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Enhancing Business Cycle Forecasting in Pakistan: A Composite Leading Indicator Approach with PLS-SEM

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ABSTRACT

Objective: This study aims to forecast the business cycles in Pakistan by developing Composite Leading Indicators (CLI) that capture multi-dimensional interactions between real, monetary, and external sectors of the economy.

Research Gap: Although the econometric techniques, like OLS, VAR, and ARIMA, proved to be valuable but they failed to capture more complex and multi-dimensional interactions between real, monetary and external sectors. This paper fills that gap by constructing Composite Leading indicators to forecast business cycles for Pakistan's economy

Design/Methodology/Approach: Based on quarterly data between 2011 and 2025, the model incorporates major indicators like narrow money, export volumes, household debt, household prices, policy rates, real effective exchange rates, and global economic conditions and constructs a CLI model through Partial Least Squares Structural Equation Modeling (PLS-SEM).

The Main Findings: Pakistan's economy is subject to GDP volatility due to short-run liquidity shocks and export fluctuations, medium-run financial imbalances, family debt and asset prices. Existing forecasting approaches fail to account for these nonlinear and complicated dynamics. A robust composite leading indicator based on PLS-SEM is required to capture these complex relationships and improve business cycle turning point prediction.

Theoretical / Practical Implications of the Findings: This study demonstrates the practicality of a multi-horizon framework of CLI estimation using PLS-SEM in that it can be used to construct more efficient early warning mechanisms and can aid policymakers in smarter macroeconomic planning against domestic and external shocks.

Originality/Value: This research offers a novel application of PLS-SEM in business cycle forecasting for a developing economy, providing new insights into non-linear macro-financial linkages rarely explored in Pakistan's context.

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1. Introduction

The economic activity of a country does not consistently change in a linear direction moving up but rather shifts between two directions, expansion and contraction. This is called the business cycle (Olivier Jean Blanchard & Diamond, 1994). These cycles, which consist of periods of boom and recessions, have a considerable influence on vital macroeconomic variables such as GDP growth, employment, inflation, and investment (Olivier Jean Blanchard & Diamond, 1994; Burns & Mitchell, 1946). It's necessary for policymakers, businesses, and financial institutions to understand and analyze business cycles in order to prepare and mitigate the impacts of economic recessions.

Background of the Study: Forecasting in the business cycle has undergone major transformations over the years. Initial studies centered around the detection of cycles within economic information used basic statistical methods (Burns & Mitchell, 1946; Frickey, 1942; Geoffrey Hoyt Moore, 1961; Schumpeter, 1964; Tinbergen, 1939). More advanced tools are now possible with the availability of econometric techniques as Vector Auto regressions (VAR), and Dynamic Stochastic General Equilibrium (DSGE) models(F. Kydland & Prescott; Sims, 1980; Smets & Wouters, 2007).Traditional approaches tend to concentrate on one macroeconomic measure at a time, which is often misleading, as various measures pinpoint turning points at various levels of time and accuracy. The Organization for Economic Cooperation and Development (OECD) proposed the concept of Composite Leading Indicators (CLI) to forecast business cycles. OEDC splits leading indicators into two clusters: short-to medium term (2-8 months) and long term (more than 8 months) (Gyomai & Wildi, 2012). In response to the issues that arise from single indicators, scholars are increasingly using Composite Leading Indicators (CLI) that utilize several economic indicators to construct more accurate forecasts (Anas & Ferrara, 2004; Lahiri & Moore, 1991; Levanon, Manini, Ozyildirim, Schaitkin, & Tanchua, 2015; Geoffrey H Moore & Zarnowitz, 1986; Ohanian & Raffo, 2011; Stock & Watson, 1999).

For developing economies like Pakistan, where forecasting business cycles is particularly important, structural weaknesses further amplify the volatility of the economy. According to Siddique, Ahmad, Sultana, Maroof, and Ilyas (2025), internal and external shocks in case of Pakistan leads to massive ups and downs in real GDP. The supply-side shocks as climate change induced agricultural volatility and demand shocks as global commodity price volatility have been instrumental in shaping business cycles (Bernanke, Gertler, & Gilchrist, 1999).The instability in fiscal policies, political discord, and external debt has caused greater oscillation in the economy which increases risk and uncertainty, making it difficult to decide the level of investment, employment, and inflationary measures in the economy (Olivier Jean Blanchard & Diamond, 1994). An agriculture sector that is prone to volatility, weak industrial output, over reliance on indirect taxes, and inefficient budgetary control increases the unpredictability of growth (G. Khan & Ahmed, 2020). As suggested by Lucas Jr (1975), there are a wide range of external impacts that affect the overall economic stability, including remittances, imbalance in trade, and fluctuating exchange rate. It is critical to comprehend business cycles for effective economic policy making, especially given Pakistan's low revenue collection, high external debt, inefficient energy sector, and other structural problems

Cyclical revenue swings disrupt fiscal planning in Pakistan, generally leading to short-term borrowing techniques (Olivier J Blanchard, 2025). A comprehensive forecasting model adapted to Pakistan's structure could improve fiscal discipline and resilience to shocks (G. Khan & Ahmed, 2020; Stock & Watson, 2003). While previous local studies utilizing ARIMA, VAR, or single-indicator techniques provide insights, they fail to capture the multidimensional dynamics of business cycles, and current composite indexes are based on arbitrary weights. Unlike Thailand, where PLS-SEM has been used to assess composite indicators (Pumjaroen, Vichitthamaros, & Sethapramote, 2020), Pakistan has yet to adopt this latent formative technique, despite its applicability for formative indicators, small samples, and non-normal data.

Statement of problem: Pakistan's economy undergoes frequent and unpredictable business cycle changes as a result of structural flaws, external shocks, and policy instability. Existing forecasting methods cannot capture these complicated dynamics since they rely on single indicators or arbitrary composite indexes. To increase forecasting accuracy and assist effective economic policymaking, a strong Composite Leading Indicator (CLI) based on modern methodologies such as PLS-SEM is urgently required.

The present research, therefore, address this gap by developing CLI for Pakistan using a formative latent construct through PLS-SEM, enabling strong structural validation and more accurate forecasting of national business cycle turning points in the short, medium, and long term. In addition, majority of the previous studies have examined independent economic variables. The current study attempts to integrate all these various pieces of monetary, fiscal, and trade through Composite Leading Indicator (CLI) model so that the predictions of the business cycles in Pakistan can become more precise.

1.1 Research Objectives

i. To Identity, select, and statistically validate the most relevant macroeconomic indicators (monetary, financial, real-sector, and trade) that can form a reliable Composite Leading Indicator framework for Pakistan.
ii. To examine the role of external and internal economic factors including trade fluctuations, financial market volatility, and supply-side shocks in shaping Pakistan's business cycles and their predictive significance.
iii. To employ PLS-SEM for modeling the formative latent construct of Pakistan's Composite Leading Indicator (CLI), validating the measurement and structural models, and capturing the direct and indirect effects of short-term liquidity, medium-term financial imbalances, and long-term global monetary trends on business cycles.
iv. To formulate evidence-based recommendations for Pakistan's monetary, fiscal, and trade policymakers by linking the forecasting outcomes to practical interventions such as countercyclical buffers, interest rate adjustments, and export diversification strategies.

The rest of paper is organized as follows. Section 2 examines the relevant literature on business cycles, and Section 3 presents the conceptual model. Section 4 discusses the research approach, whereas Section 5 describes the data collecting and filtration processes. Section 6 gives empirical findings, while Section 7 examines the implications. Section 8 ends the study -and discusses its weaknesses.

2 Literature Review

2.1 Background

The backgrounds of business cycle forecasting can be sketched to the seminal work of (Mitchell & Burns, 1938), who introduced leading indicators to predict economic downturns and expansions. In the decades that followed, other models were introduced such as time-series and econometric models. Vector Auto regression (VAR) (Sims, 1980) made a great contribution in the field of business cycle forecasting since it was the first model to admit the possibility of one economic variable affecting other economic variables. On the same note, the ARDL model led by (Pesaran, Schuermann, & Treutler, 2007) also emerged to play major roles in examining short and long-term correlations among the economic variables. Economic modeling and forecasting developed considerably in almost half of the 20th century. The integration of the stochastic aspects in econometric models enabled more accuracy in possible forecasts of the fluctuations in the economy. The introduction of Dynamic Stochastic General Equilibrium (DSGE) models, particularly by (Smets & Wouters, 2007), enhanced the capacity to simulate the impacts of policy changes and structural shifts in the economy. This period marked a shift from exclusively empirical models to those that included microeconomic behavior within a general equilibrium framework, providing a more detailed understanding of business cycle dynamics (Smets & Wouters, 2007).

