies the methodology by adjusting the number of sub–indicators within each main category.

For instance, the Egyptian banking sector performance sub–index includes 8 variables, but it overlooks key indicators for monitoring systemic risks and macroprudential policy tools, such as: loan to asset ratio limits, debt to income ratio limits, and currency mismatch.

To address this gap, this study expands the sub–index to include 11 variables, ensuring a more comprehensive assessment of financial stability. Regarding the macroeconomic conditions index, five variables were added to the existing seven core variables: real exchange rate fluctuations, net international reserves growth rate, degree of economic openness, savings–investment gap, and credit gap□□□□. For the global economic climate index, the global international reserves volume variable was included alongside the two original variables. With these additions, the total number of variables in the index designed for this study reaches 30. This study employs a methodology distinct from that of the Central Bank of Egypt (CBE), which uses a weighted average approach for index construction. Aligning with the IMF's framework in the financial stability report 2022, we adopt variable weights based on each indicator's explanatory power regarding FSI behavior (CBE, 2022). However, our methodological innovation extends further by proposing a novel approach that fundamentally differs from existing weighting estimation methods. Specifically, we introduce MLM to determine these relative weights. Consequently, the index construction follows the functional form presented below:

$$FSI_t = \sum_{n=1}^{11} \omega_{jBPI} d_{jt} + \sum_{n=1}^{12} \omega_{jMPI} d_{jt} + \sum_{n=1}^{4} \omega_{jFMI} d_{jt} + \sum_{n=1}^{3} \omega_{jGEI} d_{jt}; \quad (1)$$

Where ω_jBPI is the banking sector performance index weighting factor, ω_jMPI is the macroeconomic conditions index weighting factor, ω_jFMI is the financial market development index weighting factor, and ω_jGEI is the global economic climate index weighting factor. For converting the baseline variables x_jt to standardized values d_jt, normalization was applied using the following functional form:

$$d_{jt} = \frac{x_{jt} \quad - x_{j\,min}}{x_{j\,max} - x_{j\,min}} \; ; \quad (2)$$

While each individual variable may not fully capture financial stability, the aggregated variables can indicate potential risks. This distinction also applies to the scope of implementation, as this study utilizes quarterly time series data covering the period from 2005Q1 to 2022Q4□ to design this quarterly index. According to this methodology, an increase in the value of each variable reflects an improvement in financial stability. Therefore, the inverse value is used for variables that negatively impact financial stability. Furthermore, the index scales from 0 to 1, with proximity to 1 denoting robust financial stability, while a value near zero signifies fragility.

We consider several MLM in our horse race. These models employ supervised artificial intelligence techniques that utilize backpropagation algorithms and iterative optimization to identify patterns and relationships among variables. Through training on extensive datasets, the models develop enhanced analytical capabilities for processing complex relationships. This study implements a contemporary AI framework that facilitates: real–time interaction between training, testing, and validation phases; continuous error correction; and comparative evaluation of machine learning algorithms to select the optimal approach for data pattern recognition. The results of the proposed scheme in Figure 2 demonstrated that five machine learning models emerged as leading candidates for predicting the directional path of FSI: stochastic gradient descent (SGD), K–means, support vector machines (SVM), lasso regression, and elastic net regression. Among these, the SGD model distinguished itself as the most effective in explaining the index's behavioral patterns, surpassing other models in predictive performance.

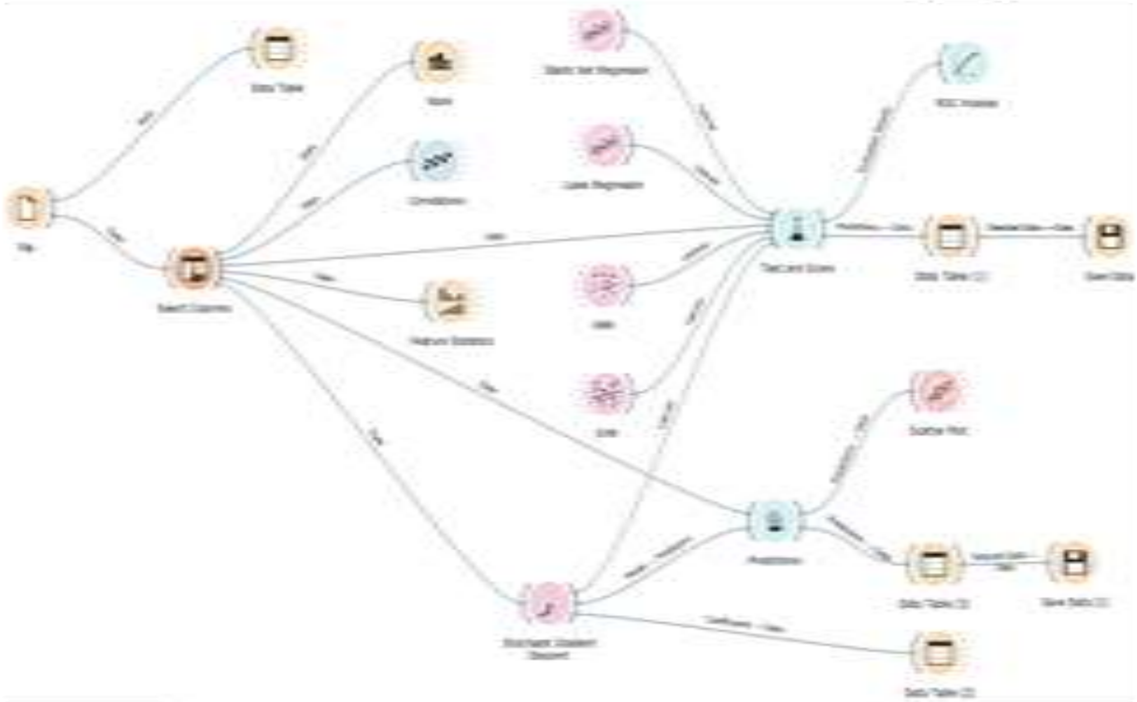


Figure 2. Architecture of

SGD model achieved exceptional results across all evaluation metrics, most notably attaining a coefficient of determination of 95.6%. Both its mean squared error and root mean squared error reached negligible values approaching zero, while its mean absolute error similarly converged near zero. These outstanding outcomes, as quantified in the machine learning model comparison matrix presented below, confirm the SGD model's superior capability in forecasting financial stability trends.

Table 1: A Comprehensive Evaluation Framework for Assessing MLM.

