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The Relationship Between a Unified Financial Condition Index and The Most Actively Traded USD Based Foreign Currency Pairs

Ikhlaas Gurrib[a]

Abstract: *This study proposes a unified financial condition index centred around the most popular financial conditions indices used in the US and tests its relationship with the most actively traded USD based foreign currency pairs, namely the British pounds, Japanese yen, Australian dollar, Canadian dollar, Chinese yuan and the Indian rupee. Using weekly data over 1993-2018, this paper proposes a Unified Financial Condition Index (UFCI) under a principal component analysis framework. The index captures 78% of the variability inherent in St Louis Federal Reserve Financial Stress Index, the Chicago Fed National Financial Condition Index and the Adjusted National Financial Condition Index. Significant p-value of UFCI, homoscedasticity and a relatively stable root mean squared errors were observed only for EUR/USD. Mixed findings, found as lags, were increased, suggesting a weak relationship between UFCI and foreign currencies. The UFCI forecasting model is compared with the VIX (volatility index) based model, and also a random walk model. Although the UFCI model was superior only for the Canadian dollar, Chinese yuan and Indian rupee after considering heteroscedasticity in errors, results were sensitive to the number of lags and insignificant p-values.*

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JEL Classification: G01, G11, G15

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1. Introduction

1.1 Background to Study

Following the housing bubble burst and the global financial crisis of 2008, financial conditions indices (FCI[1]) were created to better gauge the health of financial markets (Reinbold & Restrepo-Echavarria, 2017). While at a firm-specific level, Balfoussia and Gibson (2019) found that financial conditions played an important role in recent years by rendering financial constraints

[a] School of Graduate Studies, Canadian University Dubai, United Arab Emirates. *Email: ikhlaas@cud.ac.ae*

more binding, financial conditions, at a global level, can also provide important information related to policy and risk assessment. For instance, Dudley (2010) and Koop & Korobilis (2014) found financial conditions information useful in assessing linkages between financial markets, economic activity and policies. Rey (2013) further supported that the effect of globalisation and previous reliance on solely national policies led to the need for policymakers to take into account global factors when assessing each country's financial stability and subsequent development.

The use of financial conditions is motivated by the fact that policies and regulators are not the only drivers of financial disruptions. Disruptions in market (un)certainty, bailouts or buzzes on corporate dealings, and shifts in investor sentiment which are prompted by irrational news can all potentially affect financial markets, change asset prices firm's value, and ultimately economic performance. IMF (2017) reported that around 20% to 40% of changes in FCI could be attributed to global financial conditions, where one factor, which is correlated with the Chicago Board Options Exchange Volatility Index (CBOE VIX), tends to be the main driver. Schoenmaker (2013) also supported that implementations of efficient financial stability policies can be at play in an open economy. Baskaya, Giovanni, Kalemli-Ozcan & Ulu (2017), Bruno & Shin (2015), IMF (2014), and Calvo, Leiderman & Reinhart (1996) are all proponents that financial measures like VIX are important drivers of financial conditions, with Kliesen, Owyang, and Vermann (2012) added that the VIX is the second most popular variable used in FCI construction. While Miranda-Agrippino & Rey (2015) argue that global prices of risky securities such as institutional bonds and stocks are driven by US monetary policy shocks, which are captured by financial conditions, Hatzius & Stehn (2018) argue that financial conditions continue to affect economic activity significantly. However, the relationship between financial conditions and the federal funds rate is deteriorating.

1.2 Rational Behind UFCI

Aramonte, Rosen & Schindler (2013) find that most FCIs can predict monthly and quarterly returns on the S&P 500, with various FCI following similar long-run trends, and yet produce significantly different values on financial conditions at a given point in time. By taking into account the variation in the different and widely used FCIs, our study seeks to solve the problem of multiple financial condition indices providing similar or different information. Based on the ability on FCI to affect economic activity, we propose a unified financial condition index, not only to capture the significant positive relationship among weekly financial conditions but also to serve as one index which captures the variability among of each of the distinct Federal Reserve Boards' FCI. This paper adds to the current literature on financial conditions and financial markets by introducing a unified FCI (UFCI) which is based on the variability of three weekly based US FCIs, namely the St Louis Federal Reserve Financial Stress Index (STLFSI), the Chicago Fed National Financial Condition Index (NFCI) and the Adjusted National Financial Condition Index (ANFCI).

The STLFSI, reported from the Federal Reserve Bank of St Louis, captures the degree of financial stress in financial markets and is based on 18 variables, including six yield spreads and seven interest rate series. Each of these variables captures some aspect of financial stress (FRB St Louis, 2019). While the Federal Reserve Bank of Chicago's National Financial Conditions Index (NFCI) provides a broad weekly update on US financial conditions in equity, debt, money markets, and the traditional and shadow banking system, the Adjusted NFCI (ANFCI) segregates a component of financial conditions uncorrelated with economic conditions to offer an update on how financial conditions relate to current economic conditions (Brave and Kelley, 2017; FRB Chicago, 2019).

As reported by IMF (2017), the construction of FCIs entails the selection of financial variables to enter the FCI, the weights to be assigned to these variables, and the relationship between the FCI and the macroeconomy. The proposed UFCI index is unique in that it captures the variability inherent in the weekly St Louis and Chicago FCIs. The use of principal component analysis avoids the issue of selecting which variables to include in the index since those are already captured within the St Louis and Chicago FCIs; allocates the weights while maximising the variability within the individual FCIs, and creates principal components which are uncorrelated with each other. Further, in line with IMF (2017), the use of the adjusted Chicago FCI allows the index to provide some information related to financial stability, after accounting for changes in economic growth and inflation.

1.3 Why a Weekly Based Model?

Although the use of weekly data is prone to more volatility compared to monthly based FCI, weekly series are adopted to give more real-time information regarding rapid changes in the financial market. While Bloomberg and Morgan Stanley financial condition indices are based on daily data, these are not considered due to the daily Cleveland financial condition index which was discontinued in 2016 following some model misspecification (FRB Cleveland, 2016) and Aramonte, Rosen, and Schindler (2017) who found the daily Bloomberg FCI to report relatively inconsistent financial conditions reading during 2004-2005. The St Louis Federal Reserve Financial Stress Index, the Chicago Fed National Financial Condition Index and the Adjusted National Financial Condition Index are also used since they are constructed individually using principal component analysis (PCA), and also due to the fact that they include the same variables or similar variables which captures volatility, like the Chicago Board Options Exchange (CBOE) volatility index (VIX) and credit risk like the three-month LIBOR and the yield on a three-month US Treasury bill (TED) spread.

1.4 PCA As Opposed to a Weighted Average Measure

We do not depart from the use of PCA when proposing the UFCI, as opposed to other index methods like weighted returns, since the latter can be subjectively imposed during index construction. This is supported by Kliesen, Owyang, and Vermann (2012) who reported that each principal component analysis is determining a weighted linear combination of the variables, which is maximising the proportion of the total variance of each series. Used extensively in the field of finance and economics, as reported by Bai (2003), relevant applications of PCA includes Baker, Bloom, and Davis (2016) who constructed a policy uncertainty index and Baker and Wurgler (2006) who proposed a sentiment index to capture views of investors. Essentially, the use of PCA allows us to identify a small number of common or principal components which primarily encapsulate a significant amount of the variation among the three financial condition indices.

