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Hwee Kwan CHOW

Singapore Management University, hkchow@smu.edu.sg

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Can a Financial Conditions Index Guide Monetary Policy?
The Case of Singapore

Hwee Kwan CHOW*
Singapore Management University

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Keywords: Financial Conditions; Monetary Policy; Vector Autoregression; Forecast Performance.

* Hwee Kwan Chow, School of Economics, Singapore Management University, 90 Stamford Road, Singapore 178903.

PH:(65) 6828-0868, FAX: (65) 6828-0833, Email: hkchow@smu.edu.sg.

Can a Financial Conditions Index Guide Monetary Policy? The case of Singapore

Abstract

In this study, we explore the issue of whether a financial conditions index can serve as a useful guide to monetary policy in the context of Singapore. To this end, we construct an index that comprises not only the usual monetary variables like interest rates, exchange rates and credit expansions but also asset prices such as stock prices and house prices. The choice of these constituent series is motivated by the role they play in the monetary transmission mechanism with consideration given to the key role leverage plays in modern business cycles and the risk-taking channel magnified by the prolonged period of low interest rate environment. A weighted-sum approach of index construction is adopted whereby the weight assigned to each component is derived from the generalized impulse responses of a monetary VAR model estimated using quarterly data from 1978q1 to 2011q2. Cross correlations and Granger causality tests confirm the financial condition index developed in this paper possesses good in-sample leading qualities over consumer price inflation. More importantly, using the proposed index to generate predictions recursively from a direct multistep forecasting methodology yields substantial gains in out-of-sample prediction performance when compared with forecasts of a benchmark autoregressive time series model for inflation, particularly within the one-year forecast horizon.

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1 Introduction

The 2008 global financial crisis and the attendant economic crisis clearly illustrate how instability in financial conditions can have adverse consequences on the macroeconomy. In particular, the events confirm that asset prices tend to overshoot and the bursting of asset price bubbles can lead to financial market distress as well as destabilize the economy. There is now a general consensus that the central bank's duty is not limited to price stability alone but includes maintaining financial stability as well (see, *inter alia*, Allen and Rogoff (2010); Kawai and Morgan (2012)). This raises the question of how monetary policy should incorporate a financial stability element.

One way is for central bankers to monitor more closely monetary conditions in the economy. For instance, notwithstanding difficulties in identifying asset price bubbles, useful information can be extracted from asset price developments to portend future inflation (see Cecchetti *et al.* (2003)).¹ Rather than focusing on the benchmark policy interest rate which measures only one dimension of financial conditions, it is pertinent to track an array of financial variables. These measures reflect the dynamics of financial conditions in the economy and are themselves influenced by the monetary policy stance. The financial variables can be combined to form a financial conditions index to summarize the evolution of the overall financial conditions in the economy. Such an index will typically comprise main variables that influence output and inflation through the monetary transmission mechanism. Key candidates include the interest rate that reflect user cost of capital as well as tradeoffs between current and future consumption; the exchange rate that works through the trade channel; credit expansion that works through the banking lending channel; asset prices such as stock prices and house prices that affect household wealth and consumption; and possibly other financial measures.

The financial conditions index can, in fact, be viewed as an extension of the monetary conditions index which is a weighted sum of changes in short term interest rate and the exchange rate relative to values in the base year includes a broader range of financial conditions measures. Various central banks including the Bank of Canada and the

¹ The issue of whether monetary authorities ought to consider asset price developments when setting monetary policy was debated extensively for over nearly two decades. Some commentators are skeptical about the practicality of such a proposition in view of the bluntness of the policy instrument (see, for example, Assenmacher and Gerlach (2008)), while others like Roubini (2006) argue that monetary policy should be used to lean against rapid and excessive increases in asset prices.

Reserve Bank of New Zealand use a monetary conditions index as an operating target. In the event, the monetary authority addresses financial stability and price stability simultaneously by adopting a hybrid inflation targeting framework (see, *inter alia*, Taylor (2000); Lubik and Schorfeide (2007)). However, as the credibility of the monetary policy target is heavily dependent on its simplicity to the general public, most central banks will eschew the replacement of the consumer price index by a financial conditions index.