The literature further investigated the business cycles caused by demand and supply shocks. Demand shocks are short-run fluctuations that arise from changes in fiscal policy or monetary policy. Keynesian and New Keynesian literature emphasizes that aggregate demand shocks cause output and employment fluctuations when prices and wages are sticky. Olivier Jean Blanchard and Diamond (1994) developed the famous structural VAR decomposition to separate demand and supply shocks in GDP and unemployment fluctuations. Many empirical papers extend this idea to test whether business cycles are mainly demand-driven or supply-driven across countries (Bekaert, Engstrom, & Ermolov, 2021; Smets & Wouters, 2007).

Multiple studies affirm that supply-side shocks—such as technological change, energy disruptions, or pandemic-induced productivity declines—is a crucial reason business cycle dynamics. (Fisher, 2006) highlights the importance of investment-specific technology shocks (like faster computer chips) as significant drivers of cyclical fluctuations. Fornaro and Wolf (2021)introduce the concept of "scarring" supply shocks, where even temporary disruptions lead to permanent output losses through their adverse effects on investment and productivity. Additionally, (Baqaee, Farhi, & Sangani, 2024) propose that monetary shocks can trigger endogenous supply-side effects, enhancing productivity by reallocating capital toward high-markup, more efficient firms. These works collectively reinforce the view that supply-side dynamics—not just demand shocks—are central to understanding the depth and persistence of economic cycles. Interaction of demand and supply shocks is further complicated by the role of expectations to determine economic behavior as pointed out by Rational Expectations Hypothesis (Lucas Jr, 1972) where businesses and consumers act depending on their expectations of policies and economic situations. It explains how expectations of future policies influence current economic decisions.

F. E. Kydland and Prescott (1982) developed the Real Business Cycle (RBC) theory which concludes that business cycles are caused by technological shocks and productivity variations. It presumes that economic players react best to such changes, therefore, requiring less governmental control. Nevertheless, the RBC theory received criticisms, and this gave rise to the New Keynesian approach that acknowledges the imperfection in the market and rationalizes policy interventions in times of economic contractions. Additional theories that have been put forth, including the Financial Accelerator Model (Bernanke et al., 1999), which emphasizes the financial frictions in further worsening the business cycles. This model indicates that economic declines are increased by the declining values of assets which lower the collateral provided by the firms, resulting in limited borrowing and lower investments. It is this mechanism that explains why financial crises usually have long-term implications on economic activity. Additionally, the knowledge of behavioral economics implies that psychological aspects and ordinary sentiment of investors are also significant determinants in the decline or rise of economy (Akerlof & Shiller, 2010).

Dynamic Stochastic General Equilibrium (DSGE) framework is popular in macroeconomic model building since it places microeconomic behavior, which includes consumption and investment decisions, in a general equilibrium model. Policy impacts and structural changes in the economy are especially well-captured with the DSGE models (Smets & Wouters, 2007). As proven in international research, CLI method combines multiple indicators into one index which enhances the quality of predictions. (Gyomai & Guidetti, 2012) demonstrate that individual indicators are not as accurate in predicting downfalls in the economy as composite indices are.

2.2 Forecasting Business Cycles Using Leading Indicators

Composite Leading Indicators (CLIs) emerged as a response to the boundaries of old forecasting methods such as GDP growth projections, ARIMA models, or purely structural econometric approaches, which often required long historical data and assumed structural stability. Early work by the **OECD (1987, 2012)** showed that CLIs provide a more flexible framework by combining short-term indicators such as industrial production and credit flows, thereby improving the timeliness of forecasts compared to lagging GDP series. CLIs have been demonstrated to outperform univariate models in anticipating short- to medium-term turning points by combining many signals (Nilsson & Gyomai, 2011; Zarnowitz & Ozyildirim, 2006). Short-term indicators (e.g., confidence, stock markets) predict activity within months, medium-term indicators (credit cycles, investment) forecast over quarters, and long-term trends (demographics, fiscal policy) create multi-year forecasts (Stock & Watson, 1989). Recent advancements, such as high-frequency data and machine learning, have improved predicted accuracy (Bok, Caratelli, Giannone, Sbordone, & Tambalotti, 2018). Evidence from emerging markets highlights the utility of CLIs: (Babecký et al., 2013) associate M1, credit, and trade with crisis prediction; Sethapramote (2015) emphasizes trade and monetary spillovers; (Pumjaroen et al., 2020) use PLS-SEM CLIs in Thailand; and (Marcellino, Stock, & Watson, 2003) validate univariate models' inability to predict GDP volatility.

Fichtner (2005) found that CLIs provide more timely and reliable early warning signals than individual indicators. This is especially important in Pakistan, where single signals are frequently skewed by structural changes or external shocks. The use of CLIs in this study represents best practice by incorporating short-, medium-, and long-term signals, ensuring that liquidity, financial imbalances, and global monetary conditions are recorded for more accurate business cycle prediction.

2.3 Business Cycle Forecasting Literature for Pakistan

Early research on business cycle forecasting in Pakistan relied mostly on time-series analysis and univariate models, with a focus on particular macroeconomic variables such as GDP, inflation, interest rates, and employment to detect economic patterns and turning points. For example, (Sheikh & Malik, 2023) used basic correlation and regression approaches to examine cyclical trends in GDP growth and inflation. Similarly, Sarwar, Ali, and Hussain (2021) used ARDL (Autoregressive Distributed Lag) models to investigate the short and long-term interactions of fiscal policies and macroeconomic variables in Pakistan.

S. KHAN (2021) employed VAR (Vector Autoregression) models to investigate the interrelationships between significant macroeconomic indicators such as inflation, exchange rates, and interest rates. While VAR models are intended to capture dynamic relationships between multiple variables, they frequently limit the scope by focusing on a small number of variables and do not fully account for the complex interactions of fiscal, monetary, and external trade shocks, all of which are critical to Pakistan's economic framework. Shah, Khan, and Kamal (2022) included trade factors in their study, however their analysis was limited to linear connections and did not account for non-linearities or the interaction of other economic signals. Recent research, including Javed, Mehmood, Ghafoor, and Parveen (2024) has used financial models such as the Financial Accelerator Model to investigate how financial frictions and liquidity limitations accelerate economic downturns. These studies indicate that variations in asset values can exacerbate recessions, as evidenced by Pakistan's susceptibility to foreign financial shocks. However, these models tend to focus on individual shocks rather than incorporating a diverse set of economic data, which would allow for more thorough forecasting.

The theoretical foundations of business cycle forecasting in Pakistan are mostly based on classical and Keynesian economic theory. Neoclassical theories, such as those offered by Lucas Jr (1972), contend that supply-side shocks, such as productivity increases or technical discoveries, are the primary drivers of business cycles. In contrast, Keynesian economics stresses the importance of demand-side factors such as government expenditure, fiscal policy, and aggregate demand in determining economic fluctuations. Olivier Jean Blanchard and Diamond (1994) emphasized the importance of both demand and supply shocks in impacting economic activity in Pakistan, particularly when it comes to foreign shocks such as commodity price variations and exchange rate volatility.

2.4 Research Gap

While there is a growing amount of research on business cycle forecasting in Pakistan, there is still a substantial gap in the use of Composite Leading Indicators (CLI) and PLS-SEM to forecast business cycles. CLI is a valuable tool since it combines several economic variables into a single index, improving prediction accuracy and timeliness (Gyomai & Wildi, 2012). Babecký et al. (2013) found that CLI improves forecasting accuracy by incorporating economic data such industrial output, consumer sentiment, and financial indicators. This technique is particularly appropriate for economies such as Pakistan, whose economic oscillations are caused by a variety of internal and foreign variables.

Furthermore, while some research in other countries have utilized PLS-SEM (Partial Least Squares Structural Equation Modeling) to investigate economic links, this method has not been frequently used in business cycle forecasting in Pakistan. PLS-SEM is especially well-suited to complicated, non-linear interactions, and it can handle small sample sizes and non-normal data distributions, making it an attractive tool for forecasting in developing nations such as Pakistan (Joe Hair, Hollingsworth, Randolph, & Chong, 2017). This work uses PLS-SEM on a CLI-based model to reveal the latent structures driving Pakistan's economy cycles, resulting in more accurate and dependable predictions for policymakers. Given Pakistan's unique economic challenges, such as fiscal instability and vulnerability to external shocks, policymakers must develop a more thorough forecasting model. The present study aims to explore the potential of sector based CLI modeling to investigate turning points of business cycle more precisely and timely.

