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Constructing a Financial Conditions Index for Zambia

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Abstract

This study constructs a financial conditions index (FCI) for Zambia using monthly data from April 2012 to October 2024. The FCI is designed to serve as a tool to assess financial market tightness or looseness and to predict economic activity. A wide range of financial variables, including the policy interest rate, are incorporated in the index. Principal component analysis and Kalman filter methodologies are employed in constructing the FCI for robustness and reliability of the estimates. The results indicate that financial conditions were broadly tight during the sample period and that the FCI can serve as a leading indicator of economic activity. This provides policymakers and market participants with critical insights for policy formulation and forecasting.

Keywords: Principal Component Analysis, Kalman filter, monetary policy, financial conditions.

JEL Classification : E44 E50 E52

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1 Introduction

The high external debt episodes Zambia has experienced and the lingering effects of Covid-19 on financial conditions underscore the significant impact of macro-financial linkages[2]. It illustrates how financial market stress can severely affect real economic activity and specifically the conduct of monetary policy. In addition, the increasing complexities and interconnectivity of the global financial system following the 2008/2009 global financial crisis ignited interest in accurately measuring financial shocks and their impact on the economy and financial stability in particular. As such, financial conditions are crucial to business cycles as they not only reflect current and past economic conditions, but also market expectations about economic performance. In this context, it becomes evident that understanding and monitoring these conditions is essential for effective monetary policy implementation and economic stability. However, Borio and Lowe (2002) argue that financial instability can persist even during periods of sound and credible economic policy, underscoring the need to have a composite measure of financial conditions, the financial conditions index (FCI). Unlike the monetary conditions index (MCI), which primarily focuses on interest rates and exchange rates, the FCI provides a comprehensive view by integrating multiple financial variables, such as, interest rates, credit spreads and equity market indicators to reflect the broad state of financial markets and their potential impact on economic activity. This implies that financial conditions must be assessed during both challenging times and periods of sound economic policy. Therefore, continuously assessing financial conditions has become essential for policymakers, regulators, market participants and researchers.

A Financial Conditions Index is a composite measure that summarizes information from various financial market variables such as interest rates, exchange rates, credit spreads, equity prices, and monetary aggregates to assess financial market tightness or looseness within the economy (Adrian, et al., 2019). Changes in financial conditions are central to the transmission of monetary policy. Even small movements in short-term interest rates can lead to significant changes in credit costs, primarily through the widening of term premia and credit spreads (Borio and Zhu, 2012; Gertler and Karadi, 2015). However, movements in these financial variables can be divergent and yet imply the same underlying conditions. For instance, rising interest rates and declining bond prices both suggest tighter financial conditions. Consequently, it is imperative to construct an index that filters underlying trends in various financial variables to appropriately facilitate the interpretation of the looseness or tightness of financial conditions. This necessity has led to the development of financial condition indices, which help better understand macro-financial linkages, provide historical perspectives on financial conditions and assess the impact of financial markets on the transmission of monetary policy.

[2] Macro-financial linkages refer to the two-way interactions between the financial system and the broader macroeconomy. These connections explain how developments in financial markets such as changes in interest rates, credit conditions, asset prices, or financial stability affect macroeconomic variables like output, inflation, and employment, and vice versa (Claessens and Kose, 2018).

Studies on the construction of financial condition indices (FCIs) employ various methodologies. They include principal component analysis (PCA), dynamic factor models (DFMs), weighted aggregation, Kalman filter models, vector autoregressive (VAR) models, structural equation models (SEMs), machine learning techniques, and Bayesian approaches to capture complex financial market dynamics globally. PCA remains a preferred method due to its effectiveness in uncovering underlying financial conditions. This is supported by studies in emerging economies like Turkey (Bulut, 2016) and Iceland (Eysteinn, 2023). In the euro area, Angelopoulou et, al. (2014) employed PCA to reveal financial condition disparities and their asymmetric influence on monetary policy, underscoring this method's utility in reducing data dimensionality while capturing critical variance among correlated variables. Comparative studies across Africa (Gumata et al., 2012) have also validated PCA and Kalman filter-based FCIs for their superior predictive accuracy in economic forecasting, emphasizing the significance of methodological diversity and regional specificity in constructing FCIs. However, Goodhart and Hofmann (2001) introduced VAR impulse response functions for G7 countries, highlighting asset price impacts on economic forecasts. In Canada, Gauthier et, al. (2004) validated the predictive power of FCIs over traditional indices through VAR and other econometric approaches.

This paper constructs a financial conditions index for Zambia to assist in assessing financial conditions and also serve as a leading indicator of short-term economic activity. The study uses monthly time series data from April 2012 to October 2024 in line with the introduction of the monetary policy rate by the Bank of Zambia and transition towards inflation targeting. The principal component analysis based on the approach proposed by Hatzius et al. (2010) and utilized by Kazdal et al. (2022) is adopted in this paper. This method extracts the unobservable principal component factor, isolating it from feedback effects of economic activity. Recognizing the limitations of the principal component approach, such as, the assumption of linear relationships and being sensitive to data choices, the study incorporates an alternative methodology using the Kalman filter developed by Gumata et al. (2012) for robustness. This alternative method enhances the FCI by providing higher autocorrelation over time, ensuring a more consistent and reliable measure of financial conditions. An estimated FCI is especially important when it functions as a leading indicator of economic activity. Financial variables, such as, interest rates, credit growth and exchange rate movements often respond swiftly to changes in the policy stance and economic sentiments, making them useful for anticipating shifts in the broader economy. In this context, constructing an FCI provides a systematic way to track and summarize these developments, offering policymakers and analysts a forward-looking tool to support timely decision-making and macroeconomic assessment. This study carries out a granger causality test to establish whether the estimated FCI can serve as an indicator of economic activity.

The rest of the paper is organized as follows. Section 2 reviews the existing literature. Section 3 discusses the methodology while Section 4 describes the data. Section 5 presents and discusses the empirical results. Section 6 concludes.

2 Literature Review

The development and application of FCIs have garnered significant attention in economic literature with various methodologies and regional focus providing a comprehensive understanding of financial conditions and their impact on economic outcomes. Table 1 summarises selected literature on the construction of financial condition indices in both advanced and emerging economies.