MLM	MSE	RMSE	MAE	R2 %
SGD	0.001	0.008	0.006	95.6
Elastic Net Regression	0.003	0.008	0.007	94.2
Lasso Regression	0.003	0.013	0.011	92.3
KMN	0.005	0.020	0.028	76.6
SVM	0.009	0.045	0.039	69.1

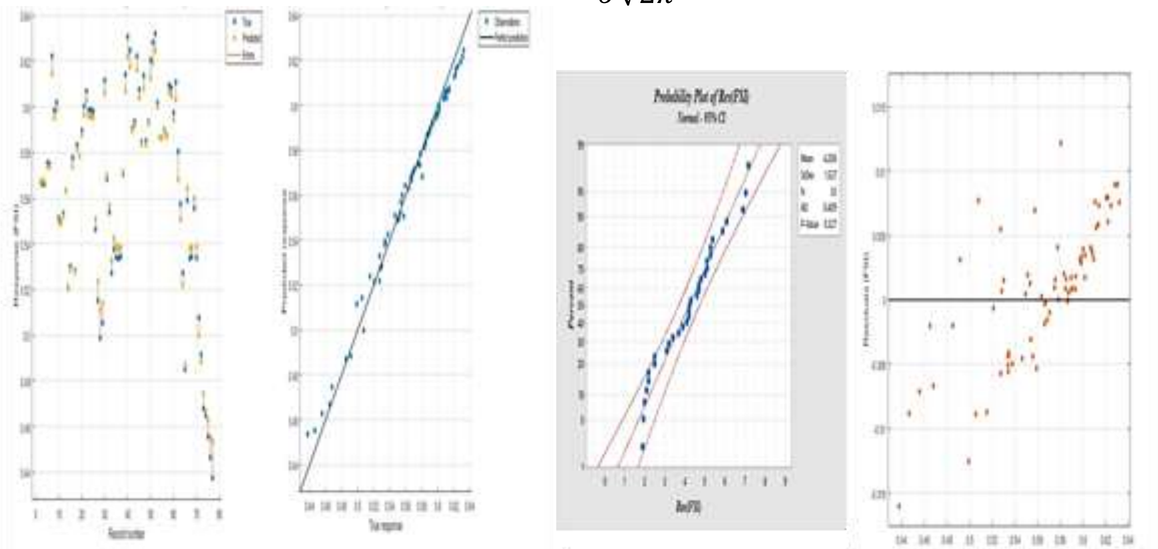
Notes. The Model Rankings Presented Here Derive From Analysis Of 76 Observational Data Points, Sorted In Descending Order By Their Respective Coefficients Of Determination (R^2).

Figure 3 demonstrates the predictive accuracy of the SGD model, evidenced by the minimal deviations observed between actual and estimated values of the Egyptian FSI throughout the study period. The figure further reveals a strong correspondence between real and predicted outputs, as reflected in the distribution of model outputs around the corresponding trend lines. This robust agreement validates the reliability of the machine learning models' results.

Given the demonstrated superiority of SGD model, as evidenced by its capacity to dynamically adjust parameter weights and minimize mean error convergence toward zero. it becomes methodologically imperative to examine whether the time series residuals $|X\_t|$ follow a normal distribution during the study period. This diagnostic testing is essential for properly evaluating the statistical hypotheses outlined below.

$$H_0: |X_t| \approx \mathcal{N}(\mu, \sigma^2) \;; \qquad f(x) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \;; \; Normality \qquad (3)$$

$$H_1: |X_t| \not\approx \mathcal{N}(\mu, \sigma^2) \;; \qquad f(x) \neq \frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \;; \; Non-Normality \qquad (4)$$



Panel A

Panel B

Panel A

Panel B

Figure 4 indicates a p–value of 0.327, which exceeds the conventional 0.05 significance threshold. This result fails to reject the null hypothesis, supporting that the residuals of SGD model follow a normal distribution. Consequently, we can conclude that the SGD model produce prediction errors that are effectively zero–centered.

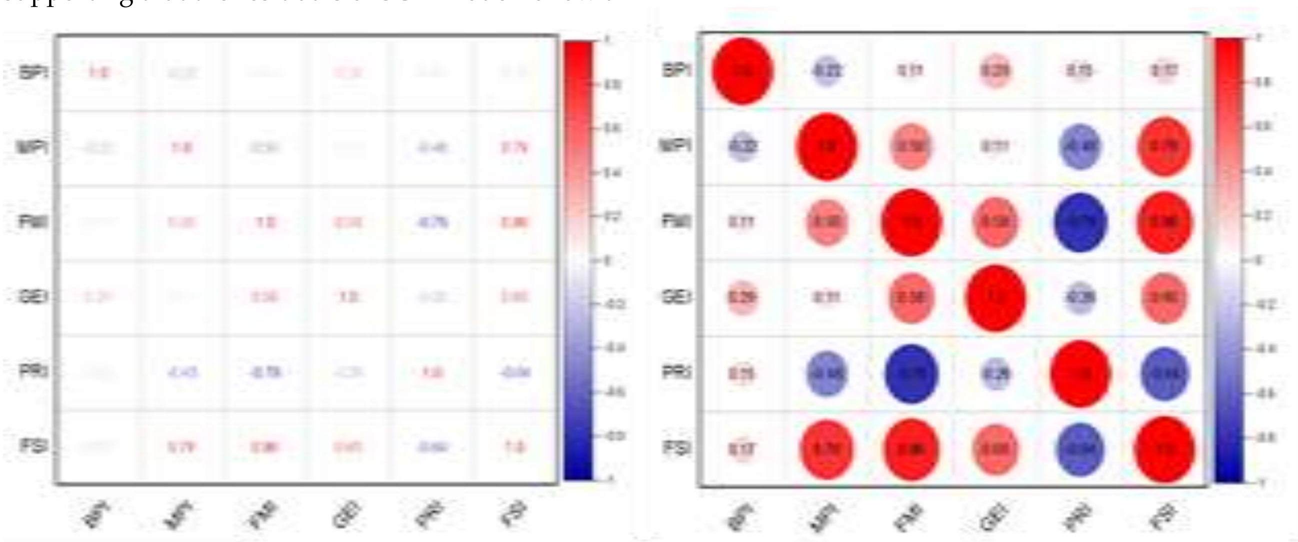
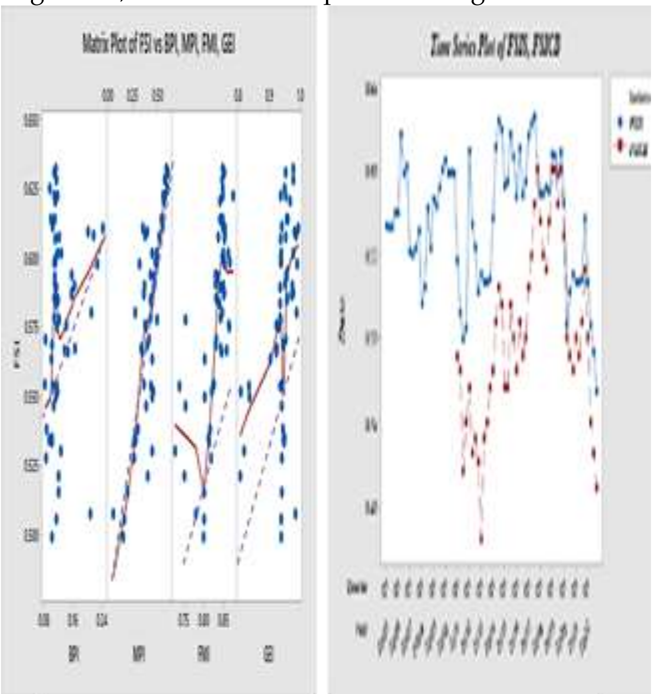


Figure 5. Direct relative

Among competing machine learning approaches, the relative weights presented in Figure 5 were applied to weight the aforementioned indicators for estimating the composite index.

The index estimation results revealed a direct complementary relationship between the composite index and its constituent components, as demonstrated by the directional correlation matrix in panel A of Figure 6. Furthermore, the analysis shows significant directional convergence between the study index FSIS and the Central Bank of Egypt's index FSICB, with periods approaching near–perfect alignment, as evidenced in panel B of Figure 6.



