The relationship between a Unified Financial Condition Index and the most actively traded USD based Foreign Currency pairs

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Abstract

Various regulatory bodies in the US use proprietary financial conditions indices as tools to measure the health of financial markets. While they share some common variables, they also differ in areas such as data frequencies of their respective models. The aim of this study is to propose a unified financial condition index centered 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. 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 was observed only for EUR/USD. Mixed findings found as lags were increased suggests 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 number of lags and insignificant p-values.

Index Terms— financial conditions, exchange rates, forecasts, principal component analysis.

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I. Introduction

The aim of this study is to propose a unified financial condition index (UFCI) and tests its predictability over the most actively traded USD based foreign currencies, including the Chinese yuan and Indian rupee as representative of leading emerging markets. Financial conditions can provide important information related to policy and risk assessment. For instance, Dudley (2010) and Koop & Korobilis (2014) found financial conditions information was useful in assessing linkages between reported financial markets, economic activity and policies. Rey (2013) further supported that the effect of globalization and previous reliance on solely national policies have led to the need for policy makers to take into account global factors when assessing each country's financial stability and subsequent development.

The motivation in the use of financial conditions in the study is backed by the notion 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 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 percent of changes in financial conditions indexes (FCIs) can 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. Calvo, Leiderman & Reinhart (1996); Bruno & Shin 2015; IMF 2014; and Baskaya, Giovanni, Kalemli-Ozcan & Ulu (2017) are all proponents that financial measures like VIX are important drivers of financial conditions. Kliesen, Owyang, and Vermann (2012) added that the VIX is the second most popular variable used in FCI construction. Lastly but not least, 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.

In addition to the construction of a unified financial condition index to capture most variability inherent in weekly financial conditions, this paper also looks in whether the major USD based foreign currency pairs can be forecasted using a unified FCI. 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 literature. Our study builds on existing literature such as Asness, Moskowitz, and Pedersen (2013) who show that momentum and value strategies for different asset classes such as stock portfolios and currency markets are closely related. 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 which is observed in the market return cash flow news variable. This paper is further motivated by the fact that FCIs for emerging market economies are rare. Despite the recent progressive transformation in their financial markets with more diversified markets, emerging market economies have relatively short times series for monitoring their financial segments which result in some difficulty to develop FCIs for these economies (Gumata, Klein & Ndou 2012). For this purpose, our study also includes the CNY/USD and INR/USD currency pairs where China and India are two of the top four leading emerging markets.

This paper adds to the current literature on financial conditions and financial markets, by introducing a unified FCI (UFCI) based on the variability of three weekly based US FCIs, namely the St Louis Federal Reserve Financial Stress Index, the Chicago Fed National Financial Condition Index and the Adjusted National Financial Condition Index. The methodology centers on the use of principal component analysis, which allows for a reduction in variable space while retaining most of the variation among the three FCIs. Around 80% of the variability inherent in each of the individual index are 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 5% and 10% level, 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 lead 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 predict exchange rates reliably. To robust test the UFCI model, results are also compared with two models, one based on the use of CBOE VIX and other on 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 heteroskedascity 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, suggests also that most exchange rates are not affected by previous period volatility measures such as VIX.

The rest of the paper is structured as follows: Some literature review on the relationship between financial conditions and foreign currency markets is provided, followed by the research methodology which is centered on the use of principal component analysis. 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.

II. LITERATURE REVIEW

Extensive literature exists regarding transmission channels across markets and economies with a lot of focus on monetary independence in setting interest rates. Other factors such as foreign exchange movements are also analyzed, 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 take external factors when pursuing domestic objectives. While IMF and OECD undertake projects of constructing and analyzing 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 percent. 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).

Paramount to the use of financial conditions, it is important to the importance of a sound functioning system as highlighted in various studies. The measurement of financial stress help identify 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) summarizes 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 are different in nature, they note important common characteristics based on the increase in uncertainty about the fundamental asset values, uncertainty about the behavior of other investors, increased asymmetric information, an increase in the willingness to shift toward 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). Similarly, uncertainty about the behavior 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 on the quality of issuers' credit ratings. Further, a flight to quality during financial stress move investors toward safer assets, expected to bring lower returns. 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.

It is also important to comprehend that FCIs have been constructed using various ways like vector autogressive models (VARs) and impulse functions (Swiston, 2008), large macroeconomic models (Beaton, Lalonde & Luu 2009), and principal component analysis (PCA). Since this study makes use of the latter method, an overview of FCI using PCA is warranted. For instance, Montagnoli & Napolitano (2005) used Kalman filtering algorithm for capturing the weight changes of financial variables in the explanation of the output gap, and constructed the FCI of the United States, Canada, Euro zone and the United Kingdom. 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 the principal component analysis method 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 on 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 the 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 globalization effect on economies, the greater the need for policy makers to understand further the implication of US led financial conditions onto their respective national markets. Further, the Aramonte, Rosen & Schindler (2013) study creates a composite FCI index, based on 4 FCI, where 2 are based on a weekly basis, and the other 2 FCI are weekly and monthly based. This suggests a lack of data or existence of a smoothing process, especially where monthly and quarterly forecasts are being pursued by the authors.