Table 1: Summary of Previous Work on the Construction of Financial Condition Indices

Author	Methodology	Findings
Goodhart and Hofmann (2001)	Contributed to the understanding of how financial variables like credit spreads, interest rates, and asset prices interact and affect economic performance. They constructed the FCI using a VAR impulse response function, utilizing quarterly data from 1973Q1 to 1998Q4 (Data for the G7 countries - Japan, US, Italy, Germany, UK, France, and Canada).	Asset prices, particularly housing and equity prices, had a substantial impact on output. The FCI was a useful predictor of future inflationary trends, which underscored the importance of financial variables in economic forecasting.
Gauthier, Graham, and Liu (2004)	Employed three distinct approaches to develop FCIs for Canada. They used the IS-curve framework, generalized impulse response function and factor analysis using monthly data from 1981 to 2000. They evaluated FCIs based on five performance criteria, including predictive power for business cycle turning points and out-of-sample forecasting performance.	FCIs significantly outperformed the existing monetary conditions index used by the Bank of Canada. Equity prices, housing prices, bond yield risk premiums, exchange rates, short-term interest rates, and long-term rates were significant explanatory factors for output.
Beaton, Lalonde, and Luu (2009)	Constructed two growth-based FCIs using quarterly data from 1979Q3 to 2009Q1 for Canada. The first FCI was constructed within the framework of structural vector error correction model (VECM) while the second was based on a large-scale macroeconomic model[3].	Restrictive financial policies amplified the impact on GDP growth during the 2007-2009 financial crisis by up to 40 percent, particularly due to the zero lower bound level of policy interest rates.

[3] A large-scale macroeconomic model refers to an extensive, detailed model that simulates the overall economy by incorporating a broad set of variables and relationships among various sectors. In the context of FCIs, a large-scale macroeconomic model would include various financial indicators (interest rates, exchange rates, asset prices) and their impact on economic growth, providing a comprehensive view of how financial conditions influence macroeconomic stability and trends.

Author	Methodology	Findings
Gumata et al. (2012)	Principal component analysis and Kalman filter using various financial indicators for South Africa.	Both FCIs outperformed the South African Reserve Bank's leading indicator and an autoregressive model of GDP growth. The PCA-based FCI demonstrated greater overall explanatory power. Joint movements in financial variables provided significant insights into future real economic outcomes. Worsening in financial conditions signaled a potential slowdown in economic activity.
Angelopoulou, et al. (2014)	Applied PCA to construct three variants of an FCI for the euro area, covering the period 2003-2011. Included monetary policy variables in one version to compare its influence on financial conditions. Examined financial condition divergence between core and peripheral euro countries before and during the financial crisis.	One key finding was that monetary policy played a crucial role in reducing the divergence of financial conditions between core and peripheral euro area countries, particularly during the financial crisis. In the absence of supportive monetary policy, financial conditions tended to tighten more in peripheral countries leading to higher financial fragmentation within the euro area.
Bulut (2016)	Constructed an FCI for Turkey using PCA on quarterly data from 2005Q1 to 2015Q3. Included six financial variables: real domestic credit gap, real effective exchange rate gap, real stock market index gap, real commercial lending rate, real short-term interest rate and real shadow rate. Tested the relationship between FCI and inflation using causality tests.	The findings revealed that the FCI was a reliable predictor of inflation in Turkey. The causality tests conducted indicated a bi-directional relationship—financial conditions and inflation jointly influenced each other. This underscored the relevance of monitoring financial conditions as part of monetary policy strategy, particularly in emerging market economies like Turkey.
Sahoo (2017)	Developed an FCI for India using PCA with quarterly data from 2008Q4 to 2015Q4. Assigned equal weights to FCI components and incorporated the impact of foreign direct investment (FDI). Other variables included short-term interest rate, exchange rate, and housing price index.	The findings showed that the FCI could effectively predict inflation trends in India. Moreover, the study highlighted the role of FDI as a significant determinant of financial conditions, emphasizing its importance in influencing domestic financial stability.
Eysteinn (2023)	Used PCA to construct an FCI for Iceland based on data from 2002 to 2023. Aimed to provide an indicator with forecasting properties for short-term economic activity. The study supported monetary and macroprudential policy decision-making by assessing financial conditions.	The findings demonstrated that the FCI effectively captured fluctuations in GDP and significant financial events. The study concluded that the FCI provided valuable insights for policymakers by helping to track real economic developments and assess evolving financial conditions.

Source: Author Compilations

Another important aspect explored in most studies on FCIs is the analysis of the relationship between financial conditions and GDP. This is on the basis that the FCI serves as a composite measure of financial markets conditions that can influence macroeconomic performance. Studies have demonstrated that tighter financial conditions, reflected by higher interest rates, reduced liquidity or depreciating currency values can constrain economic activity by dampening investment and consumption thereby lowering GDP growth (Hatzius et al., 2010). Conversely, accommodative financial conditions, often characterized by lower borrowing costs and improved credit availability, are positively associated with economic expansions (Guichard et al., 2009).

Empirical evidence from both advanced and emerging economies shows that FCIs are effective predictors of short-term GDP fluctuations making them valuable tools for policymakers in assessing the transmission of financial markets developments to the real economy (Swiston, 2008). For instance, in emerging markets, FCIs incorporating exchange rate indices and credit spreads often exhibit a stronger correlation with GDP due to the heightened sensitivity of these economies to external shocks (Akinci and Queralto, 2014).

The foregoing underscores the importance of estimating the FCI for emerging market economies like Zambia for better policy formulation and implementation.

3 Model Specification and Estimation Strategy

To construct the FCI for Zambia, the study employs the PCA proposed by Hatzius et al. (2010) and utilized by Kazdal et al (2022). For robustness check, the study constructs another FCI based on the Kalman filter, and the two indices are compared.

The PCA method is employed to extract the main components from a set of financial variables and summarize the underlying information into a single composite index by reducing the dimensionality of the data while retaining the most important variance. This is consistent with Zheng et al. (2014). On the other hand, the Kalman filter directly extracts factor sequences that depict the variation of variables without the need to determine their weights making it highly effective in filtering and predicting time series data (Durbin & Koopman, 2012). This dual approach allows for better understanding of financial conditions.