Panel

Figure 6. Directional Correlation Matrix between the Financial Stability Index And Its

The study period's index design reflected contradictory scenarios that manifested through volatile index movements. In 2005, Egyptian monetary authorities introduced significant reforms, including implementing a corridor system for overnight interbank rate management and establishing a dedicated banking sector restructuring department. This was complemented by a comprehensive four-part strategy to strengthen banking system stability, encompassing mergers, privatizations, non–performing loan resolution, and public sector bank restructuring. Concurrently, a cooperation agreement was signed with the European Central Bank and four European national banks to modernize regulatory and supervisory frameworks according to international standards. These efforts peaked with the creation of the Macro Surveillance Unit, tasked with ongoing monitoring of systemic risks through prudential indicator analysis.

The reforms yielded measurable improvements by 2006, including reduced currency mismatches and loan to asset ratios alongside strengthened capital adequacy and reserve requirements, driving the Egyptian FSI to 0.59 points. However, the 2008 global financial crisis disrupted this progress, causing the index to fall to 0.54 points–its third–lowest level during the study period. Importantly, this decline should not be interpreted as macroprudential policy failure, but rather underscores the necessity for coordinated advancement across all index components to achieve sustainable financial stability.

The index assessment results showed significant declines across key indicators between 2006 and 2008: the global economic climate index dropped from 0.93 to 0.83, the macroeconomic conditions index fell from 0.86 to 0.73, and the financial markets development index decreased from 0.49 to 0.43. In response to these challenges, the Central Bank of Egypt proactively intensified its supervisory framework by implementing additional protective measures to stabilize the financial environment. This included establishing a seventh specialized unit to enhance comprehensive oversight, building on recent successes in partial banking sector supervision. The new unit focuses specifically on systemic risk mitigation through continuous monitoring of financial soundness indicators and application of macroprudential tools. Its mandate includes developing early warning capabilities by analyzing structural trends and addressing financial vulnerabilities arising from accumulating macroeconomic risks. Since that period, Egyptian authorities have implemented systematic monitoring of banking sector indicators encompassing asset quality, liquidity, and profitability, complemented by comprehensive stress testing to assess the financial system's resilience against stochastic shocks. As Egypt's economy approached completion of its banking sector modernization and economic reform agenda, the nation confronted escalating multidimensional crises spanning security, political, economic, and social spheres from January 2011 through mid-2013 and thereafter.

The post–revolutionary political turbulence following January 2011 precipitated severe economic disruptions, manifesting principally through deteriorating security conditions that undermined tourism, trade, transportation, and investment flows, coupled with declining employment and productivity metrics. These cumulative shocks precipitated a dramatic collapse in macroeconomic conditions, with the corresponding index plunging to its study–period nadir of 0.17 by the end of 2011, while the Egyptian FSI simultaneously registered its second–lowest observed value of 0.51. This asymmetric response–wherein macroeconomic indicators suffered disproportionately relative to other index components–provides compelling evidence for the constrained effectiveness of macroprudential policy instruments during periods of acute political–economic instability, while simultaneously revealing structural vulnerabilities in Egypt's economic architecture.

By 2016, a fundamental policy misalignment had become apparent between Egypt's macroeconomic framework and its exchange rate management practices. This divergence fostered significant economic instability, manifested through increased volatility in real exchange rates across successive regimes, diminished monetary policy transmission, and widening fiscal deficits. The resulting environment elevated transaction costs while eroding industrial competitiveness, ultimately depleting net international reserves, suppressing growth and employment indicators, and accelerating inflationary pressures alongside unsustainable public debt accumulation. In response to these structural imbalances, the IMF Executive Board approved the extended fund facility arrangement in November 2016, committing SDR 8.59 billion (approximately USD 12 billion) to support Egypt's economic reform agenda.

The subsequent stabilization program achieved several critical milestones: Egypt recorded its first primary budget surplus in sixteen years (1% of GDP or EGP 4.66 billion), reduced inflation from its 2017 peak of 29.76% following exchange rate liberalization to 9.37% by 2019, and restored economic growth to 5.6% after its 2015 trough of 2.4%.

These outcomes demonstrated markedly improved policy effectiveness, reflected in the FSI's recovery to 0.60 by the end of 2019. This stabilization was underpinned by substantial financial sector reforms including reserve requirement ratios exceeding 14%, net stable funding ratios approaching 195% across currency denominations, and systemic risk buffers reaching 13%.

Even the most optimistic economists failed to anticipate the global economic arena would confront a health crisis of COVID–19's magnitude–a pandemic that within days escalated into a full–scale economic catastrophe. This unprecedented event dismantled conventional economic theories regarding crisis transmission mechanisms and temporal patterns, while paralyzing analysts' capacity to distinguish between supply and demand shocks. The crisis so profoundly mirrored the 1930s great depression that it became universally termed the great lockdown crisis. For Egypt, this global shock necessitated extraordinary policy measures to simultaneously mitigate damage and preserve hard–won gains from the nation's financial and banking sector reforms. Egyptian monetary authorities mounted a multipronged response, first identifying virus-affected sectors for targeted support through working capital financing–particularly payroll protection–and implementing six—month debt moratoriums for businesses and individuals. The tourism sector received dedicated assistance via an EGP 3 billion package featuring 5% declining–interest loans for wage payments and essential operational costs.

Regulatory flexibility measures included one–year exemptions from increased capital requirements for banks' largest exposures and special debt resolution frameworks for delinquent borrowers through March 2021, incorporating transaction ban lifts and collateral releases. Concurrent infrastructure expansions added 6,500 ATMs, bringing national coverage to approximately 20,000 machines while advancing financial inclusion objectives.

These policy interventions significantly bolstered the resilience of the Egyptian economy against COVID—19 shocks. The banking sector's robust liquidity position, enhanced profitability, and stable funding base further reduced systemic vulnerabilities, enabling the Egyptian FSI to rise modestly from 0.53 in 2020 to 0.54 in 2021. The decline in the FSI during the pandemic is largely attributed to the drop in the financial market’s development index to 0.60 by the end of 2020, losing more than 30% of its value compared to the previous year. This was due to the turmoil in emerging financial markets, including Egypt, and the outflow of foreign capital, which led to a rise in both credit default swap prices and the Egyptian stock exchange’s return volatility index, in addition to a noticeable decline in the market capitalization ratio (CBE, 2022).

Meanwhile, the drop in the global economic climate index to 0.83 during the same period ranked as the second most significant explanatory sub–indicator for the decline in Egypt’s FSI. Consequently, the slight decreases in the banking sector performance and macroeconomic conditions indices cannot be relied upon. This analysis demonstrates the success of the Egyptian financial system in containing the repercussions of the COVID–19 pandemic without disrupting its primary role in financial intermediation. At the same time, the Egyptian economy continued to achieve positive growth rates, benefiting from its resilience and diversity, as well as the necessary precautionary measures and proactive, effective economic policies supported by the gains of the economic reform program.