1.5 FCI and Emerging Markets

This paper is further motivated by the fact that FCIs for emerging market economies are rare. As reported by Marques and Ruiz (2017), the FCIs of the six most financially integrated Latin American economies are influenced by a commodity cycle, country-specific episodes of financial stress and a global financial cycle. Similarly, Lodge and Soudan (2019) propelled that financial conditions and credit represents a significant segment of fluctuations in China’s activity and inflation and that the financial tightening since 2016 could lead to a significant drag on economic activity. Despite the recent progressive transformation in their financial markets with more diversified markets, emerging market economies have relatively short times series to monitor their financial segments which result in some difficulty to develop FCIs for these economies (Gumata, Klein & Ndou 2012). In an effort to capture whether financial conditions can help predict emerging markets currency values, our study also includes the CNY/USD and INR/USD currency pairs where China and India are major players of BRICS[2].

1.6 FCI and Foreign Currency Markets

In addition to the construction of the UFCI, which captures most variability inherent in weekly financial conditions, this paper also looks at whether the major USD based foreign currency pairs can be forecasted using the unified index. Our study builds on existing literature such as Asness, Moskowitz, and Pedersen (2013) who used a three-factor model, and found momentum and value strategies for different asset classes are closely related, driven by common global risks. Burnside (2012) also argues that models which rightfully identify risk factors should be able to display joint explanatory power for both stock and currency market returns unless the two markets are segmented. Similarly, Atanasov and Nitschka (2015) found the presence of a common source of market risk in foreign currency and equity returns, observed through the market return cash flow news variable.

While potential effects of the FCI over stock markets can be evidenced, due to the inclusion of stock market returns and the S&P500 market volatility index in the construction of the FCIs, plausible relationships between FCIs and foreign currencies are yet to be found in the literature. This is supported by BIS (2018) which reported not only that volatility variables such as equities, despite low weightage, have played an important role in US-based FCI, but also that emerging markets FCIs have included debt weighted exchange rates to capture foreign currency mismatches. Alternatively stated, the key objectives of this study are (i) to propose a unified financial condition index (UFCI) and (ii) tests its predictability over the most actively traded USD based foreign currencies, namely the British pounds, Japanese yen, Australian dollar, Canadian dollar, including the Chinese yuan and Indian rupee as representative of leading emerging markets. The research design is based predominantly on the use of financial conditions and US-based foreign currency pairs data collected from the St Louis Federal Reserve database to (i) construct the UFCI using principal component analysis and (ii) and forecasts the select major foreign currency pairs using ordinary least squares. Further, the forecasting model based on UFCI is compared to a random walk model, and also another VIX based model.

Around 80% of the variability inherent in each of the individual index is captured in the UFCI. Upon constructing the unified index, this paper uses the UFCI model to test its predictive ability over the most actively traded foreign currency pairs over the 1993-2018 period. Findings suggest current UFCI values are significant in explaining the most active USD based currency pair values, with the exception of the Chinese yuan. While the British pounds, Canadian dollar and Indian rupee were still homoscedastic in errors, the Euro was the only currency found to be significantly affected by UFCI current values at the 5% and 10% levels, with homoscedastic errors. Despite relatively stable root mean squared error values, forecasting using 1, 2 and 10 lags produced mixed results across all currency pairs, suggesting poor forecasting abilities of financial conditions indices such as UFCI. This was also evidenced in the relatively wide standard error forecasting bands, and the low correlations between UFCI and the currency pairs. This suggests that despite that FCIs include volatility variables such as stock market returns and S&P500 volatility index, FCIs also include more stable measures such as three-month LIBOR and the yield on a three-month US Treasury bill (TED). The combination of both volatile and relatively less volatile variables contribute to the final FCIs values, which are used to predict the most actively traded foreign currency pairs. This suggests the volatility characteristics of both foreign currency values and FCIs values could be a root cause why UFCI fails to predict exchange rates reliably. To robust test the UFCI model, results are also compared with two models, one based on the use of the Chicago Board Options Exchange Volatility Index (VIX) and the other on a random walk. Results were mixed, with the random walk model being superior for the Euro and the British Pound. The VIX based model yielded the lowest root mean squared error values for the Japanese yen and Australian dollar. The UFCI based model was superior among the three forecasting models, for only the Canadian dollar, Chinese yuan and Indian rupee. The results for UFCI were however affected by heteroskedasticity or insignificant p-values of UFCI coefficients as lags were increased. Overall, this confirms the non-robustness of UFCI to predict exchange rates. The use of VIX as an independent variable, which led to superior results for only the Japanese yen and Australian dollar, also suggests that most exchange rates are not affected by previous period volatility measures such as VIX.

While the findings tend to be in line with Swiston (2008) who find real exchange rate was a weak contributor of to the FCI used, our findings can be distinguished from the latter in that we looked at the forecasting ability of specific US-based currency pairs using FCI, compared to Swinston's study which made use of a trade-weighted broad index. While our findings are consistent with Kliesen, Owyang, and Vermann (2012) who found strong positive correlations between FCIs and the VIX, our results our study showed that the VIX is not reliable variable to forecast foreign currency values, due to the VIX being constructed using mostly equity-based components. Lastly, this is the first study to test whether a unified financial condition index can be used to forecast US-based foreign currency pairs, involving developed and emerging markets. The significances of the study are that (i) the UFCI captures most of the variability inherent in the other weekly based FCIs, (ii) the UFCI, which is based on financial conditions, is not a reliable index to predict the most actively traded US-based foreign currency pairs, and that (iii) An index which captures foreign currency movements as opposed to the VIX which captures volatility in equity markets, is recommended to better forecast exchange rates.

The rest of the paper is structured as follows: Some literature review on transmission channels, the importance of a sound functioning system, financial conditions and foreign currency markets is provided, followed by the research methodology which is centred on the use of principal component analysis and the relationship model between foreign currency and financial conditions. The data section follows, with some descriptive statistics. Some findings related to the principal component analysis results and forecasting results are reported, before providing some conclusive remarks.

2. Literature Review

2.1 Transmission Channels

Extensive literature exists regarding transmission channels across markets and economies with much focus on monetary independence in setting interest rates. Other factors such as foreign exchange movements are also analysed, where such movements usually prompt substantial changes in financial conditions in small open economies, as reported in Kearns & Patel (2016). IMF (2017) suggests that global financial integration can complicate the management of domestic financial conditions, especially in countries which have integrated more into the global economy, recommending the need for policymakers to consider external factors when pursuing domestic objectives. While IMF and OECD undertake projects of constructing and analysing country based FCIs, the global financial conditions are led by the US, which is the key country in the international monetary system. Rey (2013) reported the average correlation between two measures of global financial conditions, and the VIX is 82%t. IMF (2014) supports this conjunction by adding that the US dollar resides as an international currency with important roles in financial assets issuance and commodity trading under the oversight of regulatory bodies such as the Commodity Futures and Trading Commission (CFTC).

2.2 Importance of a Sound Functioning System

Although the impact of uncertainty on US output has declined in recent years as documented in Mumtaz and Theodoridis (2017), Alessandri and Mumtaz (2019) found that uncertainty shocks always have recessionary impacts, with a significantly larger impact on output during a financial crisis period. This posits the critical importance of a sound function system, captured through the measurement of financial stress. The measurement of financial stress helps in identifying incipient non-diversifiable risks as encapsulated in the

Dodd-Frank Wall Street Reform and Consumer Protection Act of 2009, which led to the creation of the Financial Stability Oversight Council (FSOC) and the Office of Financial Research (OFR). For instance, a contractionary credit supply policy eventually affects investment (Campello, Graham & Harvey, 2010) and the broader economy (e.g., Bernanke, 1983; Peek & Rosengren, 2000; Calomiris & Mason, 2003).

Hakkio & Keeton (2009) summarises the features encircling financial stress, where it is defined as a disruption to the usual functions of the financial markets. While each period of financial stress is different, they note important common characteristics based on the increase in uncertainty about the fundamental asset values, uncertainty about the behaviour of other investors, increased asymmetric information, an increase in the willingness to shift towards less risky assets and an increase in the willingness to hold more liquid assets.