The use of PCA and the Kalman filter to estimate the FCI offers distinct advantages over other methodologies. PCA efficiently reduces dimensionality by summarizing diverse financial variables into uncorrelated components, avoiding multicollinearity and eliminating the need for subjective weighting. The Kalman filter, on the other hand, allows for dynamic updates, time-varying weights and robust handling of measurement errors, making it ideal for capturing evolving financial conditions and providing real time estimates. Together, these methods enhance accuracy and adaptability, particularly in contexts like Zambia, where financial markets are influenced by both domestic and external factors.

The study starts with the standardization of data to ensure comparability across variables with different scales. This is achieved by subtracting the mean and dividing by the standard deviation of each variable, which effectively normalizes the data. Once the data is standardized, PCA can be performed to extract the principal components. By applying PCA, we transform the original set of correlated variables into a smaller set of uncorrelated principal components that account for the maximum possible variance in the data. The first principal component, which explains the largest portion of the total variance, is used as the primary measure of financial conditions. This approach reduces the dimensionality of the data while retaining essential information. In the context of constructing an FCI, the weights for each financial indicator are derived from the loadings of these principal components. The loadings indicate the contribution of each original variable to the principal components. In other words, the loadings of each variable on the principal component provide insight into the contribution of each financial indicator to the overall financial conditions. By focusing on the components that explain the most variance, the FCI can capture the most important dynamics in the financial data as well as identify the key drivers of financial stability and fluctuations in the economy.

We compute a common factor for the period April 2012 to October 2024 using financial indicators that are exogenous to Zambia, reflecting global financial conditions and indicators specific to Zambia. The objective is to rescale the variables into principal components by forming weighted linear combinations. These components are arranged to capture sources of variation in descending order, ensuring that the first component accounts for the largest share of total variance. The second component will have the second biggest contribution and so on.

The form for the FCI based on the PCA method is given by:

$$FCI_t = \sum_i^p w_i f_{i,t} \qquad t = 1, \dots n \qquad 1$$

where FCI_t is the financial conditions index, $f_{i,t}$ is principal component *i*'s value at time *t*, w_i is the weight for each principal component variable used in the analysis.

The PCA is particularly useful in summarizing the information contained in a large set of variables (Stock & Watson, 2002; Hatzius et al., 2010). This ensures that the most influential financial indicators are given appropriate importance in the index, leading to a more accurate and robust measure of financial conditions. The inherent normalization process in PCA also mitigates the issue of differing scales among the indicators, providing a cohesive and standardized index.

PCA-based indices like the FCI do not require a base year because the index is constructed from standardized variables transformed to have a mean of zero and a standard deviation of one. This makes the index scale relative and centered around zero. As a result, movements in the index reflect deviations from the average financial conditions over the sample period rather than changes from a fixed base year (Angelopoulou et al., 2014).

The construction of the FCI in this study using the Kalman filter involves defining and estimating a state-space model that captures dynamic relationships between various financial indicators and a latent common factor representing financial conditions.

The state-space model framework allows us to specify the dynamic system through state and measurement equations. This model structure is crucial for capturing the unobserved common factor that drives the financial conditions over time.

The state equation below models the evolution of the latent factor f_t over time. It is defined as:

$$f_t = \alpha_1 f_{t-1} + \epsilon_t \tag{2}$$

where f_t represents the latent common factor at time t, α_1 is a parameter that captures the persistence of the factor, and ϵ_t is the state error term with variance σ_ϵ^2 . This equation implies that the current value of the latent factor depends on its past value and a stochastic error term capturing the persistence and dynamic nature of financial conditions.

The measurement equations link the observed demeaned financial indicators to the latent factor f_t. Each financial variable is expressed as a linear function of f_t plus a stochastic error term:

$$y_{1,t} = b_1 f_t + \eta_{1,t} \tag{3}$$

$$y_{2,t} = b_2 f_t + \eta_{3,t} \tag{4}$$

$$y_{3,t} = b_3 f_t + \eta_{3,t} \tag{5}$$

$$y_{12,t} = b_{12} f_t + \eta_{12,t} \tag{6}$$

In these equations, $y_{i,t}$ represents the demeaned financial indicators (e.g. lending rates, interbank rate) at time t, b_i are the loadings that indicate the sensitivity of each indicator to the common factor, and $\eta_{i,t}$ are the measurement error terms with variances $\sigma_{\eta_i}^2$. These equations capture how each financial indicator is related to the underlying financial conditions represented by the latent factor.

The parameters of the state-space model are estimated using the maximum likelihood method. This involves finding parameter values that maximize the likelihood function, which measures the probability of observing the given data under the model. The estimation process accounts for both the state and measurement equations, ensuring a comprehensive capture of dynamic relationships in the data.

The estimates of the latent factor f_t are extracted ensuring the FCI is both reliable and interpretable for policy analysis and economic forecasting. The interpretation of the computed FCI is based on both the sign and magnitude of the index. A negative FCI denotes loose financial conditions while a positive FCI connotes tight financial conditions. Further, a larger positive value of the FCI reflects tighter financial conditions whereas the opposite represents looser financial conditions.

The predictive power of the estimated FCI is assessed using pairwise Granger causality tests to evaluate its ability to forecast economic activity. The test is used to evaluate whether one time series can predict another by examining the temporary ordering of changes between variables. In this study, it helps in determining whether movements in the FCI precede changes in GDP or vice versa. This test is useful in identifying whether the FCI is a potential leading indicator of GDP and understanding the dynamic interactions between financial conditions and GDP.

4 Data and Variables

In this study, our goal is to monitor financial conditions through a single FCI. Zheng, et al. (2014) and Gary Koop (2014) suggest that three aspects need to be considered in the construction of an FCI: (a) selection of variables, (b) the construction of the model, and (c) selection of weights used to average these financial variables into an index. The selected variables encompass indicators of market risk and liquidity that influence monetary policy, financial stability and overall economic activity.