This contributed to the continued stability of economic and financial indicators and mitigated the severity of the pandemic's economic and social impacts on various sectors. As a result, the country's credit rating remained stable, foreign investors–maintained confidence in the Egyptian economy's performance, and a positive, optimistic outlook was fostered regarding its future performance in the coming years. However, Egypt's FSI was destined to be battered by successive and overlapping crises. The glimmer of hope did not last long–just as early signs of recovery emerged after nearly two years of the pandemic, unfavorable winds blew once again.

Global geopolitical risks escalated due to the Russian–Ukrainian war, accompanied by heightened uncertainty and risks following a sharp rise in global inflation rates under the pressure of increasing prices of essential goods, food, and energy, alongside an increase in capital outflows. Additionally, the persistent bottlenecks and disruptions in many value chains further disrupted global trade and worsened the terms of international exchange rates. The Egyptian economy was not spared from these successive economic disruptions and crises, and the FSI declined once again, recording 0.50 by the end of the fourth quarter of 2022.

From the previous presentation, we saw how machine learning models act as the artistic sculptors of the FSI and how this proposal contributes to providing an integrated analytical perspective on financial economics.

4. DLM FOR DIAGNOSING THE PATH OF FSI: IS IT A PANACEA?

In this section, the study aims to predict the behavioral path of the Egyptian FSI through three main stages. The first stage involves identifying the determinants of the FSI by estimating the long and short–term elasticities of the explanatory variables that influence the index's behavior. The second stage estimates the optimal FSI balance by weighting these elasticities–derived in the first stage—against the potential medium–term values of the relevant economic variables. Finally, the third stage assesses the effectiveness of macroprudential policies in the Egyptian economy by comparing the actual FSI values with the benchmark values obtained from the previous two stages. DLM, with their superior interpretative and predictive capabilities, can merge the first and second stages into a single process dedicated to estimating the optimal FSI. This interpretative power of neural networks–a prominent deep learning model–originates from Hebbian learning, which provides the theoretical basis for repetitive neuronal activation. By strengthening synaptic efficacy between input and output layers and dynamically adjusting their correlational weights, this mechanism refines both long and short–term explanatory weights to achieve optimal results (e.g., Mohamed, 2022 ; Li & Law, 2024 ; Casolaro et al., 2023)

On the other hand, the high predictive power of neural network models stems from their two–stage prediction process. The first stage predicts short–term future values of phenomena based on their past historical behavior, while the second stage predicts long–term behavior by combining historical data with short–term future estimates. Inspired by the biological neural network model, artificial neural networks consist of interconnected neurons organized into layers that exchange information. These networks receive input signals through the input layer, where each neuron represents an independent variable. Each variable influences the network's outputs with distinct weights, reflecting its relative importance in explaining the output behavior. The input layer connects to one or more hidden layers (also called intermediate or middle layers) via communication channels. In biological terms, the hidden layer's structure corresponds to the axon, while its functional mechanism resembles the nucleus (Cárdenas et al., 2025). The communication channels between layers mirror the role of neurotransmitters in biological systems. Finally, the hidden layer connects to the output layer, which contains one or more neurons depending on the model's design and the interpretation required. Before discussing activation functions in neural network models, it is useful to first examine the general functional form of these models.

$$\begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ \vdots \\ H_N \end{bmatrix} = \begin{bmatrix} \alpha_{01} \\ \alpha_{02} \\ \vdots \\ \vdots \\ \alpha_{0N} \end{bmatrix} + \begin{bmatrix} \beta_{11} \\ \beta_{12} \\ \vdots \\ \vdots \\ \beta_{1N} \end{bmatrix} X_1 + \begin{bmatrix} \beta_{21} \\ \beta_{22} \\ \vdots \\ \vdots \\ \beta_{2N} \end{bmatrix} X_2 + \cdots \cdot + \begin{bmatrix} \beta_{K1} \\ \beta_{K2} \\ \vdots \\ \vdots \\ \beta_{KN} \end{bmatrix} X_K \qquad ; {n=1,2,\ldots,N \atop k=0,1,2,\ldots,K} \tag{5}$$

The previous model illustrates how the hidden layers [H1,….,HN] receive information and signals from the input layer [X0,X1,.....,XK], where 〖[α]〗_01,α_02,.....,α_0N] represent the bias term, while the weights α_0N,β_KN represent the transmission channels between the K inputs and N outputs. The following model further demonstrates how the processed outputs from the hidden layers are transferred to the output layer [Y1,Y2,.....,YK].

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ \vdots \\ Y_K \end{bmatrix} = \begin{bmatrix} \gamma_{01} \\ \gamma_{02} \\ \vdots \\ \vdots \\ \gamma_{0K} \end{bmatrix} + \begin{bmatrix} \omega_{11} \\ \omega_{12} \\ \vdots \\ \vdots \\ \omega_{1K} \end{bmatrix} H_1 + \begin{bmatrix} \omega_{21} \\ \omega_{22} \\ \vdots \\ \vdots \\ \omega_{2K} \end{bmatrix} H_2 + \cdots \cdot + \begin{bmatrix} \omega_{N1} \\ \omega_{N2} \\ \vdots \\ \vdots \\ \omega_{NK} \end{bmatrix} H_N \quad ;_{k=1,2,\ldots\ldots,K}^{n=1,2,\ldots\ldots,N} \qquad (6)$$

In biological neurons, cellular outputs are F(x)=(e^x-e^(-x))/(e^x+e^(-x)) ; (7).

The sigmoid function can be expressed as a binary function that is continuous and differentiable over the interval [0,1]. When the function's output approaches 1, this indicates that the neuron has

determined by both the intensity of incoming impulses and the cell's internal activation and learning functions. This biological process parallels the operation of artificial neural networks, where outputs primarily depend on activation functions that process input and hidden layer variables to generate optimal network estimations. While various activation functions exist for training neural networks, nonlinear activation functions (NAFs) are particularly crucial. NAFs enable neural networks to realize their full potential by optimizing weight adjustments and producing the most accurate estimations, even with complex datasets.

The following model presents the logistic cumulative distribution function, the most widely used activation function in neural networks. The sigmoid function, a key type of nonlinear logistic activation function, is primarily employed to activate variables in either the input layer or hidden layer units. This continuous function serves two important purposes: training multilayer networks via backpropagation operations, and providing differentiable transformation through its hyperbolic form. Mathematically, the sigmoid function operates on the interval [-1,1] and can be expressed in the following functional form:

reached its maximum activation level in response to incoming signals. Conversely, when the output approaches 0, it signifies no neuronal response to the input stimuli. The binary sigmoid function can be mathematically represented by Equation 5 as follows:

$$\begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ \vdots \\ H_N \end{bmatrix} = \begin{bmatrix} \dfrac{1}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\cdots\cdots+\beta_{K1}X_K)}} \\ \dfrac{1}{1+e^{-(\alpha_{02}+\beta_{12}X_1+\beta_{22}X_2+\cdots\cdots+\beta_{K2}X_K)}} \\ \vdots \\ \vdots \\ \dfrac{1}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\cdots\cdots+\beta_{KN}X_K)}} \end{bmatrix} ; \qquad (8)$$