While it is accepted that the price of an asset today is based on the present value of all future cash flows, uncertainty in these cash flows can arise from uncertainty in future economic conditions or complex products which are difficult to value. The heightened volatility is a consequence of investors over/under reacting to new information as propelled by Hautsch & Hess (2007) and Pastor & Veronesi (2009). This was evidenced in Al-Fayoumi, Abuzayed & Arabiyat (2019) who reported investors in the US were less sensitive to stress decreases (positive news) than stress increases (negative news), particularly during the financial crisis.

Similarly, uncertainty about the behaviour of other investors can be explained by the fact that investors and lenders rely on their guesses about other investors' decisions instead of relying on fundamentals, which ultimately result in more volatile prices. Increases in asymmetric information can be substantiated with lenders having difficulty in determining the true quality of borrowers and also through investors losing confidence in the quality of issuers' credit ratings. Further, a flight to quality during financial stress move investors towards safer assets which is expected to bring lower returns (Badarinza & Ramadorai, 2018). As propelled by Caballero & Kurlat (2008), this is usually accompanied by an increase in borrowing costs for the riskier borrowers, and mostly a manifestation of investors and lenders to overestimate risk during economic bubbles (Guttentag & Herring, 1986). In the same line of thought, issuers of illiquid assets bear the higher cost of borrowing during financial stress periods, in order to compensate investors for the higher risk of not selling their assets.

2.3 Financial Conditions

It is important to grasp that FCIs have been constructed using various ways like Kalman filtering algorithm, vector autoregressive models (VARs), impulse response functions and principal component analysis. For instance, Montagnoli & Napolitano (2005) used Kalman filtering algorithm to capture the weight changes of financial variables in the explanation of the output gap and constructed the FCI of the United States, Canada, Eurozone and the United Kingdom. Using a threshold VAR (TVAR) model with non-linear impulse responses, Afonso, Baxa and Slavík (2018) found that a financial stress shock had a negative impact on output and worsened the fiscal situation in the US, the UK, Germany and Italy. Similarly, Swiston (2008) used impulse response functions to build the FCI of the United States and suggested that FCI could predict the United States' real GDP growth. Hatzius (2010) used principal component analysis to select the first principal component as the FCI, and forecast the economic growth by using the FCI. Gomez (2011) extracted the main ingredient from indicators such as interest rates, exchange rates and asset prices, and constructed the FCI for Colombia using variance probability of the principal components as the weights.

While there are papers like Gumata, Klein & Ndou (2012) which constructed country-specific FCIs using global and international factors like S&P500 volatility index, S&P 500 market index values, three-month LIBOR and the yield on a three-month US Treasury bill (TED); some US regulatory institution based FCI models like St Louis Fed Reserve, Chicago Fed Reserve are more popular. Aramonte, Rosen & Schindler (2013) find that most FCIs can predict monthly and quarterly returns on the S&P 500 and a portfolio of financial companies and also innovations to a number of macroeconomic variables. They also support that despite some methodological differences in the FCI constructions, they exhibit a large amount of common variability due to the fact that changes in the financial system affect many of the variables under most FCIs. While various FCIs follow similar long-run trends, they can produce significantly different values on financial conditions at a given point in time.

The construction of the FCIs varies considerably, although all of them are largely based on financial market variables, including implied volatilities, Treasury yields, yield spreads and stock market returns. Kliesen, Owyang & Vermann (2012) provides a detailed list of variables that underlie a range of the major US FCIs. While IMF (2017) provides a good summary of the application of the IMF FCI model on specific countries and denotes some similarity for some open economies under study, there is a need to look at the impact of US-based FCI onto global financial markets. As expressed in IMF (2017), the greater the globalisation effect on economies, the greater the need for policymakers to understand the implication of US-led financial conditions on their respective national markets. Further, the Aramonte, Rosen & Schindler (2013) study creates a composite FCI index, based on four FCI, where two are based weekly, and the other two FCI are weekly and monthly. This suggests a lack of data or the existence of a smoothing process, especially where monthly and quarterly forecasts are being pursued by the authors.

While the above depicts the use of FCIs at institutional or country level, some experts are a bit doubtful of its use in policymaking. One main issue concern double counting, where policymakers might observe a simultaneous FCI easing and economic boom, and treat those each observation as a unique reason to increase interest rates, which would result in a rather aggressive policy reaction. Comparatively, if the FCI easing only reflects economic boom, then any slowdown in growth will logically tighten financial conditions and increase interest rates slightly. Hatzius and Stehn (2018), using impulse responses, found that FCIs do not systematically respond to growth shocks. They also reported that macroeconomic events surprises have significant effects on individual asset prices such as bonds, equities and currencies, but the effects tend to offset growth shocks do not drive each other, such as FCIs. The same authors also clarified that any concern that the equilibrium federal funds rate might change equilibrium levels of FCIs is rather overstated since the impact of lower equilibrium funds rates on FCIs should be limited only to interest rates components.

A critical question which also arises is which FCIs to use in our study. As reported by Reinbold and Restrepo-Echavarria (2017), Kansas City Financial Stress Index (KCFSI), Chicago Fed National Financial Conditions Index (CNFCI), and the Bloomberg Financial Conditions Index (BFCI) use many of the same broad categories of economic variables including short term and long term treasury rates, credit spreads, and equity prices. All FCIs used by Federal Reserve agencies are highly correlated with the Chicago Board Options Exchange (CBOE) volatility index (VIX) except for the Goldman Sachs Financial Conditions Index (GSFCI). The main reason includes the fact that the St Louis Financial Stress Index (STLFSI), KCFSI, BFCI and CNFCI include the VIX into their models. Hatzius and Stehn (2018) further propelled that GSFCI, like other FCIs, shares a significant relationship with the output gap, with however the former FCI affecting output gap at a level rather than changes in FCI values.

2.4 Foreign Currency Markets

Although the literature on FCI is essential in the sound functioning of economies, it is also important to portray any potential theoretical justification between foreign currency markets and macroeconomic variables which are built into FCIs. For instance, Verdelhan (2017) found that a relatively high proportion of systematic variation in foreign currencies corresponded to a relatively high proportion of systematic variation in capital inflows and outflows. The same author found that the combined use of the carry factor (change in exchange rates between groups of high and low interest rate currencies) and the dollar factor (average change in the exchange rate between the US and all other economies) explained nearly up to 90% (75%) of changes in bilateral exchange rates for developed (developing) countries. In the same line of thought, Cerutti and Obstfeld (2018) found that despite China has moved its currency rate against a group of currencies compared to the US dollar alone, the US dollar sturdy depreciation against most currencies during 2017-2018 has been a crucial driver of increasing capital flows towards emerging markets.

Further, while uncovered interest rate parity (UIP) states that a country with a higher interest should experience depreciation in the domestic currency relative to the foreign country, such that regression of exchange rates on interest rate differences should have a slope of one, Evans (2012), Fama (1984), Bilson (1981), Hansen and Hodrick (1980), and Tryon (1979) found a slope coefficient which is smaller than one and sometimes negative. Lustig, Roussanov & Verdelhan (2014) also supported that currency excess returns on a dollar basket are significantly countercyclical to a broad set of US economic variables. Meese and Rogoff (1983) estimated multivariate regressions which link macro variables to changes in currency rates and found the random walk model yielded a lower root mean squared errors than any economic variable.