The variables selected for this analysis include the Bank of Zambia monetary policy rate, weighted interbank rate, average commercial banks' nominal Kwacha lending rate, 6-month deposit rate, interest rate spread defined as the effective lending rate minus the monetary policy rate, riskless interest rate (90-day Treasury bill and 10-year Government bond yield rates[4]), broad money (M2), nominal effective exchange rate and the capital market All-Share Price Index (average of the nominal Lusaka Securities Exchange (LuSE) share prices of all companies). These variables collectively capture the different dimensions of financial

[4] The 90-day Treasury bill and 10-year Government bond yield rates are used because of their ability to capture investor expectations and monetary policy stance. This approach, as opposed to weighted yield rates, avoids distortions from issuance volumes and enhances comparability across time and contexts (Guichard et. al, 2009; Hatzius et. al, 2010; and IMF, 2017).

conditions, including monetary policy, banking sector liquidity, interest rate environment, exchange rate dynamics and capital market performance.

The study uses time series monthly data from April 2012 to October 2024 when Zambia transitioned to inflation targeting from the monetary aggregates targeting framework. The data used for analysis is demeaned to remove any mean bias, hence, making the data more suitable for analysis by focusing on variations around the mean. Ideally, high frequency data (daily data) for financial variables is preferable for FCI. However, it was not feasible to obtain daily data on credit to the private sector and money supply as this is collected monthly.

The selection of variables is consistent with the literature for constructing FCIs, which typically includes equity wealth, borrowing spreads, housing prices and lending measures (Dudley and Hatzius, 2000; Gauthier et al, 2004; Switson, 2008). Recent studies by Ejem and Ogbonna (2020) continue to use these variables. The Bank of England (2021) expanded on earlier variables by adding the Financial Times Stock Exchange (FTSE) All-Share equity price index, weighted average cost of capital (WACC) and investment-grade corporate bond spreads. Interest rates and exchange rates are crucial as they measure the monetary policy stance and its transmission to the real economy (Gauthier et al, 2004). Although some argue that including short-term interest rates is not critical (Wacker et al., 2014), others emphasize their importance (Dudley and Hatzius, 2000). Equity and housing prices are vital for assessing financial conditions as they signal future economic growth and interact with the real economy (Kiyotaki and Moore, 1997; Hatzius et al., 2010; Koop and Korobilis, 2014). Credit spreads, reflecting financial sector risks, are also essential for FCIs, providing predictability during financial stress (Taylor, 2008; Castro, 2011). Including future interest rate changes is recommended for comprehensive FCI estimates (Castro, 2011; Driffill et al, 2006).

When estimating the FCI, a correlation test is conducted first to check the degree of association between the financial variables included, such as, interest rates, exchange rates, and asset prices. By analysing the correlations beforehand, the paper ensures that the selected variables contribute distinct information to the FCI leading to a more stable and reliable index.

Table 2: Variables and Indicators

Variable	Indicators	Label	Source
Interest rate	Bank of Zambia monetary policy rate	pr	Bank of Zambia
	Weighted average interbank rate	wir	
	Average commercial banks' nominal Kwacha lending rate	alr	
	6-month deposit rate	dr	
	Riskless interest rate (10-year Government bond and 90-day Treasury bill yield rates)	tbr, gbond	
Money supply	Broad money	M2[5]	Bank of Zambia
Exchange rate	Measures the movement of the Kwacha against its main trading partner currencies (basket of foreign currencies [6])	REER	Bank of Zambia
	Nominal exchange rate	NER	
Stock Market Index	Capital market all-share price index (average of the nominal LuSE share prices of all companies)	LuSE	LuSE
Credit to the private sector	Monthly changes	CPS	Bank of Zambia

Source: Author Construction

5 Empirical Results and Discussion

The variables considered for inclusion in the construction of the FCI are expected to be correlated. Hence, correlation tests were conducted and the results presented in Table 3.

[5]M2 was selected over M3 in constructing Zambia's Financial Conditions Index (FCI) due to its greater sensitivity to monetary policy and better representation of liquidity conditions in a bank-dominated financial system (Simwaka et al., 2012). This approach aligns with practices in other emerging market studies where M2 provides stronger co-movement with macro-financial indicators (Sahoo, 2017; IMF, 2017).

[6]The real effective exchange rate (REER) basket in Zambia includes the United States Dollar (USD), South African Rand (ZAR), Euro (EUR), British Pound Sterling (GBP), and Chinese Yuan (CNY), reflecting its major trading partners.

Table 3: Correlations among FCI Variables

	alr	arl_pr	cps	dr	gbond10	luse	m2	ner__k_us$_	pr	reer	tb91	wir
alr	1											
arl_pr	0.85	1.00										
cps	-0.23	-0.13	1.00									
dr	0.52	0.09	-0.28	1.00								
gbond10	0.65	0.76	-0.11	0.23	1.00							
luse	0.02	0.03	0.15	-0.31	0.07	1.00						
m2	-0.05	0.02	0.45	-0.07	0.02	-0.04	1.00					
ner__k_us$_	-0.38	-0.27	0.16	-0.37	-0.37	-0.34	0.09	1.00				
pr	0.27	-0.28	-0.18	0.78	-0.21	-0.02	-0.13	-0.20	1.00			
reer	0.38	0.41	-0.14	0.41	0.62	-0.39	0.05	-0.16	-0.04	1.00		
tb91	0.69	0.33	-0.24	0.88	0.43	-0.23	-0.04	-0.31	0.65	0.47	1.00	
wir	0.17	-0.30	-0.17	0.66	-0.17	0.03	-0.18	-0.21	0.87	0.07	0.58	1.00