By substituting Equation 8 into Equation 6, the fundamental function for feedforward neural network models can be derived as follows:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ \vdots \\ Y_K \end{bmatrix} = \begin{bmatrix} \gamma_{01} \\ \gamma_{02} \\ \vdots \\ \vdots \\ \gamma_{0K} \end{bmatrix} + \begin{bmatrix} \dfrac{\omega_{11}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\beta_{K1}X_K)}} \\ \dfrac{\omega_{12}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\beta_{K1}X_K)}} \\ \vdots \\ \vdots \\ \dfrac{\omega_{1K}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\beta_{K1}X_K)}} \end{bmatrix} + \begin{bmatrix} \dfrac{\omega_{21}}{1+e^{-(\alpha_{02}+\beta_{12}X_1+\beta_{22}X_2+\beta_{K2}X_K)}} \\ \dfrac{\omega_{22}}{1+e^{-(\alpha_{02}+\beta_{12}X_1+\beta_{22}X_2+\beta_{K2}X_K)}} \\ \vdots \\ \vdots \\ \dfrac{\omega_{2K}}{1+e^{-(\alpha_{02}+\beta_{12}X_1+\beta_{22}X_2+\beta_{K2}X_K)}} \end{bmatrix}$$

$$+\cdots\cdots+\begin{bmatrix}\dfrac{\omega_{N1}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\beta_{KN}X_K)}}\\ \dfrac{\omega_{N2}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\beta_{KN}X_K)}}\\ \vdots\\ \vdots\\ \dfrac{\omega_{NK}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\beta_{KN}X_K)}}\end{bmatrix}$$

DLM offer significant advantages for economic analysis, particularly their capacity to model nonlinear relationships that characterize real-world systems. These models excel at processing complex datasets featuring nonstationary, noisy, or incomplete observations while accommodating numerous variables. Unlike restrictive parametric approaches like linear regression, DLM can capture intricate, form-free relationships between variables while maintaining strong predictive performance. In modeling Egypt's financial stability, we construct the network using quarterly data spanning 2005Q1 through 2022Q4. The output layer consists solely of the Financial Stability Index 〖FSI〗_t as the target endogenous variable. The input layer incorporates four fundamental explanatory variables: banking sector performance 〖BPI〗_t, macroeconomic performance conditions 〖MPI〗_t, financial market development 〖FMI〗_t, and the global economic climate 〖GEI〗_t.

Theory suggests positive associations between 〖FSI〗_t and these core indicators-movement toward each variable's maximum value should correspond with improved financial stability. To account for recent structural shocks, we augment the input layer with a dummy variable 〖PRI〗_t capturing combined crisis impacts from the COVID-19 pandemic and Russia-Ukraine war. This specification anticipates an inverse relationship with financial stability, consistent with observed negative economic consequences. The model's architecture thus balances fundamental economic drivers with extraordinary external shocks that have disproportionately affected Egypt's economy. This initial conceptual framework is visually represented in Figure 7, which comprises two components illustrating both the correlation strength and initial weights of direct effects.

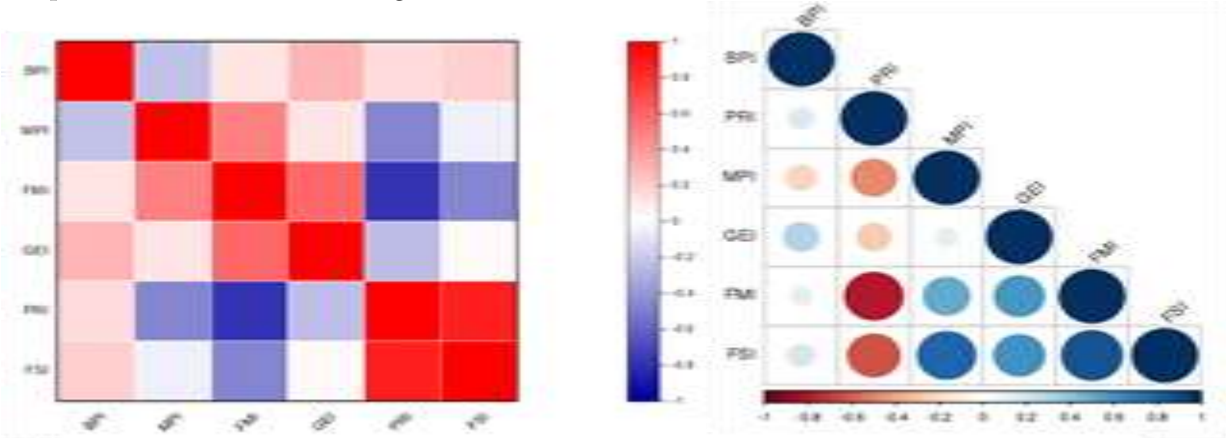


Figure 7. Initial Weights.

The study develops its proposed algorithm for training and estimating neural network models through feedforward and backpropagation approaches. Backpropagation serves as a systematic training method for multi-layer feedforward networks, employing mathematical logic and sequential rules to calculate derivatives in the error equation for the hidden and output layer weights. This process identifies discrepancies between expected and actual network outputs, then automatically adjusts internal weights to minimize errors through iterative cycles until achieving the minimal possible mean squared error-the optimal solution. A critical design consideration involves determining the appropriate number of hidden layer neurons, which mediates the network's interaction with external data while accounting for transmission channels and both direct/indirect effects between layers. Insufficient neurons may prevent signal detection in complex data, while excessive neurons unnecessarily prolong training. This study implements a trial-and-error approach with forward testing, beginning with minimal hidden neurons (initially two) and iteratively training until achieving the target 1% mean squared error threshold. Through this optimization process, the study identifies an optimal architecture of five input neurons, ten hidden neurons, and one output neuron for predicting the Egyptian FSI's directional behavior via structural financial stability analysis.

The implemented Augmented Feed–forward Back Propagation Neural Network model incorporates both direct effects (measured through short–term weights ξ between input and output layers) and indirect effects (captured through long–term weights across the input–hidden–output pathway). This dual–weight architecture enables comprehensive measurement of the FSI 's underlying dynamics.

FSI_t=γ_0+ω_1/(1+e^(-(α_01+β_11 〖BPI〗_t+β_21 〖MPI〗_t+β_31 〖FMI〗_t+β_41 〖GEI〗_t+β_51 〖CEC〗_t))) +ω_2/(1+e^(-(α_02+β_12 〖BPI〗_t+β_22 〖MPI〗_t+β_32 〖FMI〗_t+β_42 〖GEI〗_t+β_52 〖CEC〗_t)))+⋯⋯ ⋯⋯+ω_10/(1+e^(-(α_10+β_110 〖BPI〗_t+β_210 〖MPI〗_t+β_310 〖FMI〗_t+β_410 〖GEI〗_t+β_510 〖CEC〗_t)))+[█(ξ_1@ξ_2@ξ_3@ξ_4@ξ_5)] [█(〖BPI〗_t@〖MPI〗_t@〖FMI〗_t@〖GEI〗_t@〖PRI〗_t)]; (10).