As reported by BIS (2018), exchange rates tend to have a dual effect on economic activity. While a currency appreciation tends to reduce activity by net exports negatively, it also increases activity by reducing the real value of debt denominated in foreign currencies. The same report, however, adjusted for trade-weighted exchange rates only for the US and Euro area, while imposing both trade and debt weighted exchange rates for emerging markets such as Brazil and Mexico. Since the relationships between foreign currency and macroeconomic variables tend to be mixed, partly due to the specific economic variable (e.g. interest rates or capital flows) being looked at, the use of an FCI, which encompass various economic variables, allows us to look at the relationship between FCIs and foreign currencies, from a broader point of view, rather than specifically analysing currency rates and a particular economic variable relationship. In line with the above, our paper looks at the relationship between major FCIs and foreign currencies, where the FCIs incorporated significant economic variables into their construct. As reported recently by Hatzius & Stehn (2018) and Mericle and Struyven (2017), these macroeconomic variables are the drivers of changes in financial conditions and include changes in monetary policy, bond term and equity risk premiums and the credit risk premium.

Although some of the FCIs share strong correlations, they are based on different data frequencies. As supported by Kliesen, Owyang, and Vermann (2012), a weekly FCI, compared to a monthly one would help policymakers make more real-time decisions, which is particularly critical during events such as the 2008 global financial crisis. FCIs of too high frequencies might also result in fake signals. To alleviate this issue, we are proposing constructing one index using principal component analysis over weekly based FCIs. Based on the mixed evidence regarding the relationships between macroeconomic variables and exchange rates; on the fact that FCIs can help explain financial stresses like those evidenced in the global financial crisis of 2008; on the fact that FCIs encapsulates broad categories of economic variables such as interest rates; on the fact that different FCIs exist based on different horizons and yet exhibit some strong correlations; this study proceeds in constructing a unified FCI which is based on weekly FCIs and then tests its usefulness in predicting the most actively traded USD currency pairs.

3. Research Methodology

The research methodology section can be divided into two main parts, with the first part focusing on the principal component analysis (PCA) and the second part focusing on the relationship model between financial conditions and foreign currencies. As one of the most popular multivariate analysis techniques, PCA has been applied extensively to analyse financial markets due to its ability to decompose interrelated variables into uncorrelated variables. Its various applications include systemic risk measurement and cross-market correlation (Billio et al. 2012; Zheng et al., 2012), identification of risk components in the equity market (Kim and Jeong, 2005), and construction of market indices (Feeney and Hester, 1967). Essentially, the concept of principal component analysis (PCA) is based on a reduction in the dimensions that connect variables, while retaining most of the variability among the variables. Alternatively stated, the dimension-reduction tool enables us to reduce a broad set of variables to a small set, which still contains most of the information in the large set. Due to the scope of our involving financial conditions, we adopt PCA as opposed to weighted average techniques, since the latter can be subjectively imposed during index construction. This is also supported by Kliesen, Owyang, and Vermann (2012) who reported that each principal component analysis is determining a weighted linear combination of the variables, which is maximising the proportion of the total variance of each series.

The first principal component captures the highest variability in the data, with each succeeding component accounting for as much of the remaining variability as possible. The first principal component is usually called the line of best fit since the sum of squares of the perpendicular deviations of the data points from the line is a minimum. Subsequent principal components or axes are constructed with the assumption that they are orthogonal to the other principal components and maximise deviations from projected points subject to these constraints. As proposed initially by Jolliffe (1986), the PCA model is centred on eigenvalues and eigenvectors, where the former represents the variance of all variables accounted by a factor and the latter accounts for a scaled direction of a non-zero vector as follows:

$$|A - \gamma I| = 0 \tag{1}$$

$$(A - \gamma I)\varphi = 0 \tag{2}$$

Where A is a square matrix in the form of $\begin{bmatrix} cov_{1,1} & cov_{1,2} \\ cov_{1,2} & cov_{2,2} \end{bmatrix}$, φ is a vector, γ is a scalar that satisfies equation (2), and I is an identity matrix. The eigenvalues of A are calculated from the determinant of equation (1), followed by eigenvectors φ for each eigenvalue, by using a reduced matrix to row echelon form $\begin{pmatrix} a & \cdots & b \\ 0 & \ddots & \vdots \\ 0 & 0 & c \end{pmatrix}$ and reduced matrix to reduced row echelon form $\begin{pmatrix} 1 & \cdots & b \\ 0 & \ddots & \vdots \\ 0 & 0 & 1 \end{pmatrix}$. $cov_{1,1}$ and $cov_{2,2}$ represents the variance of specific FCIs, while $cov_{1,2}$ represents the covariance between any two FCIs. To identify periods which have witnessed large fluctuations, the FCI are scaled by their respective standard deviations, after having been demeaned. For instance, an index value of -1 is associated with financial conditions that are looser than on average by one standard deviation, while an index value of 1 indicates that financial conditions are tighter than average by one standard deviation. This usual standardising approach can also be found in Nelson & Perli (2007) and Cardarelli, Elekdag & Lall (2011). The uncorrelated and linear combinations of standardised variables form the principal components as follows:

$$\sigma_{PC_1} > \sigma_{PC_2} > \sigma_{PC_3} \ldots > \sigma_{PC_N} \tag{3}$$

where $\sum_{i=1}^{n} \sigma_{PC_i} =$ Number of FCIs and $\sigma_{PC_{1\ldots n}}$ represents the variance of the principal component 1, principal component 2, etc. Alternatively stated, the eigenvalues drop as we move from first principal component to the next one. The first principal component (PC1), which captures most of the variability in the FCIs is essentially the UFCI model, where the second and subsequent principal components are uncorrelated with each other. The use of the first principal component is in line with Kim and Jeong (2005), Kritzman et al. (2011), Billio et al. (2012), Zheng et al. (2012) and Yang, Rea & Rea (2017) who supported the first principal component has the highest eigenvalue, thereby capturing the biggest amount of information, and hardly any noise. The use of the PCA, compared to using simple averages of individual series is preferred since the PCA allows the possibility to capture most of the variability in the different conditions indices by constructing one data series called UFCI in our case. This is supported by Kliesen, Owyang, and Vermann (2012) who found that each principal component analysis is determining a weighted linear combination of the variables, which is maximising the proportion of the total variance of each series.

Once the UFCI is constructed, the UFCI and exchange rates series are tested for stationarity using the Augmented Dickey Fuller (ADF) test as follows:

$$\Delta y_t = \alpha + \beta t + \emptyset y_{t-1} + \pi_1 \Delta y_{t-1} + \cdots + \pi_{p-1} \Delta y_{t-p+1} + \varepsilon_t \quad (4)$$

where α is a constant, β is the coefficient on a time trend, and p is the autoregressive lag order. While imposing constraints that $\alpha = \beta = 0$ results in a random walk model, a constraint of only $\beta = 0$ results in a random walk with a drift. To allow for higher order autoregressive processes, the lag numbers are determined based on information criteria such as Schwarz Information Criteria (SIC) as reported by Schwarz (1978) as follows:

$$SIC = -2\hat{T} + ln(x)k \quad (5)$$

where $\hat{T}$ is the maximum log-likelihood of the model, x is the number of observations, and k is the number of parameters estimated in the model. The unit root rest is carried out under the null hypothesis $\emptyset = 0$ against the alternative that $\emptyset < 0$.