Rather, a financial conditions index can play a useful role as an information variable together with the consumer price index in determining monetary policy. Moreover, as a summary measure of the different dimensions of financial conditions that influence the formulation of monetary policy, the use of the index simplifies discussion of the monetary policy stance, thereby facilitating external communication. The financial conditions index should, thus, provide information on the outlook for inflation within the forecast horizon of the central bank. It follows that the components that make up the index should be useful predictors of inflation. In this context, the inclusion of asset prices in the index is pertinent since there are instances when selective asset inflation does represent a threat to the goal of overall price stability, perhaps by raising inflation expectations unduly or by over-stimulating consumption and investment spending.

Several financial condition indexes that are constructed using various approaches, have been developed for the US. These include the Bloomberg FCI, the Citi FCI, the Deutsche Bank FCI, the Goldman Sachs FCI and the Kansas City Federal Reserve Financial Stress Index, among others. Hatzius *et al.* (2010) provides a summary of the methodologies used in the construction of these indexes. By contrast, very few financial conditions indexes have been developed for countries in Asia. To the best of the authors' knowledge, the academic literature reports only one financial conditions index that was constructed for the Asian countries in Osorio *et al.* (2011). Our paper attempts to partially address this gap in the literature by developing a financial condition index for Singapore. Following Goodhart and Hofmann (2001), we adopt the weighted-sum approach of index construction whereby the weights that reflect the relative importance of the financial variables are taken as their estimated relative effects on inflation.

We expect that a financial conditions index will be more useful in financial center countries such as Singapore. After all, the structure of the financial system is a key

determinant of the importance of the various channels of monetary transmission. To determine empirically whether the financial condition index developed in this paper—hereafter referred to as *SFCI*—serves to guide monetary policy in Singapore, we examine its in-sample and out-of-sample predictive ability for annualized quarterly consumer price inflation. To preempt the results, empirical analysis using quarterly data in the period 1978q1 to 2011q2 reveal that the *SFCI* possesses good in-sample leading qualities over consumer price inflation. More importantly, the proposed index yields substantial improvement in out-of-sample prediction performance over the one-year forecast horizon when included in pure autoregressive models for forecasting inflation.

The rest of this paper proceeds as follows. The next section explains the choice of financial variables for inclusion in the *SFCI*, while Section 3 describes the construction of the index with focus on the determination of weights for the component financial series. In Section 4, we first ascertain the in-sample leading qualities of the *SFCI* before producing pseudo out-of-sample predictions of inflation from competing forecasting models and formally evaluate their overall accuracy. Finally, Section 5 concludes the paper.

2 Index Components and Transmission Mechanisms

In the construction of a financial conditions index, one has to select from a wide range of financial variables to be included in the index. The choice of these financial measures as well as their relative importance would very much depend on the nature of monetary transmission mechanism in the economy. In this paper, we select the following five variables for inclusion in the Singapore index:² (i) real interest rate (*rir*) which is the three-month interbank rate less quarterly inflation; (ii) real effective exchange rate (*reer*) expressed in terms of the units of home currency per foreign currency so that a rise in the exchange rate signals a real depreciation of the Singapore dollar; (iii) real credit expansion (*credit*) which is the total commercial bank loans in real terms; (iv) stock price index (*sp*) which is the Straits Times Composite Index (STI) in real terms; and (v) real house price index (*hp*) which is the private residential property price index in real terms.

² Initially, world oil price was included as one of the variables reflecting financial pressures in the Singapore economy. However, subsequent empirical analysis reveals that its effect on domestic inflation is very small relative to the other component variables. Hence, it is omitted in the construction of the financial conditions index.

As the real interest rate reflects the opportunity cost of present versus future expenditure, changes in the interest rate alter the incentives to defer current consumption and investment spending to a later date. Indeed, a higher interest rate raises the cost of capital that directly reduces the profitability of current investment projects. A rise in the interest rate also tends to encourage households to reduce current consumption expenditure because of the increase in both the return on saving and the cost of borrowing to finance consumption. While net borrowers are made worse off, net savers are concomitantly made better off with a fall in the interest rate. This re-distributional effect of an interest rate change implies that the overall impact on expenditures and inflationary pressures are determined by the more dominant of these two influences.

Changes in the exchange rate—which is the relative price of domestic and foreign currency—lead to movements in the relative prices of domestic and foreign goods and services. Such relative price fluctuations in turn can affect the pattern and level of spending in the domestic economy. For instance, an exchange rate appreciation lowers the domestic price of imports and thus reduces the competitiveness of domestic producers of import-competing goods and services. This encourages a switch of expenditure away from home-produced towards foreign-produced goods and services. At the same time, an appreciation of the local currency raises the foreign price of domestic exports, thereby reducing the competitiveness of domestic producers of exports. The attendant decline in exports contributes to the deterioration in the trade balance. Such exchange rate effects have a particularly strong influence on domestic inflation for small open economies like Singapore which rely on export-driven growth. Furthermore, as the economy has significant levels of wealth that are denominated in foreign currency, an exchange rate appreciation translates to a decline in net wealth that can depress the level of expenditure.

