Leading Indicators of Hong Kong Economic Output

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Executive Summary

- This paper evaluates 3 approaches of Composite Leading Indicator (CLI) compilation – the Conference Board (CB) style, the Common Factor approach (COM), and the Neural Network approach (NN). Performance of these CLIs are monitored from three perspectives – forecasting, dating of economic turning points and leading/tracking growth cycles.

- The typical use of CLIs is to assist turning point detection, and not forecasting *per se*. They offer clues on the momentum of the economy, but rarely do they provide a 1-to-1 correspondence to real GDP (RGDP) growth. We construct vector autoregression models that pool together RGDP and CLIs to do the forecasting we need. **In forecasting, the NN approach has an edge over the other two especially over long forecast horizons.**

- Based on the *ad hoc* 3-month rule, the NN approach manages to give timely warning signals in the sense that the first warning is issued on or before the peak of economic cycle. **The lead time of the warning depends on whether we are referring to the peak-trough phases or periods of successive negative annual growth. The lead time is at most 1-2 months for the former, but is significantly longer (6 months or more) for the latter**.

- **The growth cycles of RGDP and the CLIs also show that the NN approach yields the longest lead time of about 5-6 months. In practical terms, we have less time to prepare for a downturn because confirmation of the warning signals takes 3 months or longer (e.g. based on the 3-month rule), and this reduces the amount of time we can use to pre-empt a recession**.

1. Introduction

This paper considers the functionality of various composite leading indicators (CLI) and the prospect of applying them in predicting economic upturns and downturns in Hong Kong. The methodologies surveyed are the OECD/Conference Board approach (CB), the Common Factor approach (COM) and the Neural Network approach (NN). The compilation procedures are documented and the potential component variables are screened and reported.

2. Candidate Economic Variables

There is a total of 21economic indicators (the components), details of which are stated in Table 1. With the exception of gross domestic fixed capital formation (GDFCF) and inventory, all variables are available on a monthly basis. The 2 quarterly components are disaggregated into monthly series, and, together with the rest, are subject to a seasonal adjustment[1] process.

Figure 1 shows the statistical properties of these variables. Specifically, the cross-correlations (middle row) and the dynamic correlations (bottom row) are plotted with the annual growth rates (annual changes for interest rates and inventory). For the cross-correlation plots, the ideal case is to have a lot of mass over the left hand side of point 0, so that the series is highly correlated with and leads real GDP (RGDP). The lead/lag figures in the last column of Table 1 correspond to the pinnacles (or troughs) of the correlograms.

The last row of Figure 1 contains diagrams of dynamic correlations[2], which are essentially correlations of two data series *at different frequencies*. In out context, it is preferable to have relatively more correlation between the 12mo (12 month) mark and the Inf (Infinity – very low frequency) mark. This is because correlations over higher (shorter) frequencies could owe to spurious elements like common seasonal factors. The largest dynamic correlations of the variables over all frequencies are stated in column three of Table 1.

It is not reasonable to expect all component series to exhibit leading property over RGDP. As long as they are not clear laggards to RGDP, they are included in the dataset. In fact, our exercise here includes all of the 21 variables in the compilation as the differences from leaving out a subset are negligible. The final sample runs from April, 1997 to September, 2010. With certain methodologies, like the COM, there are built-in procedures to extract the most informative contents from the components without creating concern about dimensionality.

[1] Interest rates, stock prices and foreign indicators are unadjusted.
[2] See Croux et al. (2001) for details.