3 Conceptual Model and Hypothesis

The discussion in previous section provides the rationale for further investigation on the topic. This section discusses the conceptual model investigated study which is an integrated model that connects domestic and global determinants of business cycle, supported theoretically to develop a more robust early warning system to predict economic fluctuations in Pakistan. Both economic theory and widely accepted empirical practice have formed the basis of using Composite Leading Indicators (CLIs). The advantage of CLIs is that they help to aggregate several economic signals because each has different dimensions of the business cycle and they enhance predictive ability in contrast to the use of a single variable (Gyomai & Guidetti, 2012). The OECD CLI framework is highly recognized at an international level due to involvement of monetary, financial, real-sector and external indicators and forecasts turning points in economic activity six to twelve months in advance. Zarnowitz and Moore (1986) also demonstrate that the combination of the leading indicators enhances the identification of the business cycle peaks and troughs, which proves the composite index strategy.

The present research employs Composite Leading Indicators (CLIs) as latent variables affecting Business Cycle (BC). This is a multi-period model that integrates short-run, medium-run, and long-run leading indicators to understand economic fluctuation across various phases in Pakistan. The study uses composite leading indicators to analyze the business cycle at three levels. At the short-term level, the model includes the CLI of the Short-Term Activity Index (STAI), which forecasts economic activity for the next 1-3 quarters. STAI is measured using narrow money (M1) and the export volume index (EVI) (Babecký et al., 2013). The Financial Stability Index (FSI) is a medium-term CLI that measures financial system vulnerabilities that can cause medium-term oscillations. It forecasts business cycle dynamics over a four- to eight-quarter period utilizing metrics such as the housing price index (HPI), household debt (HD), and credit-to-GDP ratios (HD-GDP) (Borio, Drehmann, & Xia, 2018; Drehmann, Borio, & Tsatsaronis, 2012). The Long-Term Monetary Channel (LTMC) is included in the Long-Term CLI. These constructs integrate measures like policy interest rates (IR) and real effective exchange rates (ER) to indicate broader monetary policy changes and global macroeconomic developments that affect the domestic cycle after 9 quarters (Freedman, 1996; Pumjaroen et al., 2020).

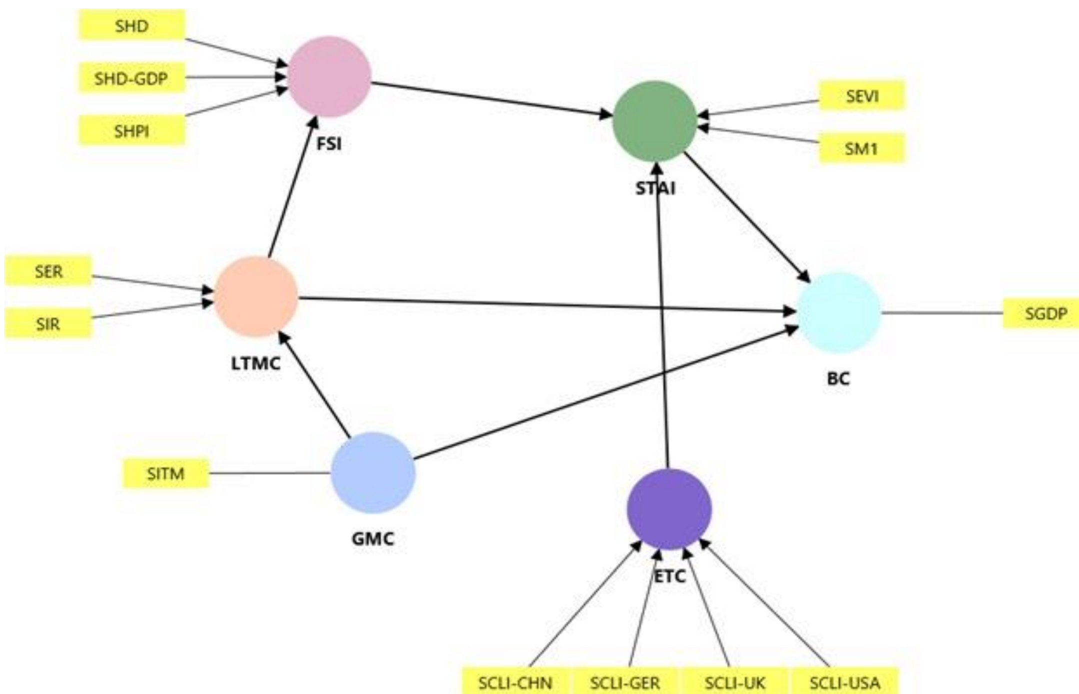
The model also incorporates two additional transmission channels that connect the global forces influencing Pakistan's domestic business cycles: the External Trade Channel (ETC) and the Global Monetary Channel (GMC). The External Trade Channel (ETC) transmits global economic shocks to the domestic economy via trade and financial linkages (Cantor & Mark, 1988; Kose, Otrok, & Whiteman, 2003). Following Pumjaroen et al. (2020), the ETC is used as a bridge between STAI and BC to determine the spillover of economic movements of Pakistan's key trading partners into its short-term activity index. The Global Monetary Channel (GMC) illustrates how international monetary variables, such as global interest rate fluctuations, affect Pakistan’s business cycles via exchange rates and capital flows (Cantor & Mark, 1988; Kose et al., 2003). Figure 2 presents the study's conceptual model.

3.1 Short-Term Indicators (1–3 Quarters)

Economic activity in the short run reacts fast to variation in liquidity conditions and external demand shocks. Short Term Activity Index (STAI) consists of narrow money (M1) and export volume Index (EVI) which have theoretical as well as practical foundations. Figure 2 presents the conceptual model of Pakistan’s business cycle framework, showing how short-term, medium-term, long-term, and global channels interact to shape economic fluctuations. The model demonstrates that Financial Stability Indicators (FSI) affect Short-Term Activity (STAI), directly feed into Business Cycles (BC). Long-Term Monetary Channels (LTMC) influence BC directly and indirectly through FSI. At the global level, the Global Monetary Channel (GMC) transmitting their effects via LTMC and FSI, while the External Trade Channel (ETC) links Pakistan’s cycles to those of key trading partners (China, Germany, UK, USA). Together, the arrows in the model show both direct effects.

Friedman and Schwartz (1965) present the argument of direct link between changes in money supply and the level of spending when the prices and wages are sticky, as developed by the Monetary Transmission Mechanism Theory (Bernanke, 1990). Empirically, the findings made by Babecký et al. (2013) and Ang and McKibbin (2007) indicate that M1 is a short-run indicator of output changes and the emergence of a crisis. The EVI reflects Real Business Cycle (RBC) Theory that shows that external trade shocks can generate cyclical dynamics. According to Artis, Kontolemis, and Osborn (1997)and Kose et al. (2003), trade volumes are strongly pro-cyclical, synchronizing domestic output with trading partners' cycles. Sethapramote (2015) confirms that trade linkages are critical in open economies, where short-term shocks in partner economies transmit rapidly through exports. Together, these indicators operationalize Liquidity Preference Theory (Keynes) and RBC Theory, capturing immediate economic responses within one to three quarters.

Figure 1: The Conceptual Model



Source: Author's own contribution

3.2 Medium-Term Indicators (4–8 Quarters)

Medium-term fluctuations are largely driven by the gradual unwinding of financial disparities, consistent with the Financial Instability Hypothesis (Minsky) and the Financial Accelerator Theory (Bernanke et al., 1999). Jordà, Schularick, and Taylor (2013) provide cross-country evidence that household debt build-ups precede deeper recessions. Mian, Sufi, and Trebbi (2014) show how excessive household leverage worsens household spending cuts during downturns, an idea supported by the financial accelerator mechanism. Borio and Lowe (2002) and Drehmann et al. (2012) find that the credit-to-GDP gap is one of the best medium-term predictors of banking crises, linking credit expansions with real economic slowdowns. The FSI thus reflects the Minskyan financial cycle, the credit cycle literature and Housing Cycle Theory, capturing vulnerabilities that shape turning points over four to eight quarters.