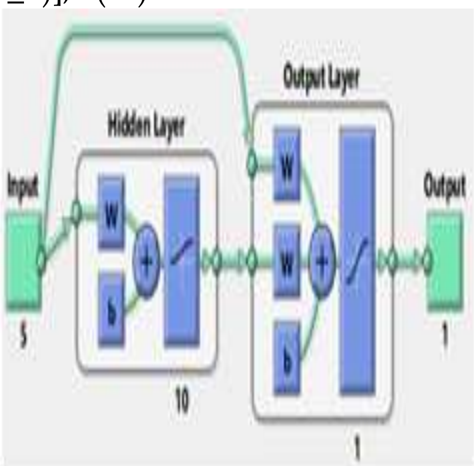


Figure 8. DLM Schema

Figure 8 presents the proposed algorithm for training and estimating neural network models, demonstrating both the direct transmission of effects from the input layer to the output layer and the indirect pathway through the intermediate layer. The network employs the TRAINLM training function coupled with the LEARNGD adaptation learning function, which work in tandem to iteratively adjust relative weights until achieving desired outputs. The training process begins with the assignment of small initial weights, followed by systematic comparison between network outputs and target outputs to calculate errors. Through backpropagation operations, these errors propagate backward to modify the weighted connections. The learning function specifically minimizes discrepancies between predicted and actual output layer values.

During each learning iteration, the network processes information sequentially across all layers until reaching the output layer, where deviations from target outputs are quantified. These error values then feedback through the network in reverse order, enabling layer–by–layer weight adjustments. This cyclical process of forward propagation and backward error correction continues until the system converges on optimal weights that produce the target outputs with minimal residual error

The dataset was partitioned following conventional neural network practice, with 70% allocated for training, 15% for validation, and the remaining 15% for testing. For activation, the study employed the sigmoid function (denoted as Logsig in the training algorithm), selected for its demonstrated effectiveness in processing the training algorithm), selected for its demonstrated effectiveness in processing explanatory variables across both input and hidden layers to optimize network estimations. As a premier nonlinear logistic activation function, the sigmoid function has become the standard choice for activating variables within neural network architectures. Through the implemented training methodology described earlier, the network achieved the following key results:

$$FSI_t = -0.08 + \frac{-2.01}{1 + e^{-(-0.5+1.2\,BPI_t 0.1\,MPI_t+1.9\,FMI_t+0.1\,GEI_t+0.5\,Dummy_t)}} + \cdots$$

$$+\begin{bmatrix} 0.774 \\ 0.893 \\ 0.541 \\ 0.237 \\ -0.387 \end{bmatrix}\begin{bmatrix} BPI_t \\ MPI_t \\ FMI_t \\ GEI_t \\ PRI_t \end{bmatrix} \quad ; \qquad (11)$$

The neural network training results demonstrate a strong, statistically significant positive relationship between all index sub-components and the overall Egyptian FSI performance during the study period. Among these, macroeconomic conditions emerged as the most influential determinant, surpassing even banking sector performance in its impact on financial stability. This finding aligns with economic theory, as systemic soundness inherently incorporates the stability of constituent financial institutions. The results validate our analytical approach of examining how macroeconomic trajectories ultimately affect financial institutions' resilience and capacity to absorb shocks. Conversely, the analysis revealed a significant inverse relationship between financial stability and contemporary economic crisis shocks. The model estimates indicate that a 1% increase in crisis-related disturbances correspond to a substantial 38.7% decline in the FSI, highlighting the severe vulnerability of Egypt's financial system to external shocks.

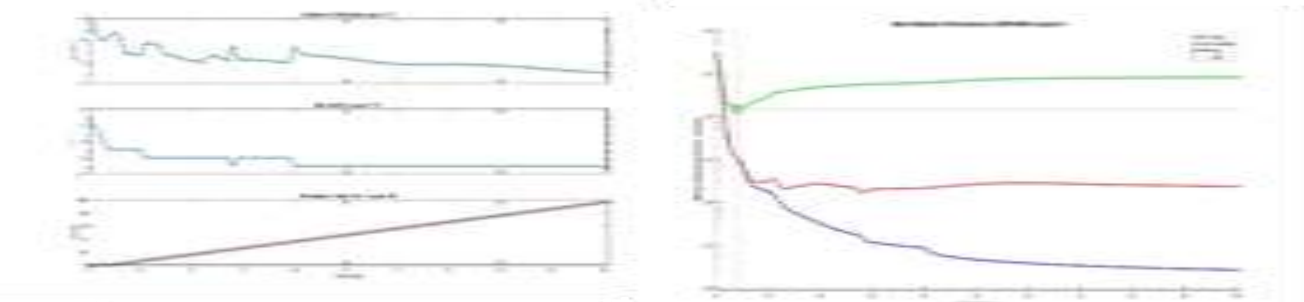


Figure 9: Validation Check Epochs.

The diagnostic testing phase demonstrated the efficiency of the proposed neural network training algorithm, which rapidly achieved its target mean squared error of 1%. As Figure 4 illustrates, the error gradient curve converged quickly toward this objective, ultimately reaching an insignificantly different value from zero by the 101st training iteration. This rapid convergence to near-zero residuals strongly indicate the model's excellent fit across all phases-training, validation, and testing—confirming its robust predictive capability.

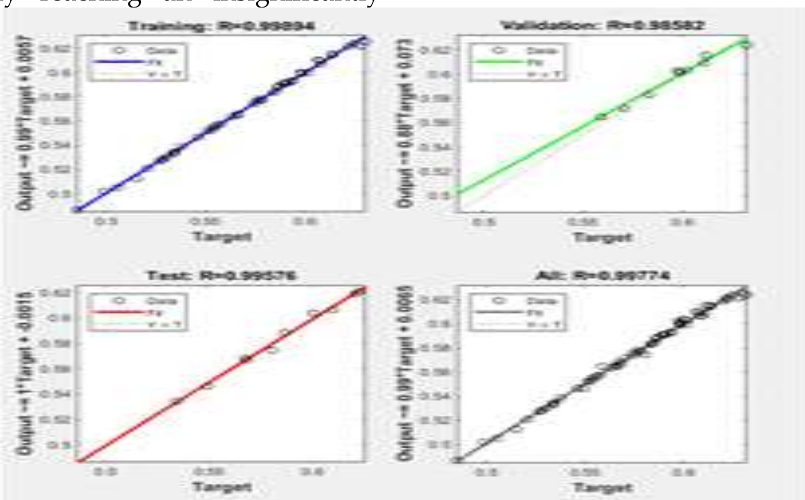


Figure 10: Correlation And Regression

Figure 10 clearly demonstrates the strong correlation between the actual Egyptian FSI-serving as the output layer in our neural network model-and its optimal estimated values. This high correspondence was achieved by weighting long-term elasticities against potential economic variable values in the input layer. The model achieved an exceptional correlation coefficient of 0.997 between actual and estimated FSI values across all samples, with residuals never exceeding 0.003. These results confirm the model's excellent fit, showing that approximately 99.7% of output layer variations can be explained by the combined influence of the five—input layer explanatory variables and their ten transmission channels through the hidden layer.

The analysis begins by evaluating the trend behavior of Egypt's FSI, building upon previous research that incorporated advanced artificial intelligence through DLM. This approach offers distinct advantages for both assessing current FSI trends and predicting future behavior, surpassing conventional machine learning models through its capacity to interpret direct/indirect input layer effects and handle multiple output variables simultaneously. Deep learning's predictive strength derives from its two–phase architecture: first predicting short–term movements from historical patterns, then projecting long–term trends by combining historical data with short–term forecasts. Our implementation completed the second phase by applying standardized weights from the initial phase to estimate the optimal FSI values. Comparing these estimates with actual data revealed critical deviations–positive values indicating effective macroprudential policies (actual FSI exceeding benchmarks), while negative values signal deteriorating financial soundness.