Table 1: Properties of Selected Economic Variables

Variable	Code	Max Dynamic Correlation	RGDP Leads (+) /Lags (-)
1. GDFCF	GDFCF	0.7224	1
2. Hang Seng Index	Hang Seng	0.7991	-2
3. M3	M3	0.4240	-21
4. Retail Sales (Value)	Retail Sales Val.	0.8900	0
5. Retail Sales (Volume)	Retail Sales Vol.	0.9102	0
6. Electricity Consumption	Elect. Cons.	-0.2113	-11
7. Air Cargo	Air Cargo	0.8167	-1
8. S&P Agreements (No.)	S&P num.	0.4195	-3
9. S&P Agreements (Value)	S&P val.	0.5393	-2
10. Inbound Tourists	Inbound Tourists	0.5036	0
11. Retained Imports	Retained Imp. (R.I.)	0.8665	0
12. Retained Imports – Capital Goods	R.I. – Capital Gds.	0.7682	2
13. Retained Imports – Consumer Goods	R.I. – Consumer Gds.	0.7578	0
14. Exports to Mainland China	Exp. to China	0.8632	0
15. Total Loans	Loans	0.5628	4
16. Total Deposits	Deposits	0.3798	-20
17. Buildings with Consent to Commence Work – 8 qtr ma	Bldg. Consent – 8 qtr .m.a.	0.4082	6
18. US Orders PMI	US Order PMI	0.4183	10
19. Inventory	Inventory	0.5343	12
20. HIBOR 1 month – 12 month Spread	HIBOR 1/12 mo. Spread	-0.2755	-2
21. OECD Leading Indicator	OECD Leading Ind.	0.6088	11

Remarks:
1. Data deseasonalized and transformed into month on month % changes.
2. Dynamic correlations performed with annual growth rates.
3. Lead / Lags in months, with a minus sign indicating leading property for the variable concerned.