With a mission to promote sustained non-inflationary economic growth, the Monetary Authority of Singapore (MAS) targets the effective exchange rate instead of the more conventional benchmark policy interest rate as its operating tool (MAS, 2000). It is the use of the exchange rate as an intermediate target that contributes to the unique nature of monetary policy in Singapore. Regarding the pass-through effect of exchange rate changes to aggregate prices, this could occur through two different channels. Firstly, an exchange rate appreciation has a direct effect on domestic prices by lowering the prices of imported services as well as imported intermediate and final products. Secondly, a reduction in

aggregate demand caused by an appreciation of the local currency, as discussed above, alleviates inflationary pressures indirectly through the easing of domestic costs such as wages.

The supply of intermediate credit works through the bank lending channel. When there is insufficient domestic liquidity, the central bank will inject funds into the domestic banking system through open market operations. This increases the availability of resources to supply funds to borrowers, particularly bank-dependent ones such as consumers and smaller firms. Moreover, as evident in recent events, more intensive credit booms during economic expansions are often associated with more severe subsequent recessions (Jorda *et al.* (2011)). Leverage, undoubtedly, plays a key role in modern business cycles, thereby raising the association of credit growth (contraction) with inflationary (deflationary) pressures. In addition, the risk-taking channel has also gained prominence whereby banks in an extended period of low short term interest rates are induced to take greater risks when granting loans (Altunbas *et al.* (2010)).

Both consumption and investment spending can also be affected by asset price changes through wealth effects and balance sheet effects. For instance, a fall in stock prices reduces household's financial wealth or increases the likelihood of financial distress, which can lead to a decline in consumption spending. Moreover, a decline in other asset values such as land and property prices not only makes households feel poorer but also makes it harder for them to borrow, especially when assets like houses are used as collaterals for loans. Such balance sheet effects also apply to firms whose loans are typically secured on assets, so that a fall in asset prices which reduces the net worth of a firm can result in a decrease in lending to finance investment spending. At the same time, asset price changes influence the level of consumer and business confidence in the economy. It is also important to monitor asset prices since inflationary pressures could appear first in asset prices in a low inflationary environment (Borio and Lowe (2002)).

In related literature, the index developed by Osorio *et al.* (2011) comprises the spread of lending rates over policy rates; the effective exchange rate; stock prices; and bank credit to the private sector. In our view, an important financial variable has been omitted from the index, namely house prices. After all, swings in house prices can have potent effects on the economy say via their impact on household wealth. Indeed, many empirical

studies have shown a significant positive relationship between wealth and consumption (see, *inter alia*, Lettau and Ludvigson (2004)). In countries where financial development has led to deeper and more sophisticated mortgage markets, house price fluctuations impact consumption increasing through the balance sheet effect (Reinhart and Rogoff (2009)). In practice, countries like Australia and Sweden are also known to discuss house prices and take them into account when formulating monetary policy from a financial stability perspective (see Cagliarini et al. (2010) and Ingves (2007)).

The Singapore housing market experienced several boom-bust cycles over the past three decades with sharp appreciations occurring in periods of rapid economic growth and mostly associated with the liberalization of the housing finance sector, in particular Central Provident Fund (CPF) regulations.³ Conversely, downturns in house prices coincided with economic recessions or the implementation of anti-speculation measures such as direct credit controls. A recent study by MAS (2012) which applies an error correction model found that consumer expenditure in the short run is not significantly affected by house prices (nor stock prices) in the case of Singapore. By contrast, Chow and Choy (2009) found using a factor augmented vector autoregressive (FAVAR) model that movements in property prices do have a significant impact on future inflation. As is shown later in this paper, house prices turn out to be important drivers of domestic inflation so that it's apt to include them in the construction of the financial conditions index.