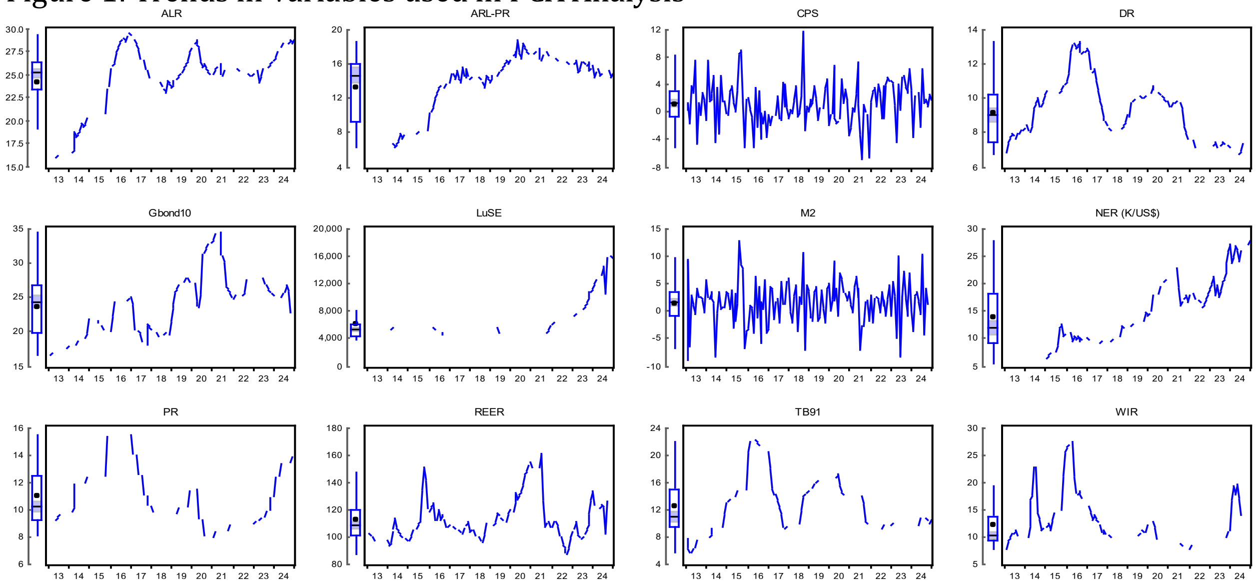
Source: Authors' Computations

High correlations were observed between the monetary policy rate and the deposit rate; 91-day Treasury bill (TB) yield rate and weighted interbank rate; 91-day TB yield rate, deposit rate and lending rate; deposit rate and the monetary policy rate, 91-day TB yield rate, and the interbank rate; 10-year bond yield rate and the exchange rate; and the exchange rate and the monetary policy rate.

As depicted in figure 1, interest rates generally trended upward, with the monetary policy rate averaging around 10.9 percent, peaking at 15.5 percent. Lending rates and interbank rates were relatively high, averaging 23.9 percent and 11.9 percent respectively. The interest rate spread (average of 13.1 percent) suggests consistent divergence between the cost of funds and lending terms. The 6-month deposit rate was comparatively stable while yields on riskless instruments such as the 91-day Treasury bill and 10-year bond were elevated, averaging 12.3 percent and 23.3 percent, respectively. These high returns indicate a strong government presence in the credit market, potentially crowding out private sector borrowing.

Broad money (M2) exhibited moderate growth over the period, with a mean monthly change of 1.5 percent, though it showed significant fluctuations, including contractions as deep as 8.9 percent. The nominal exchange rate (NER) exhibited a strong depreciating trend while the real effective exchange rate (REER) was more stable. The Lusaka Securities Exchange (LuSE) Index rose steadily to a high of 16,045 from a low of 3,609, reflecting some depth in equity markets. Meanwhile, credit to the private sector grew modestly at 1.3 percent monthly on average, but with considerable volatility—highlighting the variable credit conditions faced by businesses and consumers.

Figure 1: Trends in Variables used in PCA Analysis



Source: Author Compilations

Given the observed correlations, we estimated the PCA to obtain principal components (common factors) that summarise variations in the data set as a whole. This identifies common factors that explain the most variance in the dataset. By analyzing the observed correlations among financial variables, PCA extracts uncorrelated principal components that capture underlying financial conditions. In this process, 12 principal components were generated, representing different aspects of financial dynamics with the most significant components contributing more to the overall FCI construction (Table 4).

Table 4: Eigenvalues (Sum = 12, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.96	1.30	0.33	3.96	0.33
2	2.66	1.08	0.22	6.61	0.55
3	1.57	0.21	0.13	8.19	0.68
4	1.37	0.59	0.11	9.55	0.80
5	0.78	0.11	0.07	10.34	0.86
6	0.67	0.18	0.06	11.00	0.92
7	0.49	0.27	0.04	11.50	0.96
8	0.22	0.05	0.02	11.72	0.98
9	0.17	0.10	0.01	11.89	0.99
10	0.08	0.04	0.01	11.97	1.00
11	0.03	0.03	0.00	12.00	1.00
12	0.00	---	0.00	12.00	1.00