Figure 1: Time and Frequency Domain Properties of Selected Economic Variables

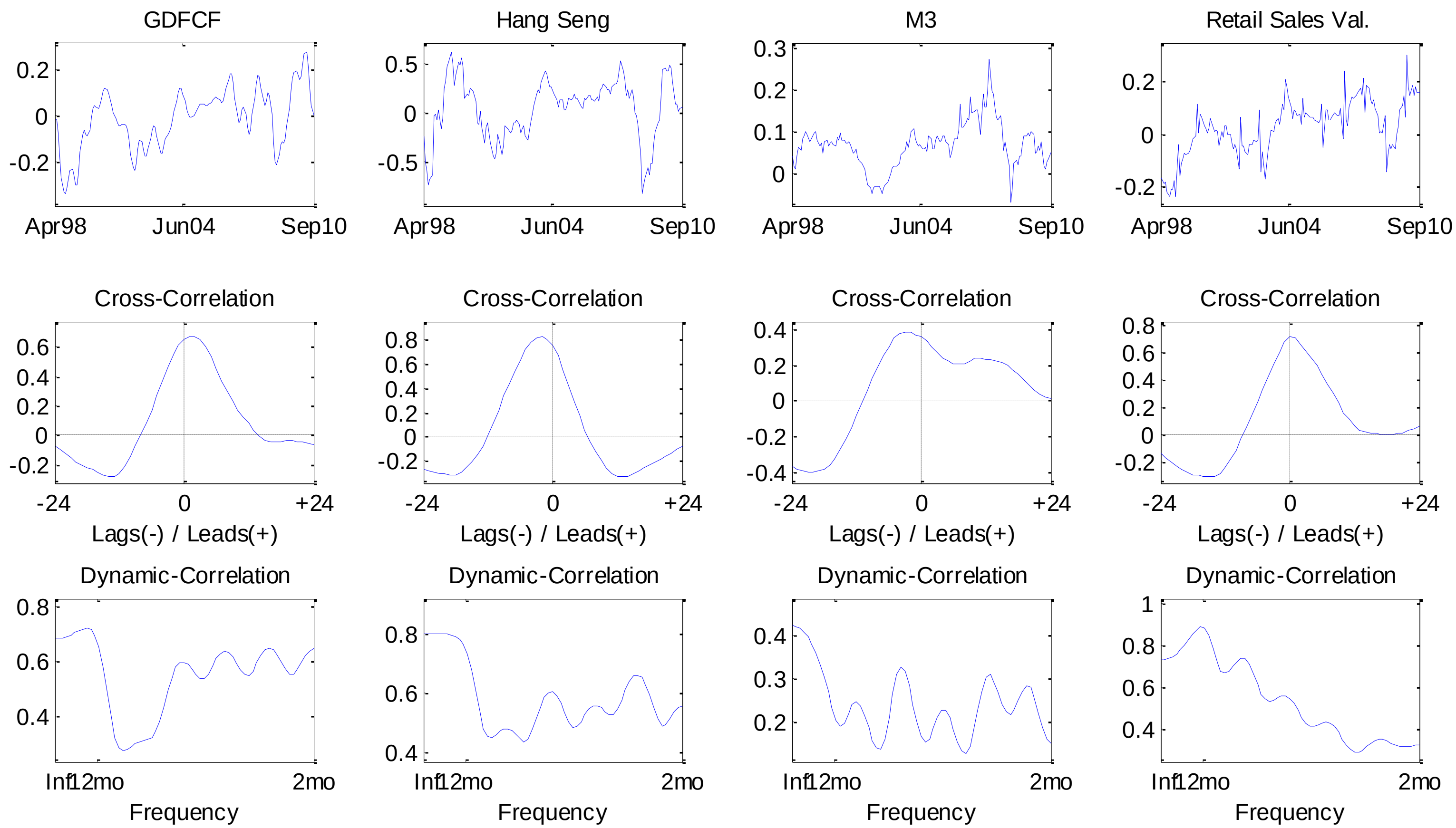
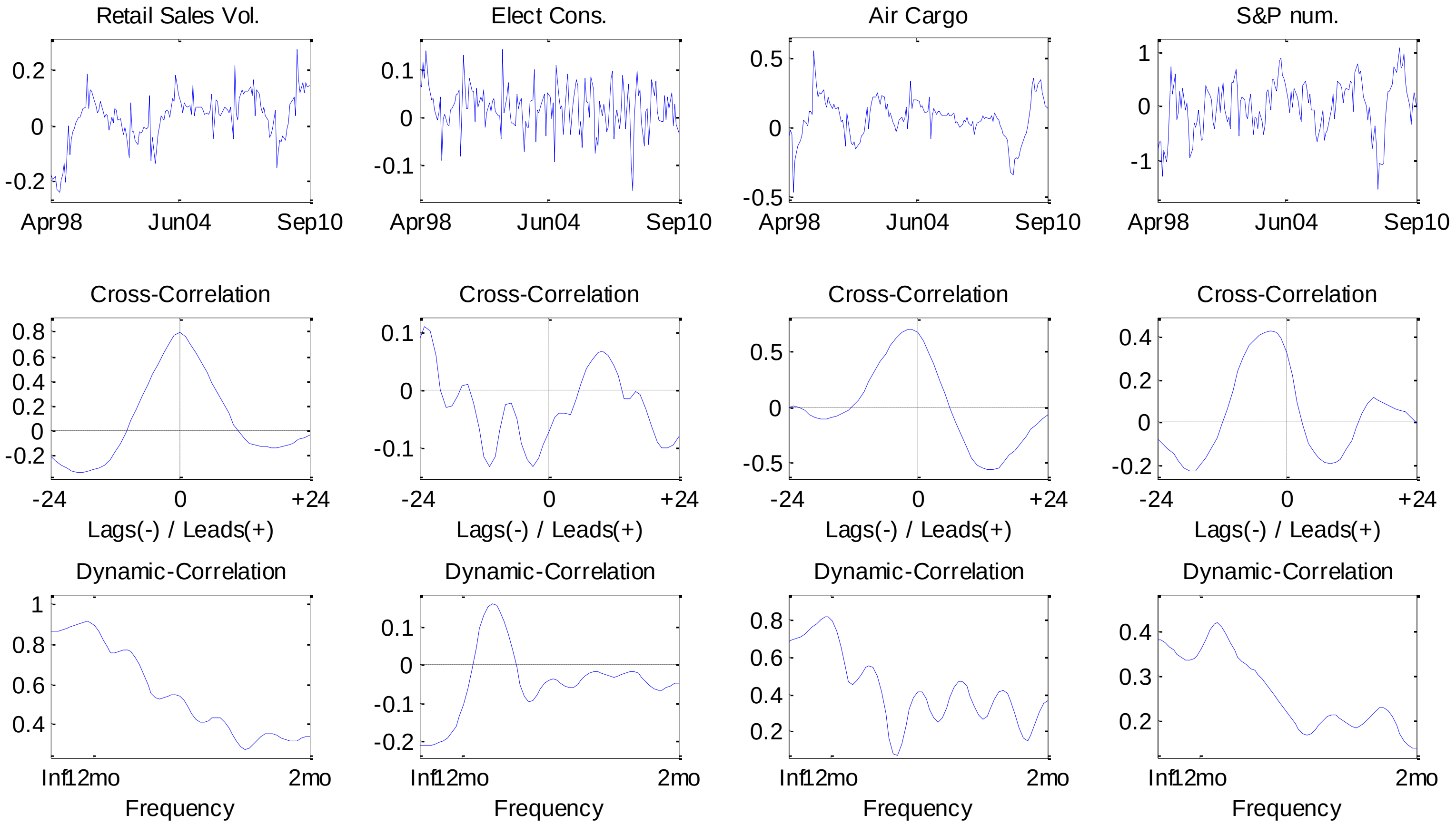