3 Construction of a Singapore Financial Conditions Index

The component financial series can be combined in a variety of ways to form an index. Stock and Watson (2003) adopted a more atheoretic approach whereby the weights assigned to the components of the index are determined by optimizing the forecasting properties of the financial conditions index. Another approach applies the principal component technique to extract a common unobserved factor from the constituent financial variables (see seminal work of Stock and Watson (1989)). The method allows the weights of the components to change as more information becomes available. Goodhart and Hofmann (2001) adopted a more conventional approach whereby the weights are backed out from a monetary vector autoregression model comprising the financial variables, output growth (*gdp*) and annualized quarterly CPI inflation (*cpi*). The weights, reflecting the relative

³ The CPF is a government-administered mandatory retirement fund that can be partially withdrawn to finance housing.

importance of the financial variables, are taken as their estimated relative effects on inflation. This weighted-sum method of index construction, which this paper follows, clarifies the reasoning behind a particular choice of variables in explaining the mechanism by which the financial variables affect output and inflation.⁴

The VAR model is estimated for the period 1978q1 to 2011q2 using quarterly, seasonally adjusted data. All data series are sourced either from the International Financial Statistics or the Singapore Department of Statistics' STS online database. With the exception of the interest rates, all variables are converted into natural logarithms. We investigate the integration properties of the series by applying the Phillips-Perron unit root test (that corrects for heteroskedastic errors). Without exception, the series are integrated of order one. Hence, we apply first differencing to all variables in order to induce stationarity in the series. Further, all the component variables are standardized by subtracting their means and dividing by their standard deviations to avoid overweighting any one series.

We build a VAR model in first differences given by:

$$y_t = \tau + \Pi_1 y_{t-1} + \dots + \Pi_k y_{t-k} + \Gamma x_t + \varepsilon_t \quad (1)$$

for $t=1,2,\dots,T$; where $y_t' = [gdp, cpi, rir, reer, credit, sp, hp]'$; x_t' comprises 4 dummy variables; Π_i and Γ are fixed (7x7) and (7x4) matrices of parameters respectively; τ is a (7x1) vector of constants; and ε_t is a multivariate white noise error term with zero mean. Four dummy variables are included to account for large outliers caused by the domestic recession in mid-1980s, 1998 Asian financial crisis, and the recent global financial crisis.

Subject to a maximum of eight lags, the Akaike information criteria (AIC) selected an optimal lag length of two. Figures 1-5 plot the generalized impulse response functions which show that dynamic effects of innovations in each index component on inflation and output. Generalized impulse responses are computed as they are independent of specific ordering

⁴ Apart from differences in the composition of financial variables, another point of departure Osorio *et al.* (2011) is we employ the weighted-sum method of construction. In comparison, a hybrid of this and the principal component approach was used in Osorio *et al.* (2011) through the averaging of the indexes derived from these two approaches.

of variables in the VAR model.⁵ Monte Carlo standard errors from 1000 replications are obtained for the impulse responses and we use them to construct two-standard error bands. These are shown as dashed lines in the figures. (Although some of the impulse response functions are marginally insignificant when two standard error bands are used, they are statistically significant when we apply 1.5 standard error bands.) The time horizon over which the responses are plotted following the monetary policy innovation extends to 10 quarters, by which time all the impulses are insignificantly different from zero.