The results demonstrate substantial alignment between deep learning outputs and traditional FSI analysis, with negative deviations (actual FSI below optimal) occurring 53% of the study period versus 47% positive deviations. This oscillation directly reflects varying macroprudential policy effectiveness. Notably, the proposed approach functions as an early warning system, with negative deviations deepening from — 0.005 in 2018 to — 0.009 in 2019, foreshadowing subsequent stability erosion. While initially validating the index's utility as a banking sector "thermometer," deeper examination reveals limitations. The index couldn't anticipate the COVID—19 pandemic, though it clearly captured subsequent shocks —most dramatically in Q1 2022 when deviations swung from +0.001 to — 0.028 following the Russia—Ukraine War. These extreme fluctuations demonstrate the index's sensitivity to external crises while highlighting its constrained predictive horizon for unprecedented events.

5. IS THERE AN OPTIMAL PATH FOR FSI? GA WILL ANSWER.

The origins of genetic algorithms date back to Turing's concept of a "learning machine" that mimics evolutionary processes. By the 1960s, researchers began actively developing computer simulations of biological evolution, with Holland's work playing a pivotal role. These algorithms are inspired by natural systems, where gene reproduction, crossover, and mutation enhance adaptability, allowing complex structures to emerge from simpler components. While traditionally rooted in Darwinian evolution and Mendelian genetics, the approach can also incorporate Lamarckian or Baldwinian principles. Goldberg and Holland (1989) highlighted the probabilistic nature of genetic algorithms, setting them apart from earlier optimization techniques that relied on deterministic, enumerative, or purely computational methods. The standard genetic algorithm, as described by Koza (1992) and Kim and Han (2000), follows a structured process beginning with the initialization of a randomly generated population of fixed–length character strings. This is followed by an iterative cycle of mutation, where individuals may undergo minor random changes, and crossover, where pairs of individuals exchange segments to produce new offspring. The population evolves through these operations until the newly formed individuals are evaluated for fitness, with only the fittest advancing to the next iteration. The algorithm terminates once an individual meets the predefined fitness criteria or another stopping condition is satisfied (Hassanat et al., 2019).

Genetic algorithms iteratively refine solutions–or approximate solutions–to a given problem, with the primary challenge being the effective encoding of the problem into fixed–length character strings for computational efficiency. The encoding can vary, with options such as binary encoding (using 0s and 1s), value encoding (incorporating real numbers, characters, or objects), permutation encoding, or tree encoding. Additionally, each stage of the algorithm–such as crossover–can be implemented in different ways, including one–point crossover (where genetic material is swapped at a random split point) or uniform crossover (where each gene is selected probabilistically from either parent). Similarly, mutation rates and fitness functions can be tailored to specific problems; for instance, forecasting tasks often use metrics like R–squared or RMSE minimization (Katoch et al., 2021). Typically, mutation probabilities are kept low to maintain stability, while crossover probabilities are set higher to promote genetic diversity and improve convergence. To enhance the analytical framework, we incorporate genetic algorithms, which provide robust optimization capabilities for economic modeling. These algorithms enable identification of optimal decision variables within specified constraints, building on established applications in various economic models including the Cobweb Model and Game Theory (Arifovic, 1996). In order to ensure a cohesive and well–connected application of artificial intelligence tools within the framework of the proposed approach, the study employed the output of the deep learning models described in Equation 11 as the fitness function in the genetic algorithm. The integration of genetic algorithm outputs strengthens our capacity to determine optimal FSI values across different economic scenarios, offering policymakers valuable insights for adaptive financial policy formulation in evolving macroeconomic conditions.

Table: 2: Future scenarios of Egypt's financial stability index using the GA.

Scenario	BPI	MPI	FMI	GEI	Probability of Crisis	Future FSI
Scenario 1	0.1	0.29	0.62	0.8	100% Crisis Probability	0.56
Scenario 2	0.08	0.15	0.6	0.8	80% Crisis Probability	0.57
Scenario 3	0.08	0.19	0.6	0.81	50% Crisis Probability	0.68
Scenario 4	0.09	0.15	0.6	0.82	20% Crisis Probability	0.76
Scenario 5	0.1	0.2	0.66	0.92	No Expected Crisis	0.95

Notes. The analysis presents five distinct future financial stability scenarios based on varying probabilities of economic crises. Each scenario outlines the optimal FSI and the required economic conditions to achieve stability.

The financial outlook can be categorized into five distinct scenarios based on the FSI and the associated probabilities. In the severe crisis scenario (100% probability), a full–scale financial crisis is projected with a future FSI of 0.56, requiring weak performance across key economic indicators. The high–risk scenario (80% probability) reflects a major economic downturn, with a slightly higher future FSI of 0.57, suggesting that modest improvements in macroeconomic conditions could help stabilize the situation. At moderate risk (50% probability), financial instability remains significant but manageable, with the future FSI increasing to 0.68, indicative of moderate economic conditions. The low–risk scenario (20% probability) represents a relatively stable financial environment, as the future FSI rises to 0.76, supported by stronger macroeconomic indicators. Finally, the no crisis scenario (0% probability) signals the most favorable outcome, with the future FSI reaching a peak of 0.95, denoting optimal economic stability.

The GA did not require extensive computational time to identify the optimal value of Egypt's FSI, which serves as a new quantitative target for macroprudential policymakers. According to the results illustrated in Figure (11), the model successfully converged to the optimal solution by the 50th iteration, with a generation rate of 0.9. The optimized values of the FSI across the selected scenarios were bounded between 0.5 and 1.0. Importantly, the results indicate a clear relationship between crisis probability and financial stability: as the likelihood of economic crises decreases, the FSI improves, reflecting enhanced financial stability. Conversely, an increased probability of crises corresponds to a decline in the FSI. These findings highlight the critical importance of improving the key economic variables under study to sustain financial stability in times of elevated economic uncertainty.