Figure 1: Cont'd



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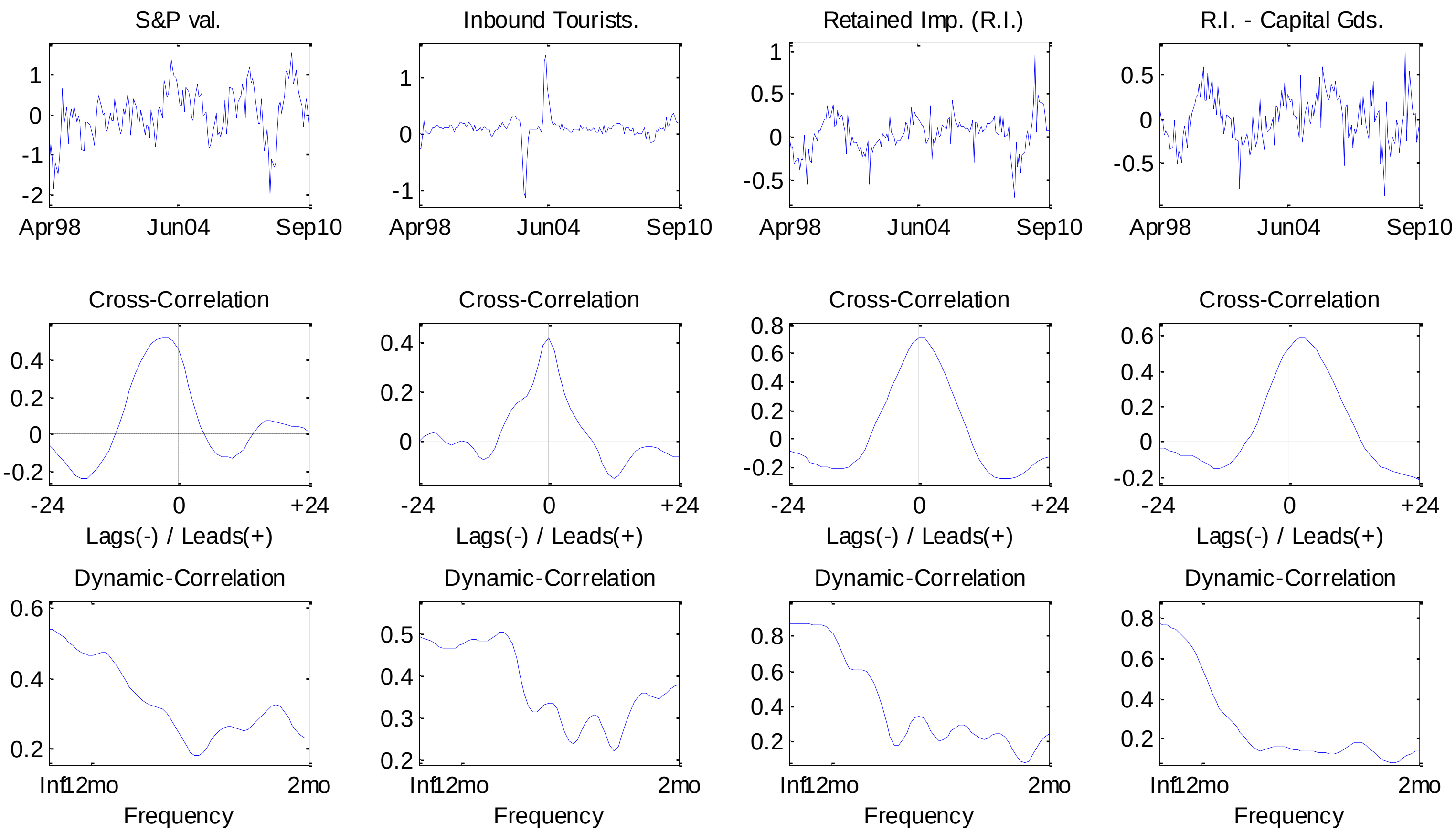