Figure 1 Generalized Impulse Responses to Interest Rate Shock

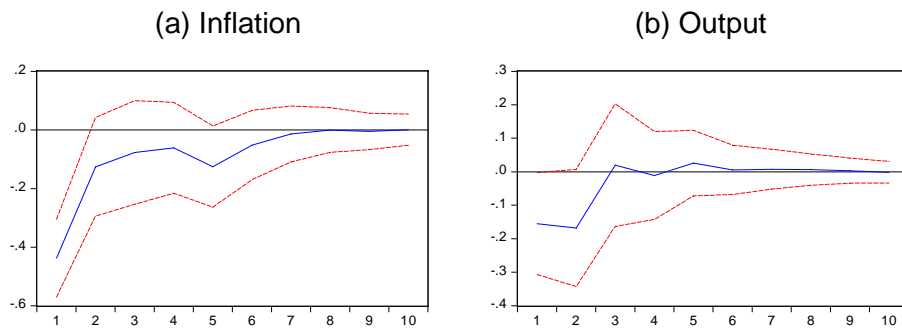


Figure 2 Generalized Impulse Responses to Exchange Rate Shock

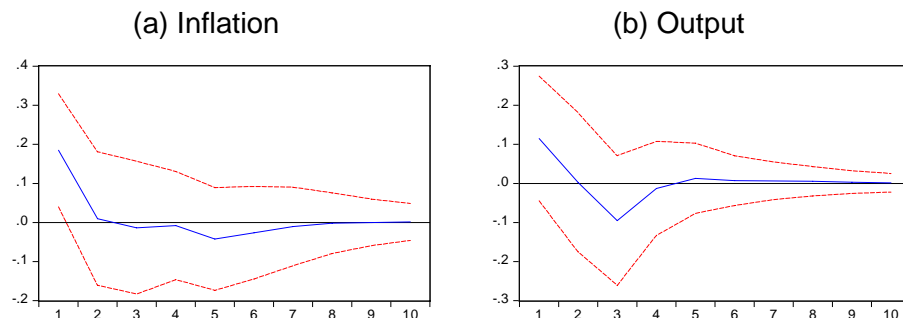
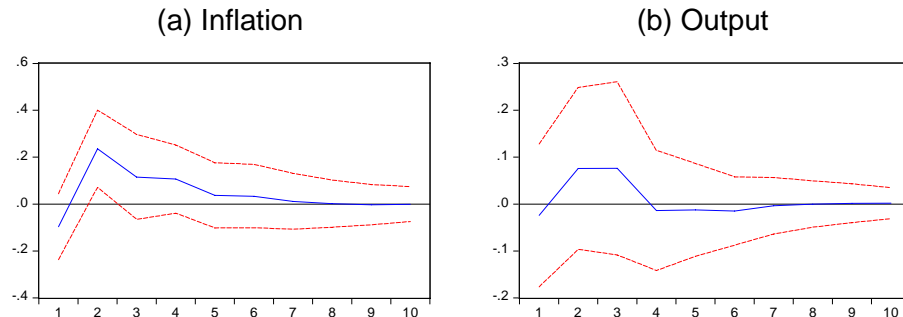


Figure 3 Generalized Impulse Responses to Credit Shock



⁵ This serves as an improvement over Goodhart and Hoffman (2001) which applied the Cholesky decomposition to derive the impulse response functions that are typically not robust to a different ordering of variables.

The dynamic generalized impulse responses produced by the VAR model are found to be generally consistent with the conventional view of the monetary transmission mechanism. It is clear from Figure 1 that a rise in interest rate leads to an immediate fall in both inflation and output. Conversely, a domestic currency depreciation elicits an immediate increase in both inflation and output (see Figure 2). However, we see that the impact in each case is relatively short lived with statistically significant impulses lasting for only one or two quarters. In comparison, the plots in Figure 3 show that an unexpected credit expansion leads to an increase in both inflation and output with a one quarter lag.

Figure 4 Generalized Impulse Responses to Stock Price Shock

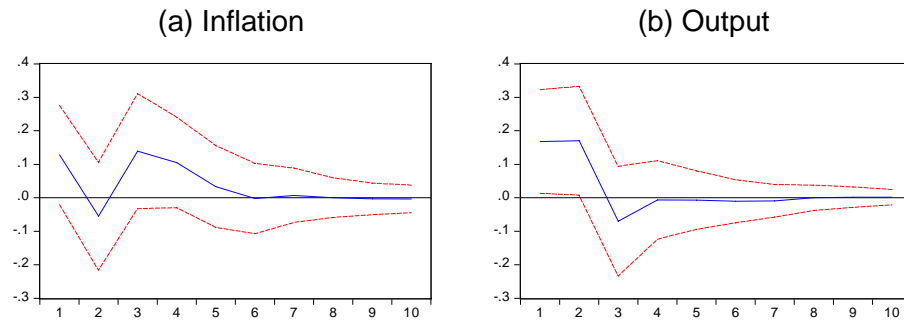
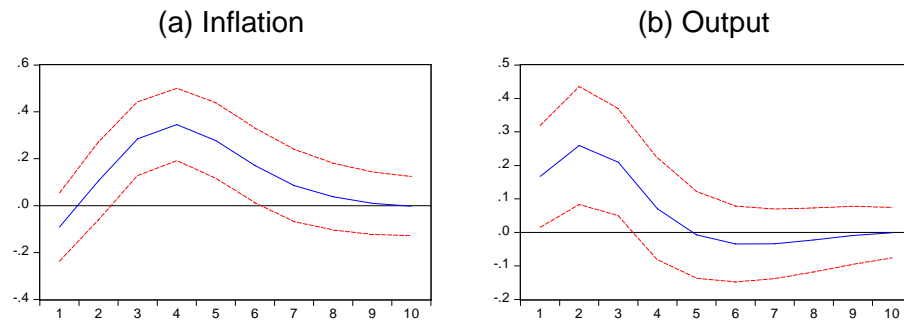