3.3 Long-Term Indicators (9+ Quarters)

Long-term drivers are primarily rooted in Monetary Policy Transmission Theory and Global Financial Cycle Theory. The Long-Term Monetary Channel (LTMC) includes policy interest rates (IR) and the real effective exchange rate (REER). According to Friedman (1961) and Bernanke (1990), monetary policy affects real output and investment with "long and variable lags," as stated in classical monetary theory. The REER relates to the Marshall-Lerner Condition, which states that exchange rate adjustments affect the trade balance and output with a time lag as downturns adjust (Edwards, 1989).Persistent misalignments can also erode competitiveness, causing longer-horizon deviations in output. The Global Monetary Conditions (GMC) reflect the Global Financial Cycle Hypothesis (Rey, 2015) which highlights that international interest rates and global liquidity conditions affect domestic capital flows and constrain monetary independence, especially in emerging economies.

These theoretical foundations align with empirical studies that operate similar constructs. The OECD's system of CLIs combines money supply, trade, housing, credit, and monetary policy variables to forecast economic turning points (Gyomai & Guidetti, 2012). Babecký et al. (2013) use M1 and credit variables as leading indicators for crisis incidence in Europe. Pumjaroen et al. (2020) employ narrow money, real exchange rates, and global CLIs in a PLS-SEM framework for Thailand. Sethapramote (2015) uses trade linkages to model business cycle synchronization in East Asia. These examples confirm that the chosen indicators and their theoretical underpinnings are both widely validated and relevant for emerging economies like Pakistan.

Hypothesis

All the paths of inner model form the hypothesis the present study intends to test. The following hypothesis are tested:

H1: All other things remain the same, Long Term Monetary Channel (LTMS) has a countercyclical effect on Business Cycle (BC)

H2: All other things remain the same, Financial Stability Index (FSI) has a countercyclical effect on Business Cycle (BC) indirectly through Short-Term Activity Index.

H3: All other things remain the same, Short-Term Activity Index (STAI) positively impacts the Business Cycle (BC)

H4: All other things remain the same, Global Monetary Conditions (GMC) influence Business Cycle (BC) indirectly through Long Term Monetary Channel (LTMS)

H5: All other things remain the same, Global Monetary Conditions (GMC) influences Business Cycle (BC) via trade channels

4 Methodology

4.1 Estimation Technique

The study's conceptual model focuses on CLI as constructs that are measured using indicators. Partial Least Squares Structural Equation Modeling (PLS-SEM) is the best appropriate technique for estimate in this model. PLS-SEM is a popular tool in economic forecasting and business research because it can simulate complex interactions between latent variables and observed indicators. Wold (1975) developed PLS-SEM, a variance-based method that uses principal component analysis and ordinary least squares (OLS) regression to estimate structural and measurement models at the same time (Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016).

PLS-SEM attempts to maximize explained variance, making it ideal for predictive analysis and forecasting applications (Sarstedt et al., 2016). PLS-SEM is becoming increasingly popular in macroeconomic forecasting due to its ability to handle small sample sizes, non-normally distributed data, and complicated models with several latent features (Henseler, 2017). PLS-SEM provides a robust and versatile framework for estimating latent constructs, integrating various reflective or formative indicators, and modeling both direct and indirect interactions between variables (Joe Hair et al., 2017).PLS-SEM is preferred over traditional time-series models such as VAR and ARIMA because of its ability to model complex, multidimensional, and non-linear connections among latent components. Unlike VAR and ARIMA, which are limited to assessing linear interdependencies between observed variables, PLS-SEM allows for the simultaneous estimate of both the model's measurement and structural components. This makes it ideal for developing formative measurement models such as the Composite Leading Indicator (CLI), in which many economic indicators determine the construct rather than being its outputs. Furthermore, PLS-SEM is highly suited for data with small sample sizes, non-normal distributions, and multicollinearity, which are common in Pakistan's macroeconomic data. This makes it ideal for simulating the complicated, multi-period structure of Composite Leading Indicators (CLIs), which are used to anticipate Pakistan's business cycle. Structural Equation Modeling (SEM) has two parts: the measurement model or outer model and the structural model or inner model.

4.2 Measurement Model

In Structural Equation Modeling (SEM), the measurement model explains how latent constructs are operationalized using observed indicators (Joe Hair et al., 2017). There are reflective and formative measurements, which are based on the theoretical relationship between indicators and constructs. Reflective models assume that the construct causes the indicators. This means that movement in the latent construct will create a simultaneous change in its observed measures. Indicators in a reflective model should be highly correlated and interchangeable (Joe Hair et al., 2017). Formative models, on the other hand, assume that the indicators form or create the construct. Here, each indicator represents a unique aspect or dimension, so they do not need to be correlated. Omitting an indicator can alter the meaning of the construct. Formative measurement models are evaluated by checking the significance of outer weights, examining multicollinearity among indicators (using VIF values) and optionally testing for convergent validity through the outer loadings (Joe Hair et al., 2017). In the present paper research, all constructs are specified as formative. This formative specification aligns with the OECD approach to constructing Composite Leading Indicators (CLI) which combines diverse economic signals that each uniquely contribute to forecasting the business cycle (Gyomai & Guidetti, 2012).

4.3 Structural Model

In structural equation modeling (SEM), the structural model referred to as the inner model in PLS-SEM specifies the hypothesized relationships among the latent constructs that form the conceptual framework (Joseph Hair & Alamer, 2022). Structural model focuses on explaining the variance in dependent (endogenous) constructs grounded on the effects of independent (exogenous) constructs. In this study, the structural model captures the multi-period transmission mechanism of Pakistan’s business cycle by integrating global monetary conditions, long-term monetary stance, financial stability, short-term activity, and the overall business cycle itself.

Key elements of the structural model include Path coefficients (β), which estimate the significance and direction of link between constructs. Significance testing is conducted through bootstrapping (5,000 subsamples) (Joseph Hair & Alamer, 2022)[1]. The coefficient of determination (R^2) for each endogenous construct is evaluated. According to Hair et al. (2022), R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively. Moreover, Effect size (f^2), which assesses the relative contribution of each exogenous construct to the R^2 value of the dependent construct is also applied for analysis inner model. The mathematical version of the

1 The estimation of the PLS SEM is done through the software SMART PLS, Version 4.1.1.2 Ringle, C. M., Wende, S., and Becker, J.-M. 2024. "SmartPLS 4." Bönningstedt : SmartPLS, https://www.smartpls.com.

conceptual model is presented below for more clarification:

Structural Model

$$BC = \beta_{0,BC} + \beta_{1,BC}\, STAI + \beta_{2,BC}\, LTMC + \beta_{3,BC}\, GMC + u_{BC}$$

$$STAI = \beta_{0,STAI} + \beta_{1,STAI}\, ETC + \beta_{2,STAI}\, FSI + u_{STAI}$$

$$FSI = \beta_{0,FSI} + \beta_{1,FSI}\, LTMC + u_{FSI}$$

$$LTMC = \beta_{0,LTMC} + \beta_{1,LTMC}\, GMC + u_{LTMC}$$

Measurement Model (Formative Measure)

$$STAI = \omega_0 SEVI + \omega_1 SMI$$

$$FSI = \omega_2 SHD + \omega_3 SHD - GDP + \omega_4 SHPI$$

$$LTMC = \omega_5 SER + \omega_6 SIR$$

$$ETC = \omega_7 SCLI - CHN + \omega_8 SCLI - GER + \omega_9 SCLI - UK + \omega_{10} SCLI - USA$$

4.4 Evaluation Criteria

To evaluate convergent validity in formative measurement models, outer weights and their significance ($p < 0.05$) are utilized, while confidence intervals for path coefficients should not include zero. Multicollinearity is assessed using VIF, with values less than 5 being acceptable. Although reflective models require convergent validity, formative models should analyze outer loadings to ensure indicators contribute meaningfully, even if weights are negligible (Joseph Hair & Alamer, 2022; Sarstedt et al., 2016). Structural route evaluation considers direct and indirect effects, supported by R^2 and f^2 values for explanatory power and impact size.