The paper then proceeds into finding any plausible relationship between the different USD based foreign currency pairs and the unified financial condition index, using an ordinary least square regression. The different exchange rates are set as dependent variables. Various lags of the independent variable (UFCI) are included to allow the possibility to look into the effect of current financial conditions indices onto exchange rate values, and also to robust test any significant relationship between FCIs and exchange rates over time as follows:

$$FX_t^i = \alpha + \beta.UFCI_{t-n} + \varepsilon_t \tag{6}$$

where i represents the EUR/USD, JPY/USD, GBP/USD, AUD/USD, CNY/USD and INR/USD foreign currency pairs, and n represents the number of the week ahead forecasts, with values ranging from 0, 1, 2 and 10. To compare the forecasting ability of UFCI over exchange rates, root mean squared errors values are reported for all exchange rates, which is calculated as:

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(\widehat{FX}^i - FX^i)^2}{N}} \tag{7}$$

where $\widehat{FX}^i$ represents the predicted values of the different foreign currency pairs relative to the current ones. Further, the standard error upper and lower bands estimates are shown to observe how reliable can financial conditions indices be used to forecast exchange rates. As part of the robust testing of the model, the residuals are tested for homoscedasticity using the Breusch-Pagan-Godfrey heteroskedasticity test as formalised by Breusch and Pagan (1979) where the squared residuals ($\widehat{\varepsilon_t{}^2}$) are regressed onto the financial condition index values ($UFCI_t$) as follows:

$$\widehat{\varepsilon_t{}^2} = \pi_0 + \pi_1 UFCI_t + \xi_t \tag{8}$$

Based on the Lagrange Multiplier (LM) goodness of fit measure, $LM = n\,(R^2), R^2$ is the coefficient of determination from the regression of the squared residuals above. With the LM statistic distributed asymptotically as $\boldsymbol{\chi_k^2}$ and k representing the number of independent variables (1 in our case), a small chi-squared value would support that the residuals are homoscedastic, i.e. the error variances are all equal. Lastly, the UFCI model is compared with a VIX forecasting based model and a random walk model. While the VIX forecasting based model is essentially substituting the UFCI for VIX as an independent variable, the random walk model assumes that the exchange rates move away from their present positions randomly and is stated as follows:

$$FX_t = FX_{t-1} + \ \omega_t \tag{9}$$

where $\omega_t \sim N(0, \sigma^2)$. FX_t and FX_{t-1} represent the current and one-week lag exchange rates.

Due to the scope of the study, it is important to point out some limitations which can be looked at as future research avenues. Firstly, while the index is constructed using weekly data, to allow for more timely policy-oriented decisions, a higher frequency unified index is recommended in the future. Secondly, although the adjusted Chicago FCI removes any variation due to changes in economic growth and inflation, its inclusion with the St Louis and Chicago FCI when constructing UFCI does not lead to a removal of variations due to changes in economic activity from the UFCI. Although ANFCI has a relatively close factor loading, relative to others, in the first principal component, we cannot ascertain if the UFCI has been purged of the effect of economic growth and inflation. Alternatively stated, we assume the UFCI still has some elements where variations in the FCI are caused due to economic activity changes, such that no inference can be made regarding instability in the index being attributable to the shadow financial system. Thirdly, while this paper compares the use of FCI and VIX in forecasting currency rates, it is recommended to use other variables like JPMorgan VXY Global index in the future, since they capture the volatility in currency markets better than the equity based VIX variable.

4. Data

We focus on a weekly data frequency based on previous support from the literature. For instance, studies like IMF (2017) used one-month-ahead and one-quarter-ahead regressions to reduce the possibility that predictions include business-cycle effects. With many FCIs consisting of the volatility Index measure (VIX), Bollerslev, Tauchen & Zhou (2009) find that the variance risk premium, which is the difference between the squared value of VIX and a measure of realised variance, can predict stock returns about three to six months ahead, with r-squared values slowly declining at longer horizons. Hatzius, Hooper, Mishkin, Schoenholtz & Watson (2010) find limited value in using FCIs as reliable early warning indicators, similar to Aramonte, Rosen & Schindler (2013) who used monthly and quarterly horizons. English, Tsatsaronis & Zoli (2005), who focus on four- and eight-quarter horizons, however, find aggregated financial variables as a proxy for the financial condition to have some predictive power for macroeconomic variables. The Cleveland FCI which was based on a daily frequency was discontinued in May 2016. Future research can tap into the use of higher frequency data towards analysing if financial stress is captured in a more real timeframe.

While the choice of weekly based FCIs reduce the number of potential FCIs under analysis, it is important to understand what’s included in these FCIs before utilising them in the principal component analysis. These mostly include interest rate spreads which capture risk premium, term premium and liquidity premium; stock market, foreign exchange and volatility indicators, and yields to maturity. Kliesen, Owyang & Vermann (2012) provides an overview of the different variables falling under each category, suggesting that the overlap across the various condition/stress indexes is quite substantial as expected. Lastly, but not least, while some authors like Carlson, Lewis & Nelson (2012) and Louzis & Vouldis (2011) tend to differentiate between financial condition index and financial stress index (FSI), this paper does not discriminate between them due to the high correlation observed among major US-based FCIs and FSIs. It is also important to note some FCIs differ in the number of variables used in their respective models, where most use a relatively small number of variables. Some major ones include the Organisation for Economic Cooperation and Development (OECD) which used seven variables to model country based FCIs of leading developed economies and the Kansas City Financial Stress Index (KCFSI) which is based on 11 variables.

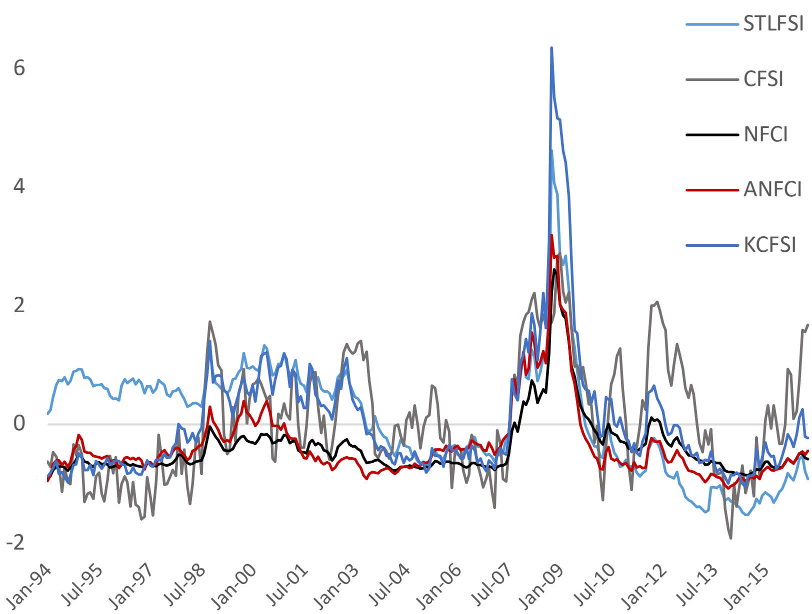
Though Hatzius, Hooper, Mishkin, Schoenholtz & Watson (2010) and the Federal Reserve Bank of Chicago used more than 45 and 100 variables respectively, Boivin & Ng (2006) stressed that including more data does not necessarily yield better results. This is further supported by Lo Duca & Peltonen (2011) who argue that adding more redundant variables may not improve an FCI and Grimaldi (2011) who find that too many variables can potentially exacerbate to more false periods of high stress in the markets. This study retains the variables used under each FCI for objectivity and comparison purposes. The analysis is conducted over the period 31st December 1993 to 26th January 2018, and all USD based foreign currency pairs and financial conditions data (STLFSI - St Louis Fed Financial Stress Index, NFCI - Chicago National Financial Conditions Index, and the ANFCI Adjusted NFCI) are collected from the St Louis Federal Reserve database (FRED).