Figure 5 Generalized Impulse Responses to House Price Shock



We see from Figure 4 that a rise in stock prices produces positive responses from both inflation and output. Meanwhile, the plots in Figure 5 show that a positive house price shock precipitates a substantial increase inflation two quarters after the initial impulse as well as an immediate rise in output. The relatively large and protracted response—impulses remain statistically significant for three to four quarters—is partly due to the fact that more expensive housing translates into higher accommodation costs for consumers. Furthermore, it is likely that the positive wealth and balance sheet effects from rising house valuations will stimulate domestic demand and exert further pressure on prices. Our finding that house

prices play a bigger role than stock prices in influencing inflation is not an uncommon finding in related literature (see, *inter alia*, Mayes and Viren (2001)). Overall, the impulse response functions confirm that a shock to each component variable produces movements in inflation and output in the expected direction.

We take a weighted average of the five component series to form a financial conditions index for Singapore. The weight assigned to each financial variable is derived based on the cumulative responses of inflation to a one standard deviation shock to that variable. In all cases, the impulse responses are cumulated over four quarters. We sum the impulses over the first four quarters for real interest rate, real effective exchange rate and stock prices since a shock to each of these variables elicit an immediate response from inflation. In comparison, we sum the responses after a one-quarter (two-quarter) lag for a credit (house price) shock reflecting its delayed impact on inflation. The resulting weights for the five components $[rir, reer, credit, sp, hp]$ are 25%, 6%, 18%, 12% and 39% respectively. Robustness checks reveal that the weights estimated by this procedure are not sensitive to slight changes in VAR lag lengths or sample sizes.

4 Forecasting Inflation with FCI

In this section, we carry out empirical analyses to assess whether the financial conditions index constructed in the previous section has any predictive content for future inflationary pressures. We recall that the variable to be forecasted is Singapore's annualized quarterly consumer price inflation denoted as cpi .

4.1 In-sample Measures of Predictive Content

We consider in-sample evidence by examining the cross correlations between the index and inflation which are plotted in Figure 6 below. It is clear from the plot that the constructed index possesses leading qualities over the inflation series. Applying two standard errors Bartlett bands at ± 0.18 , the correlations of $SFCI$ with future inflation are statistically significant for the first five quarters, with the maximum value of 0.51 occurring at lead two. In other words, the current value of the index is well correlated with future inflation figures for up to one year ahead.

Figure 6 Cross Correlations between *SFCI* and Inflation

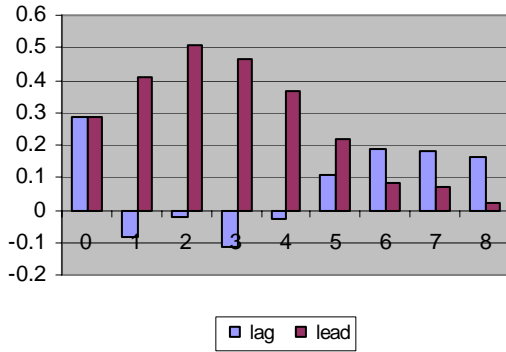
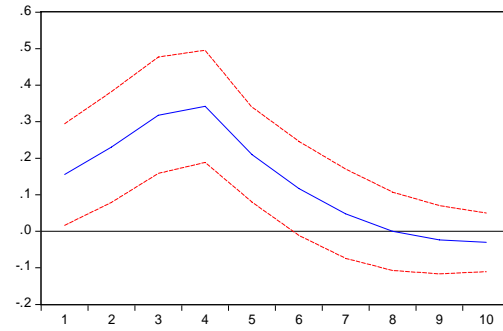


Figure 7 Generalized Impulse Responses of inflation to *SFCI* Shock



Evidence of in-sample predictive ability of the constructed financial conditions index is also found through Granger causality tests. This entails specifying a bivariate VAR model for $y'_t = [cpi, sfci]'$ with optimal lag length three as indicated by AIC. We then test to see if the subset of coefficients associated with lagged values of *SFCI* is jointly and significantly different from zero in the equation for inflation. The Wald test statistics turns out to be 31.92, giving us a *p-value* which is almost zero. Hence, the null of no causality is rejected at the 1% significant level and we conclude there is very strong statistical evidence that past values of the index have significant information for current inflation over and above the information found in past values of inflation. Moreover, an unanticipated shock to *SFCI* produces significant movements in inflation. The impulse response function derived from the bivariate VAR model exhibits a hump shaped feature reaching a peak at 3-4 quarters (see Figure 7). This adds to in-sample evidence that the constructed financial conditions index does provide useful indication of future inflation at least within the one-year horizon.