Data Collection and Filtration

The data for this study were sourced from Pakistan Bureau of Statistics (PBS), the State Bank of Pakistan (SBP), the World Bank (WB), the International Monetary Fund (IMF), the World Development Indicators (WDI), Zameen.com and the Organization for Economic Co-operation and Development (OECD). The dataset covers quarterly observations from the first quarter of 2011 (2011Q1) to the second quarter of 2025 (2025Q2), ensuring a sufficient time span to capture short-, medium-, and long-term fluctuations. This data also meets the "10 times rule" of PLS-SEM, which is a rule of thumb for calculating a minimum sample size.

Data Filtration

In quantitative forecasting, meticulous data preparation is essential for producing valid and interpretable results. It is critical to verify that the data represent only relevant cyclical signals and do not contradict crucial statistical assumptions (Joseph Hair & Alamer, 2022). Proper preprocessing, such as seasonal adjustment and trend extraction, aids in identifying the true cyclical component of economic indicators, improving model fit, reducing multicollinearity, and improving forecasting and causal inference accuracy(Hodrick & Prescott, 1997; Stock & Watson, 1988). As Gyomai and Guidetti (2012) point out, when developing Composite Leading Indicators (CLIs), which rely on clean, similar signals across variables to provide timely and credible early warnings of economic cycle turning points. For this study, quarterly macroeconomic and financial data for the period 2011Q1 to 2025Q2 is used. As these variables include trend and seasonal components, the raw data do not directly reflect the cyclical dynamics of the business cycle. Following Gyomai and Guidetti (2012) and OECD best practices for constructing Composite Leading Indicators (CLIs), the data was preprocessed using the following steps:

a) **Standardization:** All the series were standardized (mean = 0, standard deviation = 1) to allow comparability across different units and scales before estimation in PLS-SEM. Standardization also prevents certain indicators from dominating the composite indices due to scale differences.

b) Seasonal Adjustment (X-12 ARIMA): The series are seasonally adjusted through the filer X-12 ARIMA procedure in EViews to remove regular seasonal patterns and calendar effects (Findley, Monsell, Bell, Otto, & Chen, 1998). This step ensures that the cyclical signals are not confounded by predictable seasonal fluctuations.

c) **Hodrick–Prescott (HP) Filter:** To isolate the cyclical component from the long-term trend, the Hodrick–Prescott filter (Hodrick & Prescott, 1997) was applied to each series. The HP filter minimizes the squared deviations from a smooth trend while penalizing variations in the trend component. This technique is widely used in business cycle research and CLI construction (Nilsson & Gyomai, 2000).

d) **Double HP Filter:** To further refine the cyclical signal, a second pass of the HP filter (Double HP filtering) was used to remove any residual low-frequency trend components, following guidance from Maravall and del Río (2001). This step helps to extract a clean cyclical indicator that aligns more closely with the reference cycle (real GDP output gap). These data preparation steps are necessary as failure to adjust for trends or seasonality can lead to spurious relationships, biased coefficients, and misleading results.

Table 1: Constructs, Description and Data Source

Construct	Indicator	Definition	Unit of Measurement	Source	References
Business Cycle (BC)	Real GDP Growth Rate	Annual % growth of GDP at constant 2015 prices. Sum of gross value added by resident producers plus taxes minus subsidies; no deductions for depreciation or depletion.	Percent (%)	World Development Indicators (WDI)	Stock & Watson (1989)
Short-Term Activity Index (STAI)	i) Narrow Money (M1)	Currency in circulation plus demand deposits reflects short-term liquidity in the economy.	PKR Billion	SBP Easydata	Babecký et al. (2013);
	ii)Export Volume Index (EVI)	Tracks the volume of exported goods/services, excluding price changes.	Index (Base Year = 2010)	SBP Easydata	Sethapramote (2015)
External Trade Channel (ETC)	OECD CLI for major trade partners (China, USA, UK, Germany)	Measures economic fluctuations in Pakistan's major export partners and their impact on domestic cycles.	Composite Index (OECD CLI)	OECD	Kose et al. (2003); Schmitt-Grohé (1998)
Financial Stability Index (FSI)	1) Housing Price Index (HPI)	Statistical measure of changes in residential property prices; includes averages from major cities in Pakistan.	Index (Base Year = 2010)	Zameen.com	Leamer (2007); Borio & Lowe (2002)
	2)Household Debt to GDP (HD_GDP)	Ratio of total household debt to nominal GDP; indicates leverage level of households.	Percent (%)	SBP Easydata	Drehmann et al. (2012)
	3)Household Debt (HD)	Total household liabilities: consumer loans, credit cards, home financing.	PKR Billion	SBP Easydata	Mian & Sufi (2014)

Long-Term Monetary Conditions (LTMC)	1)Policy Rate (IR)	Real interest rate adjusted for inflation via GDP deflator.	Percent (%)	World Development Indicators (WDI)	Bernanke & Blinder (1992);
	2) Real Effective Exchange Rate (REER)	Nominal effective exchange rate adjusted by a price deflator or cost index.	Index (Base Year = 2010)	WDI	Edwards (1989); Rey (2015)
Global Monetary Channel (GMC)	OECD CLI for OECD and non-member countries	Aggregate leading indicator for global monetary conditions including OECD member states.	Composite Index (OECD Total)	FRED	Rey (2015); Pumjaroen et al. (2020)

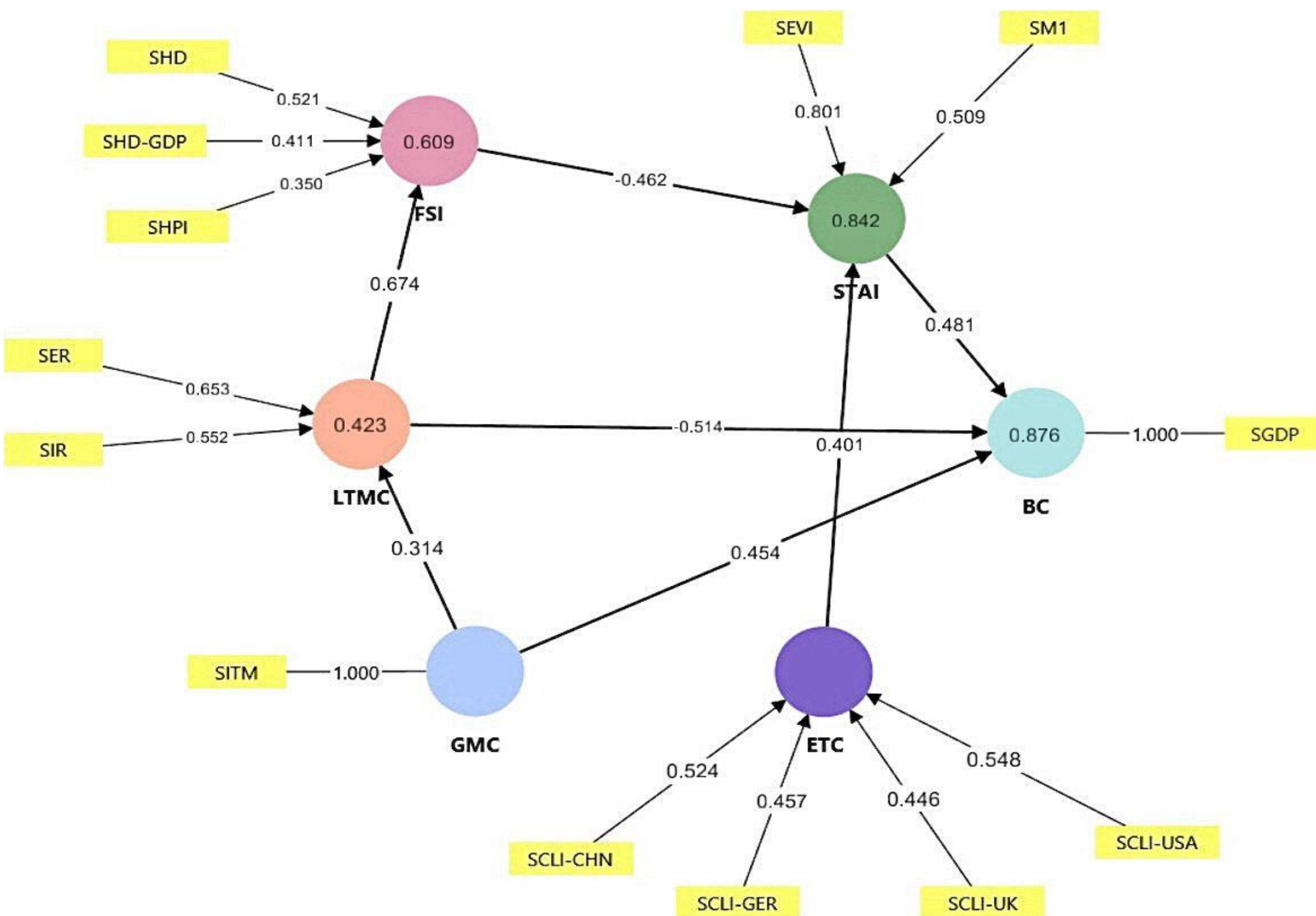
Source: Authors Own Contribution

5 Estimation and Results

This section has discussion on the results attained from PLS -Algorithm which estimates the outer model and Bootstrapping results which provide the test of significance of inner model coefficients.