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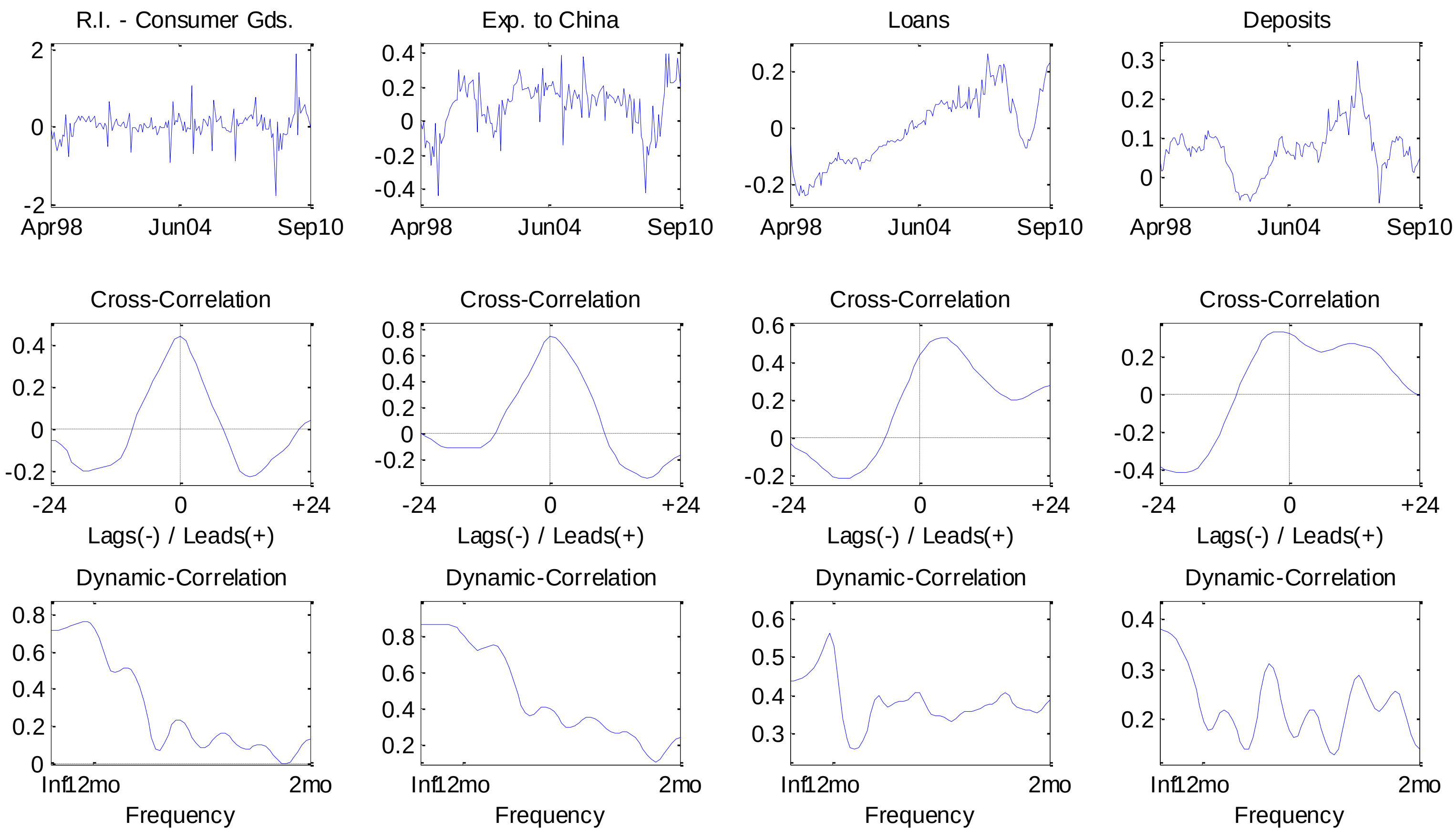