4.2 Pseudo Out-of-sample Measures of Predictive Content

It is not unusual for indicators of inflation with good in-sample predictive ability to perform poorly in out-of-sample forecasting. Hence, we carry out formal tests to investigate the ability of the index to produce out-of-sample forecasts of inflation. A common framework is adopted for generating pseudo out-of-sample forecasts from a pure autoregressive time series model and a autoregressive model augmented with *SFCI*. Initially, each forecasting model is estimated using observations over the period 1980Q2 to 2004Q4 and its *h*-step ahead predictions calculated for $h = 1, 2, 3, 4, 6$ and 8 quarters. Thereafter, the sample is augmented by one quarter, the model is respecified and its parameters reestimated and the

corresponding h -step predictions generated by moving the forecast window forward. By having lag lengths that are data dependent, the model is allowed to adapt to changes in dynamics over time. This recursive procedure is carried on until the sample's end date reaches 2011Q2, at which point the final set of forecasts are made.

A distinctive feature of the recent work on forecasting lies in the way multiperiod predictions are produced. Instead of the usual approach whereby future predictions are generated dynamically by repeatedly iterating the one-step ahead forecasting model and replacing unknown values by their forecasts, we employ a direct multistep forecasting methodology.⁶ Hence, a h -step ahead forecast could be computed directly by projecting $cpi_{i,t+h}$ onto its observable past and $SFCI$ as follows:

$$cpi_{i,t+h} = \mu_h + \alpha_h(L)cpi_{it} + \beta_h(L)sfc_i + e_{t+h} \quad (2)$$

At each prediction horizon, a separate forecasting equation is estimated by ordinary least squares and the order of the lag polynomials for the autoregressive component $\alpha_h(L)$ and the index $\beta_h(L)$ is determined by minimizing the BIC. In this way, the forecasting model can adapt to changes in dynamics over different sample periods.

On leaving the $SFCI$ out of (2), we get a pure autoregression for inflation. This constitutes the benchmark model with which the performance of the forecasting model with $SFCI$ is compared. We pick the lag length of the autoregressions through the BIC. With most of the AR models selected being of order 6 to 8, hence allowing complex roots to capture the cyclical behaviour of the data. Such models are therefore not as naïve as they might seem to be.

The comparative results of the pseudo out-of-sample forecasting exercises are expressed in the form of root mean square forecast error (RMSE) and mean absolute forecast error (MAE) measures in Table 1. These statistics are computed for the two forecast models at each forecast horizon. We observe from Table 1 that for all forecast horizons within a year i.e. $h = 1, 2, 3$ and 4 , both RMSE and MAE are lower when $SFCI$ is included the autoregressive model. The percentage reduction in RMSE (MAE) ranges from

⁶ The benefit of the direct method is that it obviates the need to model the evolution of the FCI . Furthermore, any misspecification of the one-step ahead model will not be transmitted to the longer forecast horizons since distinct models are estimated at each step of prediction.

9% to 12% (11% to 17%) when the financial conditions index is used in forecasting. That the model with *SFCI* excelled over the benchmark model is not unexpected in view of its ability to lead in-sample inflation movements as demonstrated in the previous sub-section.⁷

Table 1 Forecast comparison

Forecast Horizon (Quarters)	RMSE		MAE	
	<i>AR</i>	<i>AR + FCI</i>	<i>AR</i>	<i>AR + FCI</i>
1	1.05	0.92(-12%)	0.83	0.70(-15%)
2	1.15	0.98(-15%)	0.96	0.79(-17%)
3	1.29	1.09(-16%)	1.07	0.89(-17%)
4	1.31	1.19(-9%)	1.09	0.97(-11%)
6	1.34	1.34(0%)	1.15	1.15(-1%)
8	1.37	1.43(4%)	1.24	1.24(4%)

Note: The numbers represent the RMSE and MAE statistics for the two forecasting models at various horizons. Numbers in parenthesis are the percentage change in statistics compared to the pure AR model.