Measurement Model Results

Figu.re 2: Measurement Model (PLS Algorithm)



Source: Author's own contribution

5.1 Outer Weights and Convergent Validity

There are one endogenous and five exogenous constructs in the model which are measured formatively through fourteen indicators. Table 4 shows that all the constructs satisfy the criteria of significance of the indicators which are significant at 5% level except the weights of SCLI-GER, SHD-GDP and SIR that are found not significant. However, the outer loadings are above 0.50, which indicates convergent validity in formative models. This approach aligns with best practice for formative measurement (Joseph Hair & Alamer, 2022). Moreover, the 5% confidence interval does not contain zero which further strengthens the model indicators for the measurement of construct. Retaining these indicators ensures that each construct reflects the full scope of its theoretical dimension.

TABLE 2 MEASUREMENT MODEL ANALYSIS (FORMATIVE)

	Paths	Outer Weights	Loadings	T statistics	P values	Confidence Interval 2.5%	97.5%
ETC	SCLI-CHN – ETC	0.524***	0.949	4.696	0	0.388	0.639
	SCLI-GER – ETC	0.457	0.619	1.048	0.072	0.251	0.663
	SCLI-UK – ETC	0.446***	0.674	4.565	0	0.387	0.805
	SCLI-USA – ETC	0.548***	0.522	4.215	0	0.442	0.762
LTMC	SER – LTMC	0.653**	0.978	2.614	0.039	0.55	0.995
	SIR – LTMC	0.552*	0.891	0.049	0.121	0.453	0.711
BC	SGDP -> BC	1	1	n/a	n/a	1	1
STAI	SEVI – STAI	0.801***	0.687	35.694	0	0.495	0.819
	SM1 – STAI	0.509**	0.542	8.369	0.012	0.383	0.698
	SHD – FSI	0.521***	0.636	5.253	0	0.486	0.726
FSI	SHD- GDP – FSI	0.411	0.595	1.105	0.216	0.27	0.489
	SHPI – FSI	0.35**	0.998	4.073	0.042	0.185	0.584
GMC	SITM – GMC	1	1	n/a	n/a	1	1

Note: Authors Own Contribution

5.2 Multicollinearity Diagnosis

In PLS-SEM, multicollinearity is assessed for structural (inner) model and measurement (outer) model, particularly when using formative indicators (Joseph Hair & Alamer, 2022). The Variance Inflation Factor (VIF) is used for detecting multicollinearity and threshold value is 5 according to Joseph Hair and Alamer (2022). All indicators have VIF less than 5 and qualify for no multicollinearity.

Table 3: Indicators and their VIF values

Indicators	**Outer VIF**
SCLI-CHN	1.849
SCLI-GER	1.917
SCLI-UK	1.893
SCLI-USA	2.29
SER	1.883

SGDP	1
SHD	2.502
SHD-GDP	1.304
SHPI	1.896
SIR	1.883
SITM	1
SM1	1.222
SEVI	1.222

Source: Author's own contribution

The structural model estimation is done through bootstrapping with 5000 iterations using software Smart PLS 4(v 4.1.1.2) and results are reported in Figure 4 as well as in Table 4. Results of path coefficients, direct effect, indirect effect, total effect and mediation paths are discussed in following section.

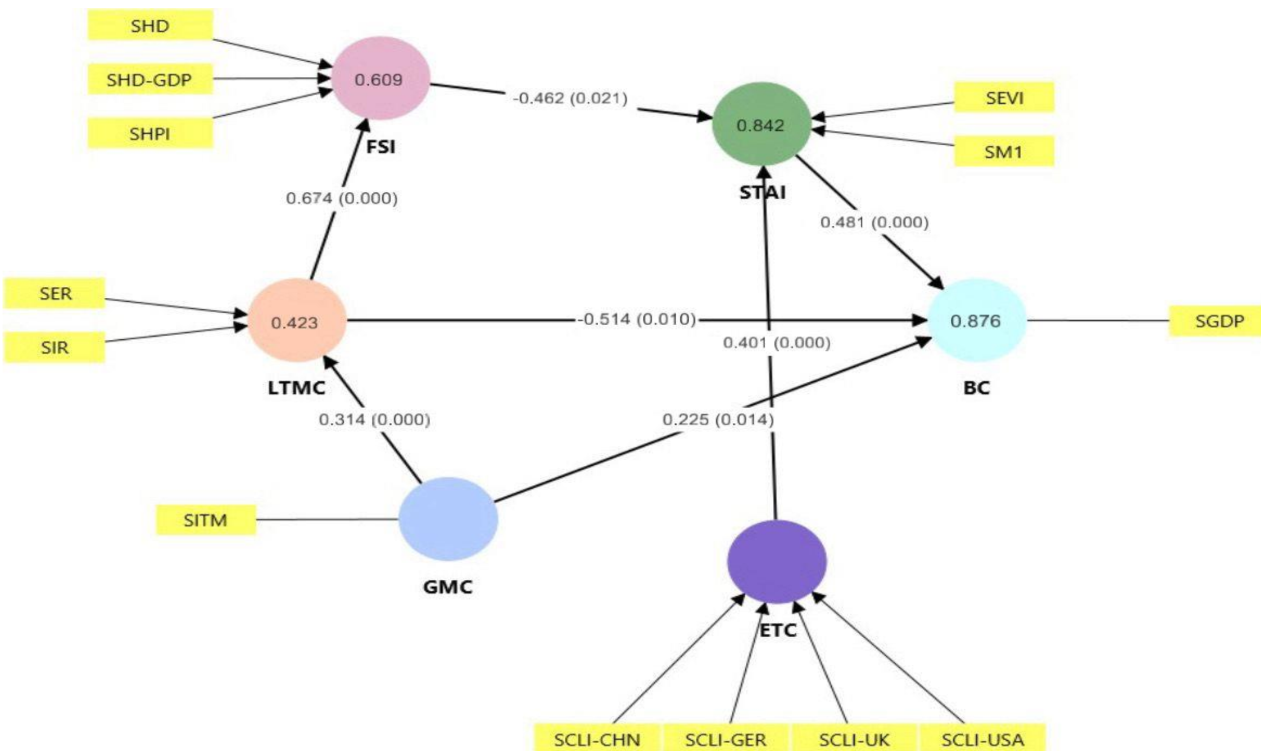
5.3 Path Coefficients and Hypothesis-Direct effect

In Partial Least Squares Structural Equation Modeling (PLS-SEM), the path coefficients represent the estimated strength and direction of the hypothesized relationships among latent constructs in the structural (inner) model (Joseph Hair & Alamer, 2022). Each path coefficient (β) is interpreted similarly to a standardized regression weight in ordinary least squares (OLS) regression. Inner model is estimated through bootstrapping and results are shown in Table 4. The results reflect that all hypothesized paths are statistically significant, with p-values below 0.05 and 95% confidence intervals that do not include zero.

The link between Financial Stability condition (FSI) has negative path coefficient with Short Term Activity Index (STAI). FSI is an index which is measured through Household debt and Household debt to GDP ratio. The increase in FSI is an indication of financial instability of an economy. The construct STAI is measured through M1(narrow money) and EVI (export volume index). The path Coefficient between STAI and Business Cycle (BC) is positive and highly significant (β=0.481, t= 32.761), emphasizes that an rise in short term activity will have pro-cyclical effect on business cycle.

Similarly, all the coefficients which have direct link with BC and are positive path coefficients show a procyclical effect or expansion of economy whereas, those with negative sign show the counter cyclical fluctuation of business cycle. Long Term Monetary Channel (LTMC) and Global Monetary Conditions (GMC) are long-term CLI. The path coefficient between LTMC and BC is negative indicates counter cyclical effect on business cycles. The results also show that GMC has a positive effect on BC. By tracing these indirect effects, the model shows how external shocks are transmitted step by step through the economy. The model further has an impact of CLI through mediators which is captured through Specific indirect effect and total effect. In Table 5 and Table 6.