Source: Authors' Computations

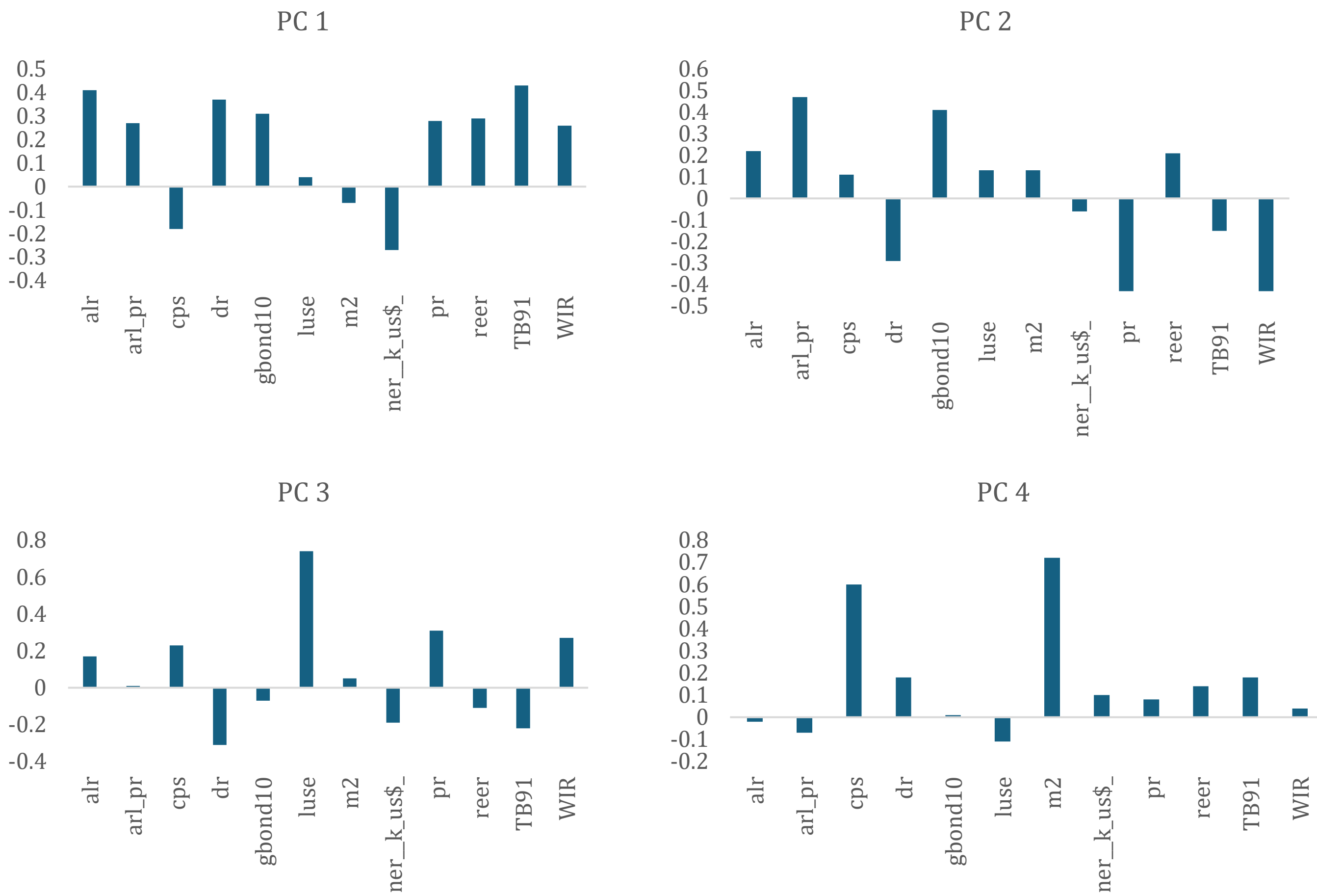
However, considering all the 12 principal components in constructing the FCI would affect parsimony and lead to imprecise estimation of financial conditions. Thus, we apply the Kaiser rule to select the components with eigenvalues great than 1. This is consistent with Zheng et al. (2014) who contend that only principal components that explain up to 80 percent of the total variations in the data should be considered for inclusion in the FCI. Following this argument, the first four components in Table 4 are selected for the purpose of estimating the FCI. The eigenvectors in Table 5 give us the factor loadings, that is, the contribution of each variable to a respective principal component. Figure 2 displays the four PCs.

Table 5: Eigenvector (Loadings)

Variable	PC 1	PC 2	PC 3	PC 4
alr	0.41	0.22	0.17	-0.02
arl_pr	0.27	0.47	0.01	-0.07
cps	-0.18	0.11	0.23	0.60
dr	0.37	-0.29	-0.31	0.18
gbond10	0.31	0.41	-0.07	0.01
luse	0.04	0.13	0.74	-0.11
m2	-0.07	0.13	0.05	0.72
ner__k_us$_	-0.27	-0.06	-0.19	0.10
pr	0.28	-0.43	0.31	0.08
reer	0.29	0.21	-0.11	0.14
TB91	0.43	-0.15	-0.22	0.18
WIR	0.26	-0.43	0.27	0.04

Source: Authors' Computations

Figure 2: Influence of Selected Variables on Principle Components



Source: Author Compilations

Reviewing the individual principal components is both necessary and insightful. Each component captures distinct underlying financial dynamics that help in the interpretation of the composite FCI more meaningfully. For instance, PC1 is dominated by interest rates. PC2 is broadly balanced between interest rate and non-interest rate influences. In PC3, the equity market appears to have a more pronounced influence. PC4 is more driven by monetary aggregates (money supply and credit). In aggregate, the PCs are mainly driven by interest rates, equity markets and monetary aggregates.

Next, we calculate the contribution of the four principal components to the final FCI. This involves determining the proportion of the total variance in the data explained by each principal component as shown in the last column of Table 6. These proportions represent the relative importance of each component in explaining overall variations in financial conditions.

Table 6: Variance Decomposition for Selected PCs

	Variance from Selected PCs	Share of Total Variance
PC1	0.36	0.42
PC2	0.28	0.32
PC3	0.12	0.14
PC4	0.10	0.12
Total Variance	0.86	

Source: Estimation output from E-views

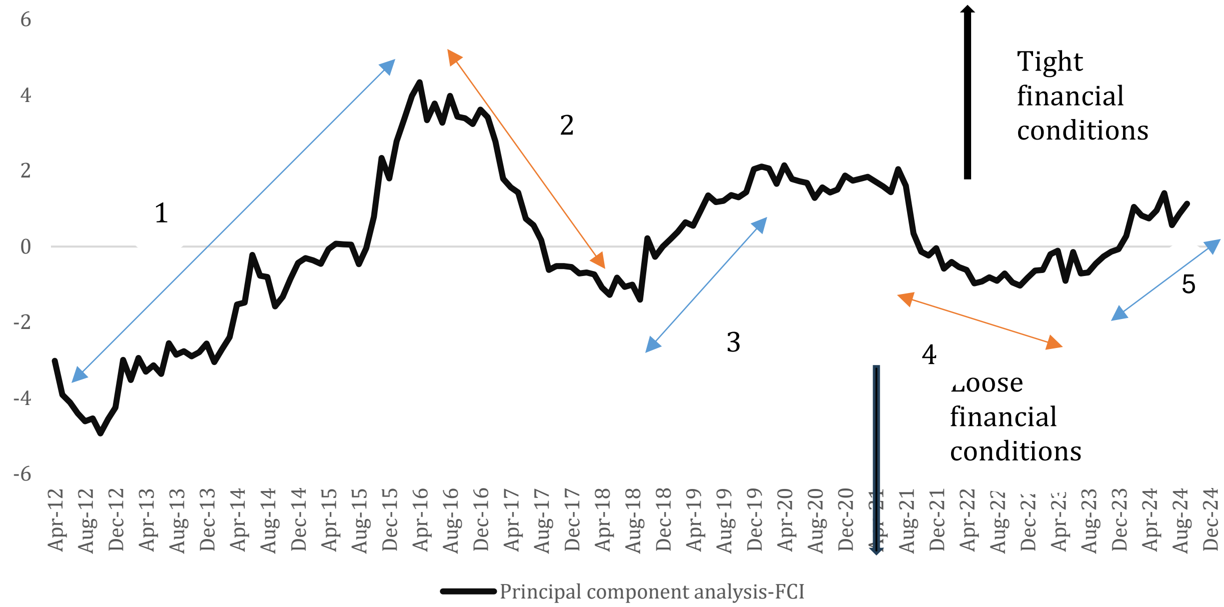
To compute the weights for each financial variable included in the FCI, the variance proportions are applied to the factor loadings in Table 5. The final weight for each variable is calculated as the sum of its contribution across all the four components as follows:

$$W_i = \sum_i^4 X_i PC_i \quad 7$$

where X_i is derived from the proportional variance explained by each principal component in Table 6 and PC_i is the contribution of each variable to a respective principal component (factor loadings) presented in Table 5. The FCI is then computed by applying the variance proportions to the factor loadings of each variable obtained from the principal component analysis. Specifically, for each financial variable, its weight in the index is calculated as the sum of its loadings across the four principal components—each multiplied by the corresponding proportion of the total variance explained by that component. The computed weights are then applied to the standardized values of the financial variables to produce the final index, which aggregates the weighted contributions of all variables into a single time series reflecting financial conditions.

Figure 3 presents the FCI derived using the PCA approach. Periods of financial tightness (upward movement in the index) and looseness (downward movement in the index) are evident in figure 3.

Figure 3: Financial Conditions Index, 2012-2024



Source: Authors' Compilations

Movements in the FCI depicted in figure 3 reflect a sequence of tight and loose financial conditions, with each shift attributable to specific underlying financial dynamics captured through principal components.

Broadly, financial conditions were tight during the sample period. They gradually tightened between 2012 and April 2016 (arrow 1), primarily underpinned by movements in PC1 and PC4. PC1, which accounted for the largest share of the variation in the data, largely captures movements in short-term interest rates. During this period, the monetary policy rate, commercial bank lending rates, interbank rate, and the deposit rate generally increased, especially from 2014, reflecting the restrictive monetary policy stance to combat persistent inflationary pressures. Monetary policy was tightened as the Bank of Zambia raised the policy rate to 15.5 percent in November 2015 from 9.75 percent in 2012 to control rising inflation (Bank of Zambia, 2015).

Following a peak in policy tightening in late 2015, the Bank of Zambia began to ease monetary policy boost private sector credit, support economic activity, and maintain stability in the financial sector. Thus, the policy interest rate was reduce to 9.75 percent by February 2018 (Bank of Zambia, 2018). This signified loose financial condition (arrow 2), largely explained by movements in PC2.

However, financial conditions reversed after December 2018 until 2020 as increases in PC1 signaled restrictive dynamics. The monetary policy rate was raised to 11.5 percent by November 2019 from 9.75 percent in May 2018 to combat elevated inflation and stabilize the exchange rate. Despite maintaining the policy rate at 11.5 percent in early 2020, market interest rates remained elevated and credit growth softened, reinforcing the tightening of financial conditions (Bank of Zambia, 2020).

Between 2021 and 2022 (arrow 4), Financial conditions loosened, primarily driven by declines in PC1 and PC2. The monetary policy rate, which had been raised to 9.0 percent in 2021, was maintained throughout 2022 despite emerging inflationary pressures. During this period, monetary policy was deliberately focused on supporting recovery from Covid-19 (Bank of Zambia, 2022). Consequently, market interest rates (lending and deposit rates) trended downward.

The period 2023 to 2024 marked renewed tightening of financial conditions, reflected in arrow 5. This was primarily driven by increases in PC1 and PC3. PC1 rose as the monetary policy rate increased to 11.5 percent by November 2023 from 9.0 percent in May 2023 in response to elevated inflation and renewed pressure on the exchange rate (Bank of Zambia, 2023). In addition, tighter liquidity management and adjustments to the statutory reserve ratio amplified short-term interest rate pressures. PC3, which captures capital market sentiments through the LuSE All-Share Index and government bond yields, also rose. The increase in government bond yields reflected increased government borrowing requirements, while the equity market recorded gains, as indicated by the rise in the LuSE index (Bank of Zambia, 2023). These dynamics contributed to the tightening of overall financial conditions in the economy during this period.

The pairwise Granger causality test results in Table 7 reveal significant insights into the relationship between financial conditions and GDP. The FCI exhibits a statistically significant influence on GDP evidenced by an F-statistic of 7.19 with a corresponding p-value of 0.01. This outcome suggests that changes in FCI precede and Granger cause movements in GDP—the index can serve as a leading indicator of future economic activity. On the other hand, the test examining whether GDP Granger causes FCI yields an F-statistic of 0.72 and a p-value of 0.40—do not reject the null hypothesis that GDP does not Granger-cause FCI. This implies that GDP does not provide significant predictive information for changes in financial conditions. The result points to a predictive relationship that underscores the importance of the FCI as a forward-looking indicator of economic performance. This is because the FCI encompasses multiple financial variables, such as, interest rates, exchange rates, and stock market indices, which influence both domestic economic activity. As these financial variables react to macroeconomic policies and external shocks, they collectively provide an early signal of the macroeconomic outlook.