5. Research Findings

5.1 Descriptive Statistics

Figure 1 provides a historical perspective of the major FCIs during the period 1994-2016. STLFSI represents the weekly St Louis Fed Financial Stress Index; CFSI is the daily Cleveland Financial Stress Index which was discontinued in May 2016. NFCI represents the Chicago National Financial Conditions Index, and the ANFCI is the Adjusted NFCI. Lastly, the KCFSI is the monthly Kansas City Financial Stress Index. Although there is a strong correlation between them, some are based on different frequencies, which introduces gaps in data modelling that can be adjusted with proxy data based on measures like mean or median, or a specific reference data period. To keep the paper as objective as possible, only the weekly series (STLFSI, NFCI and ANFCI) are used for later analysis. Correlations among the three conditions indexes range between 0.56-0.77. The high correlation in the different FCIs can be explained due to the fact that most used variables which are either the same or display the same characteristics as to how markets react following specific events. For example, the most recurrently used variable is the TED spread, which is used in various FCI indexes as reported by Cardarelli, Elekdag & Lall (2011), Hatzius, Hooper, Mishkin, Schoenholtz & Watson (2010) and Hakkio & Keeton (2009). Likewise, the Chicago Board Options Exchange Volatility Index (VIX) is also popular as found by Nelson & Perli (2007).

Figure 1: Major Financial Condition Indices (1994-2016)



Note: Figure 1 displays the major financial condition indices over the period 1994-2016. STLFSI represents the weekly St Louis Fed Financial Stress Index; CFSI is the daily Cleveland Financial Stress Index which was discontinued in May 2016. The daily NFCI represents the Chicago National Financial Conditions Index and the ANFCI is the daily Adjusted NFCI. Lastly, the KCFSI is the monthly Kansas City Financial Stress Index.

With no missing data and based on 1257 weekly observations, STLFSI had the highest range of 6.832, with a minimum value of -1.588 and a maximum of 5.244, compared with the other 2 indexes. It is important to note that the other 2 had negative averages over the 1993 –2018 period, accompanied by higher deviations from their means. As expected, they all had relatively positively correlations ranging from 0.67 to 0.9. The higher correlation between NCFI and ANFCI can be attributed to the fact that the ANFCI is an adjusted model to the NCFI where the former is purged of variation happening due to changes in economic activity (Brave & Butters, 2012).

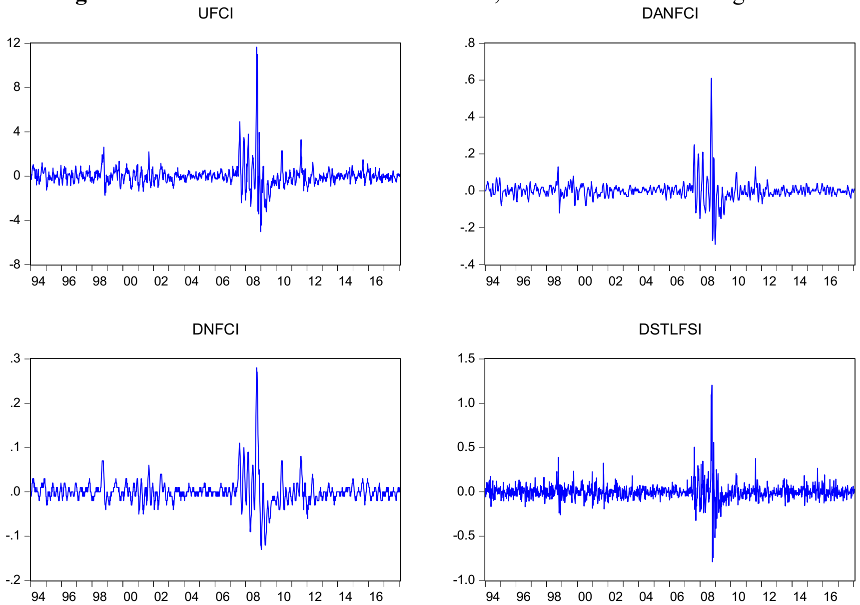
5.2 Stationarity Test

In line with Becker & Hall (2012) who found stationary series allow r-squared values of the first principal component to converge to its true value of (1/number of series) as $t \rightarrow \infty$ and avoid spurious regressions, the three weekly FCIs are tested for stationary using the Augmented Dickey Fuller (ADF) stationary test at 5% level. Using the Schwarz Information Criteria (SIC) for the lag selection in the test, all series (including foreign currency pairs) were stationary after 1st order differencing.

5.3 Unified Financial Condition Index

The principal component analysis reveals that the first principal component (UFCI) shows an eigenvalue of 2.333 explains nearly 78% of all variations which exists among the three FCIs. The cumulative variability increases only slightly after including the second principal component (PC2), suggesting that the first principal component is sufficient to account for major variations between the three FCIs. The correlation circle supports that the second principal component only contributes to another 15% of the total variation in FCIs. This is in line with relatively higher squared cosine values of UFCI (PC1) compared to PC2 and PC3. Eigenvalues for the second and third principal components drop significantly to 0.45 and 0.21 respectively. The factor loadings for the first principal component of STLFSI, NFCI and ANFCI are 0.606, 0.578 and 0.546. Roughly equal loadings on the 3 FCIs and strongly positive correlations between the UFCI and the three conditions indexes, ranging from 0.84 to 0.93, support the use of UFCI as a unified financial condition index as observed in Figure 2.

Figure 2: Unified Financial Conditions Index, St Louis FCI and Chicago FCIs



Note: UFCI represents the Unified Financial Conditions Index based on the principal component analysis, which explains 77% of the variability in the other 3 financial conditions indexes. DANFCI, DNFCI and DSTLFSI represent the stationary series of the St Louis and Chicago Federal Reserve FCIs.

5.4 Financial Conditions and Foreign Currency Markets

In line with IMF (2017), Ludvigson & Ng (2007) and Stock & Watson (2002) who used principal component analysis to predict excess stocks returns and macroeconomic variables over different time periods, this study extends the application of principal component analysis onto major foreign currency markets. In line with BIS (2016) which reported that the top five most active currencies during 2013 and 2016 were the USD, EUR, JPY, GBP and the AUD, and Gurrib & Kamalov (2019) who also included the CNY and INR in the analysis of the foreign currency, crude oil and natural gas markets, this study analyses the impact of UFCI onto each of the above foreign currencies. All currencies are paired against the USD, since the USD shared 87 and 87.6 per cent of all OTC foreign exchange transactions during 2013 and 2016 (BIS, 2016).

The impact of the unified financial condition index on the foreign currency pairs for the various week ahead forecasts are included in Table 1. Due to the inclusion of the Euro currency in the late 1990s, the forecasting model for the EUR/USD is based on a data starting from 8th January 1999. Other forecasting results are based on the full 1994-2018 sample.

Table 1: Model Evaluation

		EUR/ USD	***GBP/ USD***	***JPY/ USD***	***AUD/ USD***	***CAD/ USD***	***CNY/ USD***	***INR/ USD***
UFC_t	RMSE	0.129	0.093	13.720	0.241	0.183	1.761	5.263
	p-value of UFCI	*0.036*	0.066*	*0.000*	*0.000*	*0.000*	0.844	*0.000*
	Obs* r-squared)	*0.870*	*0.516*	0.007	0.000	0.064**	*0.969*	0.054**
UFC_{t-1}		0.127	0.091	13.730	0.232	0.179	0.391	4.997
		0.501	0.781	*0.003*	*0.000*	*0.000*	0.936	*0.000*
		0.019	*0.365*	0.001	0.000	0.000	*0.380*	*0.662*
$UFCI_{t-2}$		0.129	0.096	13.733	0.233	0.182	0.391	4.986
		0.027	*0.000*	*0.001*	*0.000*	*0.000*	0.584	*0.000*
		0.016	*0.974*	0.006	0.000	*0.808*	*0.235*	0.079**
$UFCI_{t-10}$		0.124	0.089	14.273	0.240	0.184	0.390	4.752
		0.026	0.679	0.075*	0.126	0.067*	0.864	0.737
		0.042	*0.238*	*0.656*	*0.244*	*0.860*	*0.153*	*0.115*