\- Figure 3: Structural Model Estimation (Bootstrapping)



Note: Authors' Own Contribution

TABLE 4: INNER MODEL ESTIMATION (BOOTSTRAPPING) AND HYPOTHESIS-DIRECT EFFECT

Path	Path coeff	t-Stats	p-Value	Confidence	Interval
ETC → STAI	0.401	22.111	0	0.207	0.801
FSI → STAI	-0.462	2.958	0.021	-0.545	-0.243
GMC → LTMC	0.314	7.489	0	0.185	0.828
LTMC → FSI	0.674	8.628	0	0.147	0.601
LTMC → BC	-0.514	6.372	0.012	-0.706	-0.024
STAI → BC	0.481	32.761	0	0.008	0.713
GMC → BC	0.225	2.457	0.014	0.185	0.828

Source: Author's own contribution

5.4 Specific Indirect Effect

A specific indirect effect (SIE) refers to the distinct pathway by which one construct affects another via a single, clearly defined chain of relationships, (Joseph Hair & Alamer, 2022). By decomposing the total effect into its direct and specific indirect components, researchers gain deeper insight into how complex mechanisms and mediation processes operate within the model (Nitzl, 2016). Mathematically, each specific indirect effect is estimated as the product of the path coefficients along the mediating path.

Mediation can be partial when both the direct effect and the indirect effect are significant whereas, full mediation occurs in case when only indirect effect is significant while the direct effect is not (Zhao, Lynch Jr, & Chen, 2010). The estimation results demonstrate that all tested mediator pathways are statistically significant at the 5% level, supporting the study's multi-channel transmission framework for Pakistan's business cycle.

First, the indirect effect FSI → STAI → BC (β = –0.222) shows a t-statistic of 2.869 and a p-value of 0.042, with a 95% confidence interval [–0.544, –0.006] that does not include zero, confirming its significance. This pathway supports H2, indicating that higher financial instability reduces short-term liquidity and economic activity, which in turn depresses GDP growth — a pattern consistent with Minsky's (1986) Financial Instability Hypothesis. The significant indirect effect alongside the absence of a direct FSI → BC path suggests complete mediation through STAI. Second, the chain GMC → LTMC → FSI → STAI → BC is also significant supporting H4. This confirms that global monetary conditions influence the business cycle indirectly through multiple domestic channels: first shaping long-term monetary conditions, then affecting financial stability and short-term activity. The presence of both direct and indirect GMC impacts implies partial mediation, consistent with the Global Financial Cycle hypothesis (Rey, 2015).

Third, the link GMC → LTMC → BC is significant. This direct transmission through domestic monetary tightening highlights how global shocks immediately influence GDP via long--term rates and exchange rates. Again, the significant direct GMC → LTMC and indirect GMC → BC effects imply partial mediation, reinforcing H4. Finally, the significance of path LTMC → FSI → STAI → BC validates H1, confirming that tighter long-term domestic monetary conditions increase financial stress, which then suppresses short-term activity and GDP.

The path FSI → STAI → BC confirms H2, demonstrating that financial instability affects the business cycle indirectly through short-term liquidity, consistent with the Financial Instability Hypothesis (Minsky, 1986). Collectively, these significant indirect effects highlight that partial mediation occurs, as the indirect paths complement significant direct effects in the structural model, demonstrating that both direct and mediated channels jointly shape Pakistan's business cycle dynamics.

TABLE 5: SPECIFIC INDIRECT EFFECT

	Spe Ind Eff	T values	P values	2.50%	97.50%	Hyp
FSI -> STAI -> BC	-0.222	2.869	0.042	-0.544	-0.006	**H2 Accepted**
GMC -> LTMC -> FSI -> STAI -> BC	-0.047	2.069	0.039	-0.384	-0.021	**H4 Accepted**
GMC -> LTMC -> BC	-0.161	3.341	0.033	-0.453	-0.053	**H4 Accepted**
LTMC -> FSI -> STAI -> BC	-0.149	2.922	0.005	-0.336	-0.031	**H1 Accepted**

Source: Author's own contribution

5.5 Total Effect

In Partial Least Squares Structural Equation Modeling (PLS-SEM), the total effect represents the sum of the direct and all possible indirect effects between an exogenous (predictor) construct and an endogenous (outcome) construct (Joseph Hair & Alamer, 2022). Mathematically, the total effect is computed by summing the direct path coefficient with all relevant specific indirect effects that link the predictor to the outcome variable through one or more mediators (Nitzl, 2016). Interpreting total effects is essential because they show the net strength and direction of relationships in complex models where multiple mediators and transmission channels are present.

A substantial total impact with partial mediation indicates that both direct and indirect channels contribute considerably to the relationship, whereas a significant total effect with just indirect paths shows full mediation (Zhao et al., 2010). The calculated overall effects confirm that each postulated channel makes a significant contribution to understanding Pakistan's business cycle dynamics.

First, the total effect from Financial Stability Index (FSI) → Business Cycle (BC) is statistically significant. This supports H2, demonstrating that higher levels of financial instability indirectly reduce GDP growth, consistent with the Financial Instability Hypothesis (Minsky, 1986). Second, the total effect of Global Monetary Conditions (GMC) → BC is positive suggesting this effect is significant at the 5% level. This finding justifies H5, indicating that global monetary shocks have a meaningful total influence on domestic economic fluctuations through both direct and indirect channels, aligning with the Global Financial Cycle literature (Rey, 2015). Third, the total effect for Long-Term Monetary Channel (LTMC) → BC is strongly confirming its statistical significance supporting H1 showing that tighter long-term domestic monetary conditions exert a substantial dampening effect on GDP growth, in line with the Monetary Transmission Mechanism and Financial Accelerator Theory (Bernanke et al., 1999). Finally, the total effect for Short-Term Activity Index (STAI) → BC is positive further demonstrates the strength and consistency of this relationship. This strongly supports H3, confirming that higher short-term liquidity and trade activity have a direct expansionary impact on the business cycle, reflecting the role of money supply and confidence channels in driving economic growth.

TABLE 6: TOTAL EFFECT

	Total Effects	T value)	P values	2.50%	97.50%	Hypothesis
FSI -> BC	-0.222	2.869	0.042	-0.544	-0.006	**H2 Accepted**
GMC -> BC	0.017	1.998	0.046	0.001	0.475	**H5 Accepted**
LTMC -> BC	-0.663	2.323	0.007	-0.804	-0.412	**H1 Accepted**
STAI -> BC	0.481	32.761	0	0.008	0.713	**H3 Accepted**

Source: Author’s own contribution

5.6 f² Effect Size

Hair et al. (2022) defines the effect size (f^2) in PLS-SEM as the unique contribution of each predictor to the R^2 of an endogenous construct. STAI has a significant impact on BC ($f^2 = 0.35$), making it the most important factor in explaining business cycle changes. ETC and LTMC have moderate impacts on their targets, but GMC and ETC have smaller direct effects, operating primarily through indirect routes.

TABLE 7: f^2 EFFECT SIZE

Path	f^2	Interpretation
STAI → BC	0.35	Strong
LTMC → FSI	0.27	Medium

ETC → STAI	0.22	Medium
LTMC → BC	0.15	Medium

Source: Author's own contribution

5.7 Coefficient of Determination (R^2) and Adjusted R^2

Hair et al. (2022) defines the coefficient of determination (R^2) as the extent to which exogenous constructions account for endogenous constructs' variance. The CLI framework explains a significant percentage of the business cycle's variance ($R^2 = 0.876$), with modified R^2 confirming this strong explanatory power even when model complexity is taken into consideration.

TABLE 8: COEFFICIENT OF DETERMINATION (R^2)

Constructs	R-square	R-square Adjusted
BC	0.876	0.877
FSI	0.609	0.609
LTMC	0.423	0.422
STAI	0.842	0.842

Source: Author's own contribution

5.8 Inner Model VIFs

Table 10 presents the VIF values for the structural paths. All VIF values in the inner model fall below the more conservative threshold of 3.0. This indicates that the predictor constructs do not exhibit challenging multicollinearity, confirming that each construct contributes unique information to the structural model.