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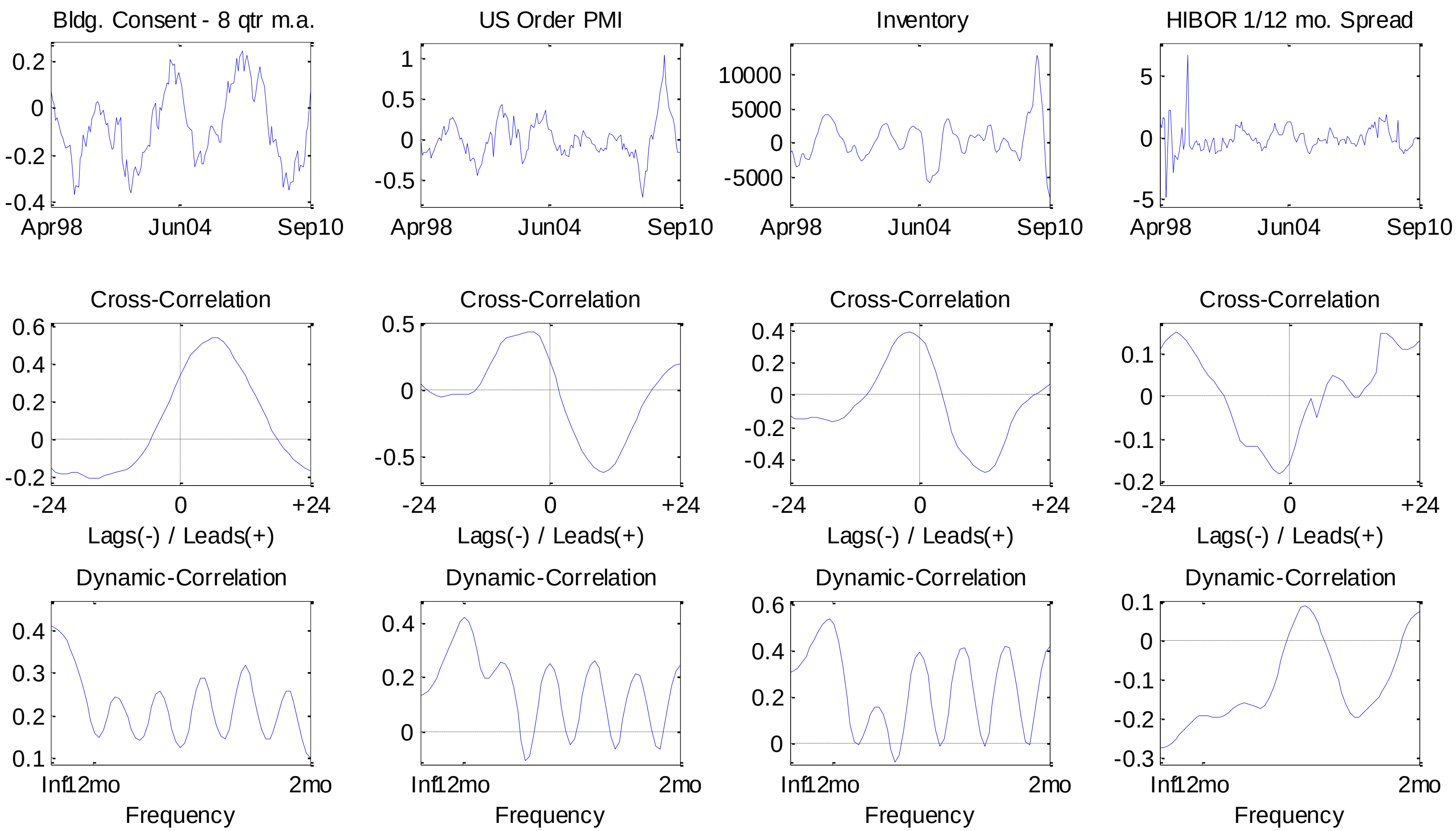

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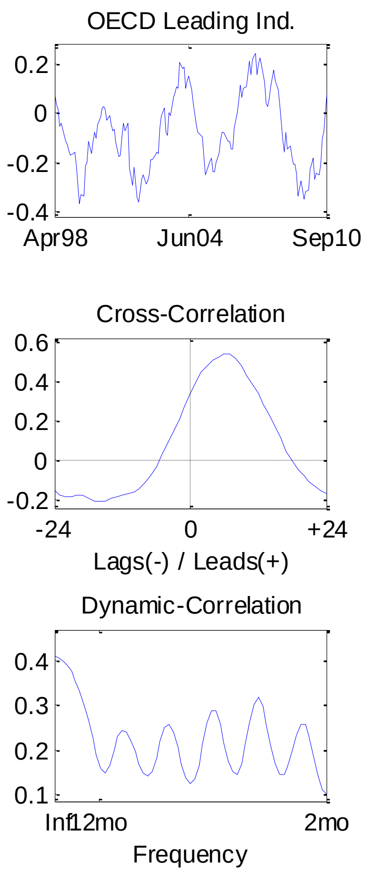


3. Compilation of CLI

We briefly recapitulate on the three approaches used to construct CLIs in this paper.