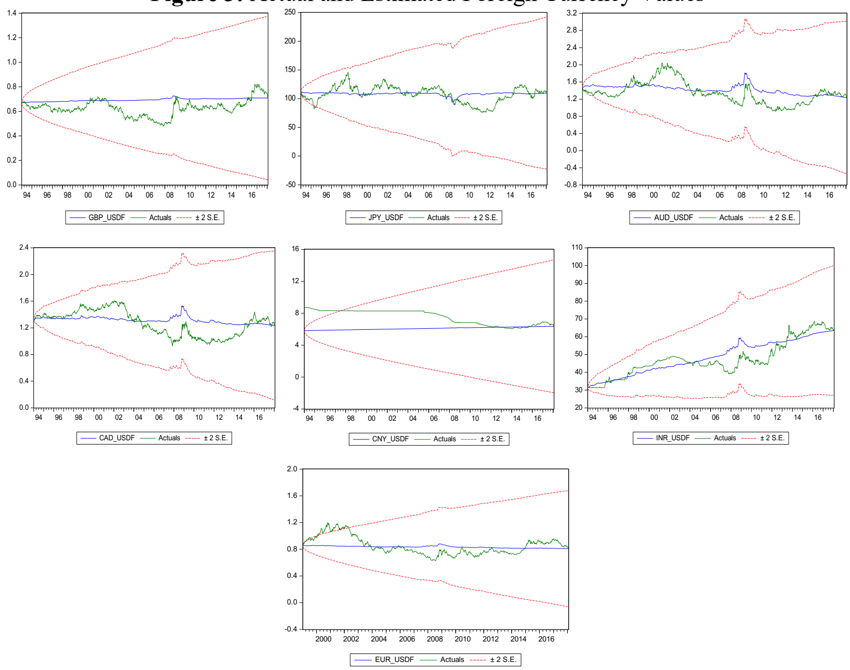
Note: Except for the EUR/USD where the first week of data was from 8th January 1999, other foreign currency markets' RMSE values are based on the January 1994- January 2018 period. RMSE stands for root mean squared errors for the forecast, The independent variable is $UFCI_{t-n}$, with lags ranging from 0, 1, 2 and 10. The Probability of the Observations*r-squared from the Breusch-Pagan-Godfrey test reported as a measure of the presence of heteroscedasticity in the residuals. * values are significant at 10% but not 5% levels. ** values are significant at 5% but not 10% levels. Italic numbers are significant at 5% and 10% levels.

Results from Table 1 show that the unified financial condition index has a mixed effect on the predictability of the most active USD based currency pairs. With the exception of the Chinese yuan, the p-values of current UFCI are mostly zero, suggesting the UFCI is significant in explaining the different currency pairs' values.

5.5 Robustness of Model

To ensure the residuals in the model are homoscedastic, the Breusch-Pagan-Godfrey heteroscedasticity test is carried out, and the *p*-values of the observed r-squared values are reported. The EUR/USD, GBP/USD, and CNY/USD based model were homoscedastic at both 5% and 10% level, with CAD/USD and INR/USD being homoscedastic at 5% level only. JPY/USD and AUD/USD models based on current UFCI values were both showing signs of heteroscedasticity in the residuals. Only the EUR/USD qualified for homoscedastic errors, a significant p-value of the UFCI coefficient at 5% and 10% level, with an RMSE of 0.129 under the current value UFCI based model. The GBP/USD also had homoscedastic errors, but significant p-value of the UFCI coefficient at 5% level only, with an RMSE of 0.093. The relatively higher RMSE observed in JPY/USD, CNY/USD and INR/USD can be explained by the range of values in which the Japanese yen (75-146), Chinese yuan (5.82- 8.73) and Indian rupee (31.37-68.65) trade against the US dollar.

Figure 3: Actual and Estimated Foreign Currency Values



Note: GBP_USDF, JPY_USDF, AUD_USDF, CAD_USDF, CNY_USDF, INR_USDF and EUR_USDF represent the estimated values of the currency pairs. Actuals are the actual currency values. $\pm 2\ S.E$ represents the lower and upper band of estimated values.

When the UFCI lag is increased to 1, 2 and 10, results are mixed. While the JPY/USD, AUD/USD, CAD/USD and INR/USD models continue to have significant p-values of UFCI with 1 and 2 lags, a 1-week lag (2-week) of UFCI values was found to be insignificant (significant) in explaining EUR/USD current values. The p-value of UFCI, lagged by 1 week (2 weeks) was insignificant (significant) in explaining GBP/USD current values. Although RMSE of CNY/USD dropped as independent variable lags increased, p-values of UFCI, under all lags, were insignificant in explaining CNY/USD current values. RMSE values were mostly consistent, with little fluctuations observed as UFCI lags increased from to 1 to 10. Although not reported here, correlation coefficient values of the model relating UFCI and the foreign currency pairs were mostly small, ranging from -0.13 to 0.32. The low correlation coefficients, relatively constant forecasting errors, and relatively wide standard error lower and upper bands in the forecast estimates, as shown in Figure 3, suggest the unified condition index have poor predictive abilities on the 1,2, and 10 week weeks ahead forecasts of the most active foreign currency pairs traded globally.

5.6 Comparison of UFCI with VIX Based Model

Lastly, but not least, due to the fact most of FCIs incorporate the CBOE VIX variable, we test whether VIX can provide a better forecasting measurement of the leading foreign currency pairs. Although not displayed here, UFCI and VIX share a strong positive correlation value of 0.80 from 1999 to 2018. Further, the highest correlations in pre (1993-2018) and post-Euro (1999-2018) periods between exchange rates and VIX were for the Australian dollar, followed by the Canadian dollar, with values of 0.34 and 0.33 respectively. Most exchange rates posted very low correlations, except for the Japanese yen and Indian rupee which witnessed negative correlations since 1999. Compared with the UFCI and exchange rate correlations, VIX and exchange rate correlations, in absolute values, were higher, except for the British pounds and the two emerging markets. For comparison purposes, the root mean square errors (RMSE) are reported for each exchange rate being forecasted over the 1999-2018 period, using 1 week lagged UFCI model, 1 week lagged VIX model and a random walk model.

As observed in Table 2, the root mean square errors values were mostly close, with the difference between the smallest RMSE and the average under the three different models for each exchange rate ranging from -2% for the Euro and -22% for the British Pound. For these two currencies, the random walk model was superior to the VIX based forecasting model UFCI and UFCI model, by posting the lowest RMSE values. In line with the relatively higher absolute correlation values between the VIX and AUD/USD, VIX and JPY/USD, the forecasting model using VIX was superior for these two currencies. For the remaining three currencies, the UFCI model was preferred with the lowest RMSE values. Noticeably, however, the UFCI model is subject to varying RMSE values, heteroscedasticity, and insignificant p-values of UFCI coefficients as the number of lags is increased. Overall, the results still confirm the weak ability of financial conditions to be used as a robust and sustainable forecasting tool of leading USD based currency pairs.

Table 2: Root Mean Square Errors

	VIX	UFCI	Random Walk	% Difference
EUR/USD	0.131	0.129	0.126	-2.0%
GBP/USD	0.12	0.09	0.08	-22.1%
JPY/USD	11.85	13.72	14.05	-10.3%
AUD/USD	0.23	0.24	0.24	-2.3%
CAD/USD	0.25	0.18	0.22	-14.7%
CNY/USD	0.44	0.39	0.43	-7.3%
INR/USD	6.73	5.26	5.76	-11.1%

Note: The table displays the root mean squared error (RMSE) values using three different models. The VIX model is based on the CBOE VIX variable; the UFCI is based on the Unified FCI; and the last model is a random walk model without any drift. The RMSE values under the UFCI model are based mostly on 1 lag except for CNY/USD where 2 lags were used. Only 1 lag is used for the VIX based model. The % difference represents the proportion of the smallest RMSE value relative to the average of the three models RMSE value, per each currency.