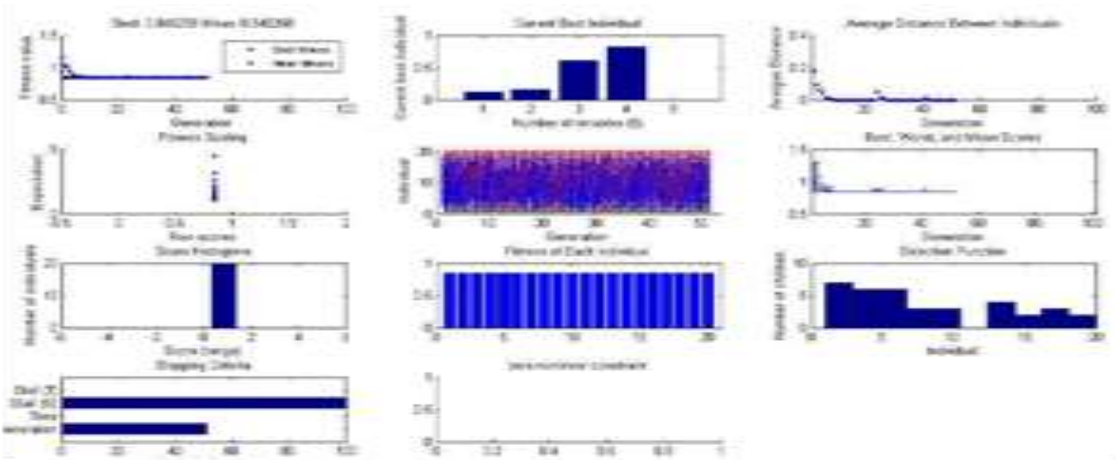


Figure 11. Results of the GA optimization process

5. CONCLUSIONS

This study investigates the generation of a new hypothesis to test and evaluate FSI by proposing a novel vision for designing a structural approach. This approach will assess and correct the path of FSI in the Egyptian economy through quarterly data from 2005Q1 to 2022Q4. This hypothesis enables the assessment of the path and status of FSI. We use artificial intelligence applications as a tool to study decision–making, focusing specifically on how economists diagnose the path of the FSI. The proposed approach, designed to evaluate the status of FSI, relies on three fundamental stages to achieve its goal. The results of the current analytical scenario, based on the proposed approach using ML and DL models, support the acceptance of the first part of the study's main hypothesis "The FSI, which the study aims to design, is suitable as a thermometer through which the strength and soundness of the Egyptian banking sector can be measured". Furthermore, the future analytical scenario–emerging through the adoption of one artificial intelligence application, namely the GA–also validates the second part of the study's main hypothesis: "It is possible to rely on AI applications to control and correct the directional path of the FSI within the Egyptian economy".

Based on the outcomes of the proposed future scenarios and the validity of the study's hypotheses, the following policy recommendations are offered to guide decision makers in designing strategic actions aimed at reinforcing Egypt's financial stability. Adopt DLM leverage the predictive power and explanatory capacity of deep learning models to anticipate directional changes in Egypt's FSI. These models offer a robust foundation for macroprudential policy formulation by identifying current policy deviations and forecasting systemic vulnerabilities. Institutionalize the proposed FSI model: Rapid adoption of the newly designed Financial Stability Index–developed in this study and aligned with IMF and World Bank frameworks–should be prioritized. The model has demonstrated strong predictive capacity for pre-crisis downturns, particularly relevant given recent shocks such as the COVID–19 pandemic and the Russia–Ukraine war. Dynamic targeting of macroprudential instruments: The effectiveness of macroprudential tools depends on their alignment with the financial cycle. A top–down framework is essential, starting with macroeconomic variables (which carried the highest input weight of 0.89) and then focusing on banking sector indicators (input weight of 0.77). This dual–level targeting reduces systemic risks and enhances resilience to unexpected shocks. Address structural weaknesses in the financial system: Egypt's financial stability hinges on implementing an optimal risk management framework. This includes a flexible and adaptive macroprudential regime that dynamically integrates with other economic policies to ensure macroeconomic and financial system stability. Finally, policymakers should focus on improving key economic indicators to mitigate risks and enhance resilience.

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APPENDIX

Table 3. Variables and results from DLM were used to diagnose the path of financial stability index.

Quarter	*BPI*	*MPI*	*FMI*	*GEI*	*FSI*	*FSI(A)*	*OFSI*	*OFSI(A)*	*DEV*	*DEV(A)*
Mar-05	0.166	0.335	0.843	0.925	0.567		0.569		-0.00206	
Jun-05	0.146	0.349	0.846	0.923	0.566		0.566		0.00058	
Sep-05	0.138	0.347	0.858	0.922	0.566		0.567		-0.00033	
Dec-05	0.142	0.374	0.865	0.921	0.575	0.569	0.576	0.569	-0.00064	-0.00061
Mar-06	0.117	0.389	0.865	0.929	0.575		0.576		-0.00116	
Jun-06	0.117	0.561	0.875	0.936	0.622		0.618		0.00381	
Sep-06	0.112	0.478	0.866	0.937	0.598		0.6		-0.00163	
Dec-06	0.117	0.49	0.862	0.939	0.602	0.599	0.603	0.599	-0.00061	0.000102
Mar-07	0.118	0.46	0.821	0.807	0.551		0.548		0.00349	
Jun-07	0.114	0.446	0.803	0.835	0.549		0.546		0.00288	
Sep-07	0.116	0.44	0.824	0.834	0.553		0.549		0.00427	
Dec-07	0.102	0.446	0.803	0.903	0.563	0.554	0.556	0.55	0.00713	0.004443
Mar-08	0.121	0.406	0.751	0.805	0.521		0.53		-0.00935	
Jun-08	0.128	0.447	0.727	0.818	0.53		0.528		0.00193	
Sep-08	0.122	0.499	0.754	0.936	0.578		0.578		0.0002	
Dec-08	0.106	0.435	0.738	0.834	0.528	0.539	0.527	0.541	0.00121	-0.0015
Mar-09	0.115	0.444	0.84	0.934	0.583		0.582		0.00148	
Jun-09	0.108	0.429	0.843	0.934	0.578		0.578		0.00082	
Sep-09	0.114	0.466	0.843	0.935	0.59		0.589		0.00043	
Dec-09	0.114	0.505	0.847	0.935	0.6	0.588	0.601	0.587	-0.00063	0.000525

Table 3. (Continued)

Quarter	*BPI*	*MPI*	*FMI*	*GEI*	*FSI*	*FSI(A)*	*OFSI*	*OFSI(A)*	*DEV*	*DEV(A)*
Mar-15	0.111	0.471	0.83	0.951	0.591		0.592		-0.00125	
Jun-15	0.158	0.432	0.83	0.954	0.594		0.593		0.00038	
Sep-15	0.109	0.578	0.848	0.953	0.622		0.62		0.00193	
Dec-15	0.123	0.519	0.838	0.952	0.608	0.604	0.608	0.603	-0.00034	0.00018
Mar-16	0.119	0.429	0.834	0.956	0.585		0.585		-0.00066	
Jun-16	0.111	0.543	0.842	0.96	0.614		0.615		-0.00109	
Sep-16	0.108	0.443	0.831	0.958	0.585		0.587		-0.00204	
Dec-16	0.11	0.472	0.836	0.955	0.593	0.594	0.596	0.596	-0.00233	-0.00153
Mar-17	0.111	0.563	0.841	0.966	0.621		0.619		0.00109	
Jun-17	0.115	0.573	0.847	0.978	0.628		0.623		0.00513	
Sep-17	0.113	0.589	0.849	0.978	0.632		0.625		0.00731	
Dec-17	0.129	0.45	0.85	0.977	0.602	0.621	0.605	0.618	-0.00293	0.00265
Mar-18	0.158	0.363	0.851	0.974	0.587		0.592		-0.00562	
Jun-18	0.158	0.366	0.851	0.971	0.586		0.591		-0.00504	
Sep-18	0.165	0.37	0.851	0.974	0.59		0.595		-0.0049	
Dec-18	0.158	0.363	0.853	0.976	0.587	0.588	0.593	0.592	-0.00611	-0.00542
Mar-19	0.203	0.401	0.853	0.981	0.61		0.633		-0.02308	
Jun-19	0.218	0.376	0.854	0.985	0.608		0.612		-0.00338	
Sep-19	0.228	0.319	0.854	0.989	0.597		0.604		-0.00705	
Dec-19	0.243	0.354	0.854	0.992	0.611	0.607	0.614	0.605	-0.0028	-0.00908