3.1 Conference Board/OECD type CLI

This approach is common among official government bureaus and quasi-governmental bodies. It requires relatively little statistical manipulation of the data, and the aggregation procedures are easy to implement. Denoting the CLI compiled via this approach by CLI-CB and the number of individual indicators by $N = 21$, the aggregation involves the following steps:

a) Convert the constituent indicators (components x_i) into month on month growth rates (and month on month changes for variables with negative values).
b) Assign to each component weights that are inversely proportional to their variances:
$$w_i = \left(\frac{1}{s_i}\right) / \sum_i \left(\frac{1}{s_i}\right)$$
where s_i is the standard deviation of x_i.
c) Work out the weighted sum of the components:
$$C_t = \sum_{i=1}^{N} w_i x_{it}.$$
d) Adjust the weighted sum to match the trend and amplitude of the (monthly growth rates of) RGDP:
$$\tilde{C}_t = \mu_{RGDP} + \frac{s_{RGDP}}{s_C}(C_t - \mu_C).$$
e) Convert the index back to levels:
$$(CLI\_CB)_t = (CLI\_CB)_{t-1} \frac{200 + \tilde{C}_t}{200 - \tilde{C}_t}.$$

So the CLI-CB is basically a fixed weight average of the underlying components.

3.2 Factor Based CLI

The second approach considered in this paper belongs to the class of Factor Models promulgated by Stock and Watson (1989). The idea is to decompose a set of variables into a sum of common component(s) and idiosyncratic components. Notationally, we can write:
$$x_{it} = \lambda'_i f_t + u_{it}$$

where λ_i is a k dimensional vector of factor loadings, f_t is a k dimensional vector of common factors, and u_{it} the idiosyncratic components. The product $\lambda'_i f_t$ is the common component – a linear combination of the common factors – and the dimension k is unknown. In fact, all items on the right hand side of the equation above are unknown which is what make the estimation complicated.

In our context, we restrict k to 1[3]. There are a few ways to solve for the common factor f_t, and the algorithm of Bai and Ng (2002) is used here. Like some other methods, this involves finding appropriate eigenvectors from the covariance matrix. The solution f_t is the set as CLI-COM. A small refinement adopted here is that a 3-month exponentially weighted moving average is applied to CLI-COM as the raw series shows a jagged surface.

3.3 Neural Network CLI

(Artificial) Neural network (ANN) is a data-mining technique which prides itself in the area of pattern recognition and forecasting. It mimics the structure of biological neural systems and processes information via a group of artificial neurons. Essentially, one can think of it as an input-output network with hidden layers of neurons that take on weighted sums of inputs. The ANN is "intelligent" in that it learns (or is trained to learn) from the errors between desired output and the computed output until an objective is achieved.

ANN is a viable option for the task at hand because of its good record in forecasting, and like CLI compilation, it concerns finding optimal input weights during the process. The model considered in this paper is a multi-layer feedforward ANN, reminiscent of the one of Qi (2001). It can be expressed as:

$$f(X) = g\left(\sum_{j=1}^{N_2} \beta_j \, g\left(\sum_{k=1}^{N_1} \alpha_{kj} \, x_k + \theta_j^1\right) + \theta_j^2\right).$$

Here, x_k are the inputs (the constituent indicators in our context) and $f(X)$ the output (the CLI). The function g is a logistic transfer function $g(z) = 1/(1 + e^{-z})$. In brief, the N_1 inputs are weighted by α_{kj}, aggregated into binary values by the logistic transfer function and corrected for the bias θ_j^1 before being fed to the N_2 neurons in the layer. The composite signal is then passed onto a layer with N_2 neurons where they are weighted by β_j, aggregated and corrected for bias θ_j^2 in a similar fashion.