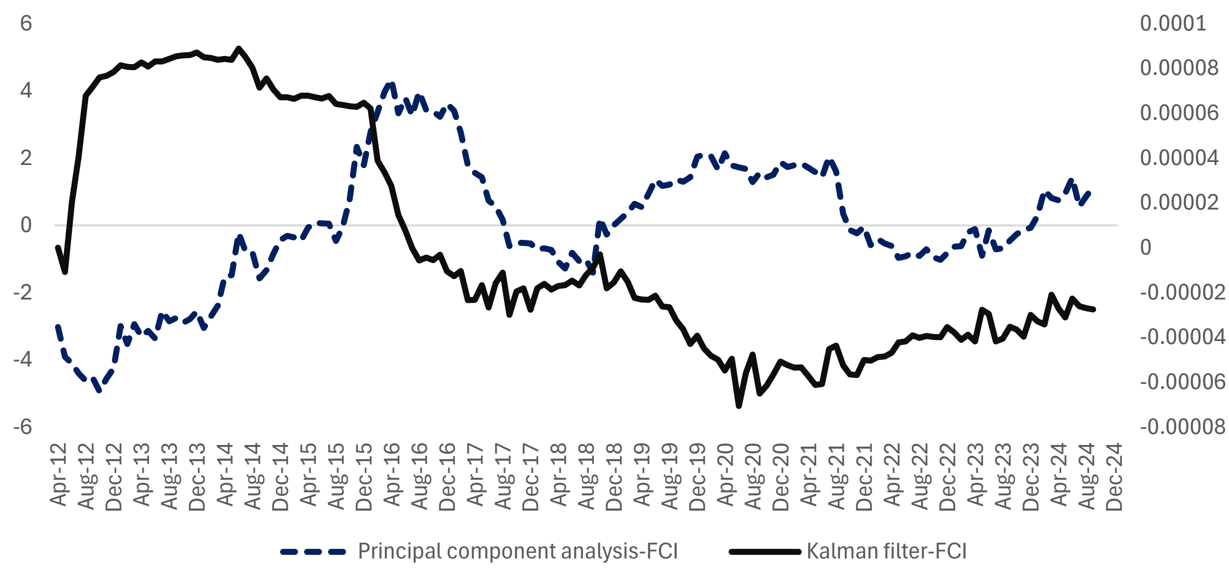
Table 7: FCI Predictive Power

Pairwise Granger Causality Tests Lags: 1			
Null Hypothesis:	Obs	F-Statistic	Prob
FCI does not Granger Cause GDP	25	7.19	0.01
GDP does not Granger Cause FCI		0.72	0.40

Source: Author Computations

As earlier indicated, the Kalman filter was used for robustness check. Figure 4 shows that both the Kalman filter and PCA FCI generally move in the same direction. However, the FCI derived from the PCA method appears to be smoother than the FCI produced using the Kalman filter, which demonstrates more pronounced spikes and dips. The difference in the two series suggests that the Kalman filter methodology may be more sensitive to short-term changes and more adept at capturing immediate market reactions consistent with Borrero and Mariscal (2022). In addition, the apparent persistence of the Kalman filter FCI reflects how it updates estimates over time using both past values and new information, making it responsive to shocks yet slower to adjust in periods of structural change. This is consistent with the findings by Gumata et al., (2012) for South Africa. For instance, over the period 2016–2018, conditions were generally loose, as indicated by a declining by both PCA-FCI, and Kalman filter FCI. Further, as indicated in Figure 4, the PCA-based FCI recovers faster than the Kalman filter-based FCI after the economy experienced adverse conditions. Both methodologies, however, broadly align in identifying major trends and shifts in financial conditions, offering valuable insights for economic analysis and policymaking.

Figure 4: Principal Component Analysis and Kalman Filter Financia Conditions Index



Source: Author Compilations

5 Conclusion

The study developed a Financial Conditions Index (FCI) to offer a robust and comprehensive measure of the financial environment using monthly data from April 2012 to October 2024. The FCI integrates critical financial variables, including the policy interest rate, interbank rates, lending rates, deposit rates, interest rate spread, risk-free interest rate, broad money, exchange rate index, and the capital market All-Share Price Index. By employing a dual methodology—Principal Component Analysis (PCA) and the Kalman filter—the study ensured the estimated FCI effectively captures the key components of financial conditions in Zambia. PCA reduced the dimensionality of the dataset, extracting the most significant components and simplifying complex relationships, while the Kalman filter provided a dynamic framework for estimating the unobserved common factor of financial conditions, accounting for time-varying characteristics and enhancing the accuracy of the index.

The constructed FCI offers a holistic perspective on financial conditions in Zambia, reflecting the cumulative impact of diverse financial variables and serving multiple purposes. Firstly, it acts as a diagnostic tool by providing insights into the looseness or tightness of financial markets, helping policymakers and investors understand the broader economic environment. Secondly, it serves as a leading indicator of short-term economic activity, enabling policymakers to anticipate potential economic downturns or favorable trends and implement timely interventions. The forward-looking nature of the FCI incorporates market expectations and trends, making it an invaluable tool for monetary policy formulation and economic forecasting. Evidence in this paper points to a strong correlation between financial conditions and economic activity, reaffirming the utility of the former in guiding policy decisions and enhancing economic analysis. The study also contributes to the broader literature on financial condition indices, particularly in the context of emerging economies like Zambia where financial markets are more volatile and influenced by external shocks to a large extent. The adoption of PCA and the Kalman filter methodologies offers a robust and adaptable framework that can be applied to other economies and time periods, ensuring the relevance and accuracy of the constructed FCI.

The evolution of the FCI over the sample period reflected key financial and macroeconomic developments in Zambia. The index rose between 2012 and April 2016, signaling tight financial conditions, primarily driven by rising short-term interest rates and constrained liquidity. From 2016 onward, the index captured alternating periods of monetary easing and tightening, with notable loosening observed during 2016–2018 and 2021–2022 and renewed tightening over 2018–2020 and again between 2023 and 2024. The shifts were underpinned by changes in the monetary policy stance as well as movements in credit and liquidity aggregates. The trends affirm that financial conditions are shaped more by interest rates, credit and liquidity variables than by capital market indicators, which played a relatively limited role due to the underdeveloped nature of the domestic capital market.

However, the study acknowledges limitations, including the lack of high-frequency data (daily or weekly), which could improve the granularity and responsiveness of the FCI. Incorporating more variables, such as those reflecting international capital flows and external financial shocks could further enhance the comprehensiveness of the index.

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