However, some of the observed differences between the RMSEs or MAEs could just be attributed to chance. Table 2 assesses the influence of sampling variability on the prediction errors by presenting the Diebold-Mariano (1995) test statistics for the null hypothesis of equal forecast accuracy between the model with *SFCI* versus the benchmark model. In view of the relatively small number of observations involved, the following small sample version due to Harvey *et al.* (1997) is reported:

$$DM = \sqrt{\frac{T+1-2h+h(h-1)/T}{T}} \cdot \frac{\bar{d}}{\sqrt{V(\bar{d})}} \quad (3)$$

$$V(\bar{d}) = \frac{1}{T} \left(\hat{\gamma}_0 + 2 \sum_{k=1}^{h-1} \hat{\gamma}_k \right)$$

⁷ Robustness checks reveal that this index also outperforms a similarly constructed index that omits the house price variable (following Osorio *et al.* (2011)). The financial conditions index that includes house prices has higher predictive power with invariably smaller RMSE and MAE statistics compared to the index without for forecast horizons up to one year ahead. This result establishes the predictive content in Singapore house prices and highlights the usefulness of including this variable in *SFCI*.

where T is the number of forecasts made, h is the forecast horizon, \bar{d} is the mean difference between the squared forecast errors or mean absolute error from any two competing models, $V(\bar{d})$ is its approximate asymptotic variance, and $\hat{\gamma}_k$ is the estimated k -th order autocovariance of the forecast error differences. To assess statistical significance, the modified DM statistics are compared with the one-tailed critical values from the t -distribution with $T - 1$ degrees of freedom.

Table 2 Tests of predictive accuracy

Forecast Horizon (Quarters)	DM for difference in RMSE	DM for difference in MAE
	<i>AR + FCI</i>	<i>AR + FCI</i>
1	-2.68	-2.85
2	-2.39	-2.77
3	-1.86	-1.91
4	-1.05	-1.60
6	-0.09	-0.16
8	0.87	0.73

Note: The numbers represent the small sample Diebold-Mariano statistics for the model with a financial conditions index *vis-à-vis* the AR model. Bold figures denote statistical significance at the 10% level or lower

A negative Diebold-Mariano statistic in the table indicates that the model with the constructed index shows an improvement in forecast performance over the benchmark model while a positive number implies a deterioration. If the difference in accuracy is statistically significant at the 10% level or better, the figure appears in bold. For comparisons based on RMSE, Table 3 reports that the hypothesis of equal predictive accuracy between the augmented and pure autoregressive models can be rejected at conventional significance levels for $h = 1, 2$ and 3 . When it comes to comparisons based on MAE, all the DM statistics within the one year forecast horizon i.e. $h = 1, 2, 3$ and 4 are negative and statistically significant. These findings suggest that the model augmented with *SFCI* dominates the benchmark model when predicting up to one year ahead.

Without exception, none of the DM statistics are significantly positive indicating that the pure autoregression model is not superior to the model with *SFCI* even at a longer forecast horizon of $h = 8$. In summary, the gains in out-of-sample predictive accuracy in terms of relative RMSE (MAE) over the pure AR model are significant at the one to three (four) quarters forecast horizon. We infer that the information content on future inflation summarized in the financial conditions indexes manifested in their good forecast performance.

5 Conclusion

In this study we explore the issue if whether a financial conditions index is useful to guide monetary policy in the context of Singapore. To this end, we constructed an index that comprises not only the usual monetary variables like interest rates, exchange rates and credit expansions but also included asset prices such as stock prices and house prices. The choice of these constituent series is motivated by the role they play in the monetary transmission mechanism. A weighted sum approach is adopted whereby the weight assigned to each component is derived from a monetary VAR model and determined by the magnitude of cumulative generalized impulse responses of inflation to a shock to the financial variable. In particular, the house price variable is of relative importance in its estimated effects on inflation, with a high weight of almost 40%. Chow and Choy (2009) amongst others also found the house price variable to have predictive information content for future inflation and is a good indicator of the financial pressures on the Singapore economy.

The constructed financial conditions index show in-sample leading qualities over quarterly consumer price inflation, based on cross-correlation analysis and Granger causality test. Furthermore, inclusion of the index in an autoregressive forecasting model for inflation improves its forecasting accuracy substantially for forecast horizons of up to one year. We conclude that useful information for monetary policy can be extracted from the constructed financial conditions index as it provides a useful summary of the state of financial conditions in Singapore. A natural extension of this study is to construct financial condition indexes for other Asian countries.

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