TABLE 9: VIF VALUES OF STRUCTURAL MODEL

Paths	VIF
ETC – STAI	1.271
FSI – STAI	1.897
GMC –LTMC	1
GMC –BC	2.918
LTMC –FSI	1
LTMC –BC	1.772
STAI – BC	2.787

Source: Author's own contribution

6 Discussions

The model demonstrates a large direct effect from STAI to BC, highlighting the importance of short-term liquidity and export demand in GDP fluctuations. This is consistent with Keynesian and monetary transmission theories (Friedman & Schwartz, 1963), as well as empirical findings by Babecký et al. (2013) and Ang and McKibbin (2007), which identify money supply and trade indices as important short-term economic indicators in emerging markets. The FSI has a large countercyclical effect on the economic cycle which aligns with Minsky's Financial Instability Hypothesis and the Financial Accelerator Theory (Bernanke et al., 1999). This suggests that rising household debt, credit gaps, and property price volatility increase vulnerability and exacerbate downturns, as evidenced by Jordà, Schularick, and Taylor (2017)and Drehmann et al. (2012) in OECD nations.

The LTMC has a strong negative influence on the business cycle (β = -0.514), supporting the monetary transmission lag argument that tighter conditions, higher real rates, and currency appreciation reduce expansion (Bernanke et al., 1999; Friedman & Schwartz, 1965; Taylor, 1993). This multi-channel process consists of economic cycle synchronization theories (Kose et al., 2003) and OECD CLI methodologies (Gyomai & Guidetti, 2012), which emphasize the importance of several indicators. Consistent with Sethapramote (2015) and Pumjaroen et al. (2020), the findings show that short-term liquidity and exports are immediate drivers, while LTMC and ETC have medium-term implications.

Beyond verifying global-monetary-real links, the model demonstrates how domestic vulnerabilities influence external shock transmission. The mediating function of FSI demonstrates how family debt, housing markets, and credit gaps exacerbate cycles, repeating Borio and Lowe (2002) and Mian et al. (2014), and emphasizing the importance of flexible macro prudential policy. The results also confirm the External Trade Channel's relevance, but with a less pronounced effect than the monetary and financial channels. According to Sethapramote (2015), Pakistan's concentrated export base makes ETC important for short-term forecasting but insufficient to dominate, meaning that trade diversification must support macroeconomic stability. The significant indirect pathways also highlight that Pakistan's business cycle is not driven by isolated shocks but by complex interdependencies among domestic and global drivers. This supports the OECD's approach that reliable CLI frameworks should include not just single leading indicators but a balanced mix of short-term, medium-term, and long-term variables to capture shifts across horizons (Gyomai & Guidetti, 2012).

Another key insight is that the high R^2 values and significant f^2 effect sizes for the Short-Term Activity Index (STAI) confirm Keynesian theory and empirical evidence from Babecký et al. (2013) and Ang and McKibbin (2007), who emphasize that money supply and short-term sentiment measures are the most reliable predictors of short-term business cycle turning points in emerging markets.

From a methodological perspective, the study shows the added value of PLS-SEM over traditional VAR or ARIMA models. The capacity to estimate indirect impacts and test mediating relations, as well as quantify the effect of many compound constructs, differentiates this strategy to a single-equations or univariate forecasting model. As is the case with Thailand shown by Pumjaroen et al. (2020), the inclusion of CLIs in PLS-SEM augment the explanatory quality of the early warnings systems and offers policymakers a more informed look at shock transmission across sectors and time spans.

Lastly, the findings also emphasize the role of regional and global coordination particularly in addressing spillover effects of global monetary conditions. According to Rey (2015), the developing economies find themselves in a dilemma where they are restricted by the global financial cycle thereby limiting the ability of domestic monetary independence. This model confirms this dilemma by showing that although Pakistan is affected by the Global Monetary Conditions (GMC) and Long-Term Monetary Conditions (LTMC), the major contribution in this direction is by the former, and thus, requires the State Bank of Pakistan and the policymakers to keep a keen eye on how global liquidity trends and to change the domestic policy before any signal of lapse in macroeconomic stability.

The results are compatible with the study's objectives. Short-term liquidity and export performance (STAI) emerge as the most significant positive drivers of Pakistan's business cycle, thereby accomplishing Objective 1. Medium-run financial imbalances (FSI) have a countercyclical effect, supporting Objective 2 by underlining the destabilizing implications of household debt and asset price volatility. Long-term monetary conditions (LTMC) have a negative influence, which meets Objective 3 by emphasizing the contractionary effects of tighter global and domestic monetary policies. These results support the CLI's ability to capture complex cyclical activity and increase forecasting precision.

On the whole, these findings indicate that the business cycle in Pakistan is determined by a stratified interaction between short-run liquidity, medium-term financial imbalances, and long-run global monetary transitions each path enabled by economic theory and confirmed by analogous empirical studies in other similar settings. This combined view does not only serve as a valuable addition to the literature on the business cycle in Pakistan but also includes a realistic path of action to better macroeconomic surveillance and policy formation.

7 Conclusion, Policy Recommendations and Limitations of the Study

The findings of the study have important implications within the economic theory, as well as policy formulation in Pakistan. Theoretically, the work brings newfound evidence to the use of multi-horizon business cycle theory as it can be seen that short term liquidity, medium term financial stability and long-term global monetary trends show dynamic interplay in creating the cyclical fluctuation. This adheres to the Monetary Policy Transmission Mechanism (Bernanke, 1990; Taylor, 1993), the Financial Instability Hypothesis (Minsky, 2004) and to the Global Financial Cycle Theory (Rey, 2015). By incorporating these channels into one structural equation model, it is confirmed that business cycle turning points are inexplicable with real-sector indicators only but depend on well-rounded knowledge of financial and external transmission channels.

Such theoretical evidence is more applicable in emerging markets such as Pakistan, which are more exposed to international monetary shocks and volatility of capital flows (Kose et al., 2003). The large indirect effects of global monetary conditions on Pakistan Business cycles through Financial Stability index signifies the link of global conditions on growth of Pakistan’s GDP. Such stratified transmission process supports the argument by OECD (Gyomai & Wildi, 2012) that properly constructed Composite Leading Indicators (CLIs) may offer sound early warning indicators as long as they incorporate domestic and external drivers in a combined fashion.

Policy-wise, the outcomes point at the necessity of an integrated macroeconomic monitoring system. In addition to following the short-run liquidity and trade developments, policymakers should also take notes of the medium-term financial stability indicators, including the levels of household debts and credit-to-GDP gaps. These variables, as demonstrated by Jordà et al. (2017) and Drehmann et al. (2012), develop into amplifiers of downturns as the credit conditions contract. Central bank and financial regulators are, therefore, advised to rely on such signals to adjust macro prudential policies, such as by changing loan-to-value ratios or countercyclical capital buffers in credit booms. The findings also suggest that the traditional time-series forecasting predictors such as VAR or ARIMA might not be adequate business cycle forecasting tools. PLS-SEM model proves that the inclusion of composite relations and indirect effects provides additional explanatory strength, allowing a more viable early warning system (Babecký et al., 2013; Pumjaroen et al., 2020).

These findings have practical consequences for policymakers and financial institutions. The State Bank of Pakistan can use the Composite Leading Indicator (CLI) to proactively adjust interest rates, liquidity, and credit conditions. Similarly, trade and fiscal authorities might use these findings to diversify exports and improve macroeconomic resilience to global shocks. However, it is important to acknowledge certain limitations of this study. As with many empirical studies in developing nations, the study struggled to get consistent and reliable macroeconomic data, particularly for earlier time periods and financial variables. The PLS-SEM model, while effective at capturing multidimensional correlations, is constrained by its reliance on indicator selection and linear approximation of complex economic processes. These factors may limit the generalizability of results and suggest the need for continuous refinement as more comprehensive datasets become available.

Lastly, the research results provide directions to future research. The model can be extended in the future to incorporate structural breaks, sectoral shocks or geopolitical variables to further improve the CLI framework. It is also possible to conduct comparative research into how the multi-horizon drivers in Pakistan are different to other South Asian economies, helping to prevent crises in the region and ensure macro-financial stability. To conclude, the estimated model shows that integrated and forward-looking macroeconomic management approach is important. Integrating the observations of the Keynesian liquidity effects, the financial accelerator and the global financial cycle, the research presents a set of recommendations that policymakers in Pakistan can utilize to make the country much more resilient to domestic and external cyclical fluctuations.

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