5.7 Discussion of Results

As expected, the unified financial condition index captured a significant amount of variations inherent in the weekly financial conditions, due to the first principal component, which captured nearly 80% of all variations. Consistent with other studies like IMF (2017), Stock and Watson (2002) and Ludvigson and Ng (2007) who used principal component analysis to predict stock returns and macroeconomic variables, we proposed the use of the unified financial condition index to predict foreign currencies. Upon using the most actively traded currency pairs, in both developed and emerging markets, the unified financial condition index showed mixed results in terms of forecasting US-based foreign currencies. While the unified index reported significance towards explaining different currency values, robust testing of the results proved otherwise. The results were mixed with some currencies displaying significant p-values but also accompanied with heteroskedastic errors. While RMSE values were mostly consistent when lags were increased, forecasting using UFCI was weak, mostly explained by the low correlation values, and wide standard error lower and upper bands in the forecast estimates.

This is unexpected since the financial condition index is based purely on other US-based FCIs such as STLFSI and NFCI and it would have been anticipated that USD based foreign currency would be affected whenever there is a deterioration or improvement in the financial conditions. Despite some foreign currencies like the CAD, AUD and EUR sharing strong correlations among each other, the same conclusion was not reached when relating the financial condition indexes with the foreign currencies. One plausible reason is that the financial conditions indexes are constructed mostly using premiums which are based on fixed income and equity markets. A model based on predicting the most volatile markets, i.e. foreign currency markets, using less volatile ones like fixed income and stocks is mostly susceptible to less predictive power. This is in line with Aramonte, Rosen & Schindler (2013) who find FCIs to have some predictive power when forecasting monthly and quarterly returns of stock markets index such as the S&P500. Alternatively stated, our findings suggest that the proposed financial condition index (UFCI), which is based on the STLFSI, NFCI and ANFCI index values, which consist inherently of multi variables (volatile (e.g. stock market returns) and less volatile (e.g. three-month treasury bill rate) is not a reliable forecasting tool for currency markets or currency portfolios.

Upon a closer look at the economic variables used in each of the STLFSI, NFCI and ANFCI, none of them included foreign exchange indicators such as the UK-US covered interest rate differentials (as previously incorporated under the Cleveland FSI - CFSI), the Federal Reserve Board broad exchange rate index (as incorporated under the Monetary and Financial Conditions Index - MAFCI) or the real Goldman Sachs trade-weighted dollar index (as incorporated under the Goldman Sachs Financial Stress Index - GSFCI). As postulated by Kliesen, Owyang, and Vermann (2012), these foreign exchange indicators help measure the interconnectedness of international financial markets and the overall strength of economies relative to the international markets, and that flight to quality effects during global financial turmoil also tend to be reflected in foreign currency values. Overall, our findings are consistent with previous literature like Meese and Rogoff (1983) which support that the foreign currency markets can be better predicted by a random walk model compared to the use of macroeconomic variables or data like FCIs which incorporate macroeconomic variables.

In line with prior studies like Baskaya, Giovanni, Kalemli-Ozcan & Ulu (2017), Bruno & Shin 2015, IMF (2014), and Calvo, Leiderman and Reinhart

(1996) who postulated the importance of VIX in predicting economic activity, we evaluated the forecasting ability of the unified condition index with that of the VIX in predicting foreign currency values. While we also found strong correlations between the UFCI and VIX, as expected, a comparison of the root mean square errors of the VIX, UFCI and a random walk model show mix evidence among the three models. These suggest both the unified condition index and the volatility-based index are both not reliable towards making foreign currency forecasts. This can be partly explained by the VIX not capturing foreign currency movements as found in other foreign currency-based indices like the JPMorgan VXY Global index.

6. Conclusion

The aim of this paper is to introduce a unified financial index (UFCI) based on three major US-based financial conditions indexes and test its predictability over the most actively traded foreign currency pairs. Using principal component analysis based on weekly data ranging from 1993 to 2018, the UFCI model is constructed, where it represents nearly 77% of the variability among the three existing FCIs. As shown, the standardised model tends to track the major historical events witnessed throughout the period under study, on average, consistently in the same fashion as the STLFSI, NFCI and the ANFCI, with strongly positive correlations among the four FCIs. The paper then proceeded to test the predictability of financial conditions indexed on the most active USD based currency pairs. Using one, two and ten weeks ahead forecasts, the RMSE among all the FCIs were fairly close. The EUR/USD was the only instance when current UFCI values significant in explaining the currency pair value, complemented with homoscedastic errors and a stable RMSE. However, as the independent variable lags were increased, mixed results appear among the different currencies in terms of homoscedastic errors and significance of the UFCI. The correlation coefficients among all the currency pairs and the UFCI were mostly low, with the lower and upper band of the forecast estimates being wide in capturing the movements of actual foreign currency values over time. When compared with a model using the VIX variable as a forecasting measure, and also a random walk model, the UFCI was superior only for the Chinese yuan, Indian rupee and Canadian dollar, with root mean squared errors being between 7% and 14% different from the other models' RMSE values. UFCI forecasting results were also subject to heteroscedasticity in errors, and insignificant UFCI coefficients as the number of lags were increased.

The implications of this study are, firstly, the need of not using financial condition indexes which are based on a mix of short term and long term variables, since these results in FCIs which are weighted down in terms of the variability of the long term variables like 30-year Treasury yields. This can partly explain why the UFCI failed to be a strong predictor of exchange rates, where the latter are the most actively traded USD based currency pairs and tend to be more volatile in nature than the UFCI. The inclusion of exchange rate volatility measures within the STLFSI, NFCI and ANFCI is warranted to be able to provide a more reliable forecasting tool for exchange rates. The use of VIX as a measure of volatility failed to predict exchange rates, and suggest that volatility measures such as VIX which essentially captures the volatility of equity markets do not transmit into the volatilities in other markets such as currency markets. It is further recommended to consider the use of other variables like the JPMorgan VXY Global index, which captures the volatility of at-the-money options on 23 USD currency pairs. Secondly, findings suggest the need for future research to revisit higher frequency financial conditions indexes like the Bloomberg Financial Conditions Index model which is released daily to account for the volatility inherent in the foreign currency markets, whether for informative or predictive purposes. This would help regulatory bodies such as the Financial Stability Oversight Council (FSOC) and the Office of Financial Research (OFR) obtain more real-time information, towards the mandate of overseeing sustained stability in financial markets. Thirdly, the relatively poor forecasting ability of the Unified Financial Conditions Index in predicting foreign exchange rates, despite the fact that it captured nearly 80% of the variability among three of the most popular FCIs, also guides the use of more FCIs which incorporate some indicators of foreign exchange exposures such as the Federal Reserve Board broad exchange rate. Only then, any plausible relationship between financial conditions indices and exchange rates can be better assessed. The most commonly used variables among all existing FCIs is the TED spread which captures the difference between the rates at which banks can lend to each other and the rate at which governments can borrow within three months. A future research avenue can tap into whether the TED spread can be used to forecast foreign exchange rates, since the latter is more short term and expected to be volatile in nature, compared to the use of longer-term FCI variables like 30-year Treasury yields, which tend to be more stable over time. Alternatively stated, it is also recommended for policymakers in future FCI constructs, to look into the variability of the variables being incorporated.

Notes

1. FCI is used interchangeably for Financial Conditions Index or Financial Conditions Indices.

2. BRICS is a group of major emerging markets and stands for Brazil, Russia, India, China and South Africa. It was previously BRICs until South Africa joined the group in 2010.

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