Although literature on FCI is important in the sound functioning of economies, it is also important to exhibit any potential theoretical justification between the foreign currency markets and macroeconomic variables which are in built in 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 U.S. and all other economies) explained nearly up to 90% (75%) of changes in bilateral exchange rates for developed (developing) countries. Further, while uncovered interest rate parity (UIP) states that a country with a higher interest should experience a depreciation in the domestic currency relative to the foreign country, such that a 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) all 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 large set of U.S. economic variables. Meese and Rogoff (1983) estimated multi-variate regressions which link macro variables to changes in currency rates and found the random walk model yielded lower root mean squared errors than any economic variable. 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 analyzing currency rates and a particular economic variable relationship. The question which then arises is which FCIs to use in the 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 model. In a similar fashion, this paper looks at the relationship between major FCIs and foreign currencies, where the FCIs incorporated major economic variables into their construct. Lastly, but not least, despite some of the FCIs share strong correlations, they are not based on different data frequencies. As supported by Kliesen, Owyang, and Vermann (2012), a weekly FCI, compared to a monthly one would help policy makers 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 results 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 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.

III. RESEARCH METHODOLOGY

The concept of principal component analysis (PCA) is essentially based on a reduction in the dimensions that connect variables, whilst retaining most of the variability among the variables. Alternatively stated, it is a mathematical procedure which transforms correlated variables into a number of uncorrelated ones called principal components. The first principal component captures the highest variability in the data, followed by the second principal component and so on. The PCA model is centered 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:

$$|A-\gamma I|=0 \qquad (1)$$

$$(A-\gamma I)\varphi=0 \qquad (2)$$

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 satisfy 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 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 tighter than on average by one standard deviation, while an index value of 1 indicates that financial conditions are looser than average by one standard deviation. This usual standardizing approach can also be found in Nelson & Perli (2007) and Cardarelli, Elekdag & Lall (2011). The uncorrelated and linear combinations of standardized variables form the principal components as follows:

$$\sigma_{PC_1} > \sigma_{PC_2} > \sigma_{PC_3} \ldots > \sigma_{PC_N} \qquad (3)$$

$\sum_{i=1}^{n} \sigma_{PC_i} = \text{Number of FCIs}$ $\sigma_{PC_{1\ldots n}}$ 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 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.

Once the UFCI is constructed, the UFCI and exchange rates series are tested for stationarity using the Schwarz Information Criteria. 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. To compare the forecasting ability of UFCI over exchange rates, root mean squared errors values are reported for all exchange rates. As part of the robust testing the model, the residuals are tested for homoscedasticity using the Breusch Pagan Godfrey heteroskedasticity test. The standard error upper and lower bands estimates are shown to observe how reliable can financial conditions indices be used to forecast exchange rates. Last, but not least, 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:

$$FX_t = FX_{t-1} + \omega_t \quad (4)$$

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

IV. DATA

We focus on a weekly data frequency based on previous support from 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 realized 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 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 analyzing if financial stress is captured in a more real time frame.

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 utilizing them in the principal component analysis.

These mostly include interest rate spreads which captures 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 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 Organization 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).

V. RESEARCH FINDINGS

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. 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).

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 with 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). 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. Correlations among the three conditions indexes range between 0.56-0.77. 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 that the second principal component only contribute to another 15% of the total variation in FCIs. This is in line with relatively higher squared cosinus 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 positively 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.

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 (2017) who also included the CNY and INR in the analysis of foreign currency, crude oil and natural gas markets, this study analyzes 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 root mean squared error values (RMSE) are calculated based on the following model:

$$FX_t^i = \alpha + \beta . UFCI_{t-n} + \varepsilon_t \qquad (5)$$

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 week ahead forecasts, with values ranging from 0, 1, 2 and 10. The impact of the unified financial condition index on the foreign currency pairs for the various week ahead forecasts is analyzed. Due to the inclusion of the Euro currency in 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.

Findings 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. 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 sign of heteroscedasticity in the residuals. Only the EUR/USD qualified for homoscedastic errors, significant p-value of the UFCI coefficient at 5% and 10% level, with a 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 a 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. 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 estimatessuggest the unified condition index have poor predictive abilities on the 1, 2, and 10 week ahead forecasts of the most active foreign currency pairs traded globally.

Since the financial condition index is based purely on other US based FCIs such as STLFSI and NFCI, it would have been expected that USD based foreign currency would be affected whether 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.

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 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.

VI. CONCLUSION

The critical object 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 standardized model tends to track the historical major 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 4 FCIs. The paper then proceeded to test the predictability of financial conditions indexed on the most active USD based currency pairs. Using 1, 2 and 10 week ahead forecasts, the RMSE among all the FCIs were fairly close. Only for the EUR/USD was the 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 volatility of equity markets do not transmit into the volatilities in other markets such as foreign exchange. 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 provides guidance towards 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. Fourth, 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 a three-month period. 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 policy makers in future FCI's constructs, to look into the variability of the variables being incorporated.

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