[3] Setting k=1 is intuitively appealing as we need a CLI, and preliminary forecast exercises show that the forecast accuracy of CLI obtained this way by letting k to range from 1 to 4 does not vary much.

Figure 2: RGDP and Various CLIs

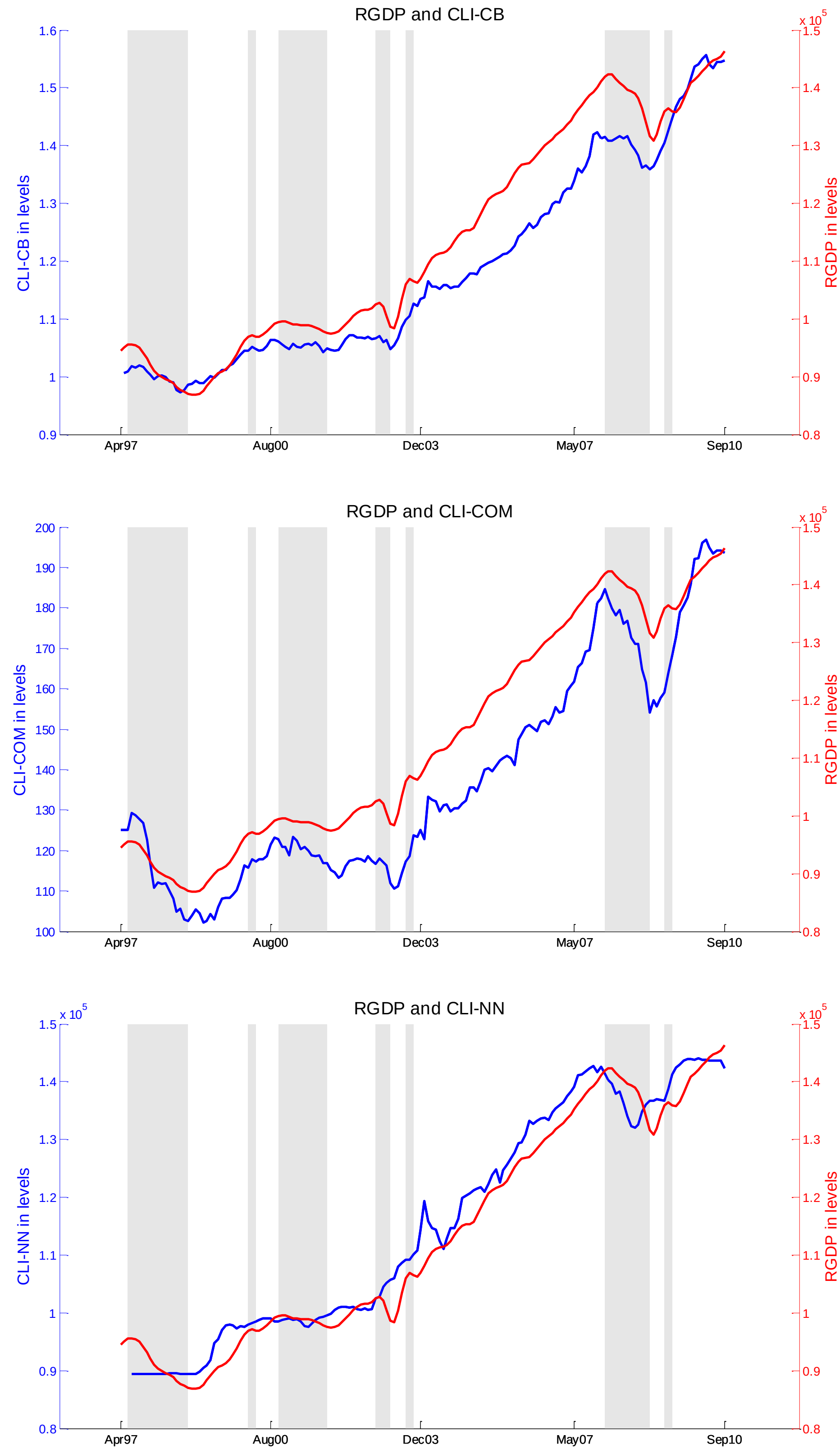


Figure 3: Growth Cycles of RGDP and CLIs

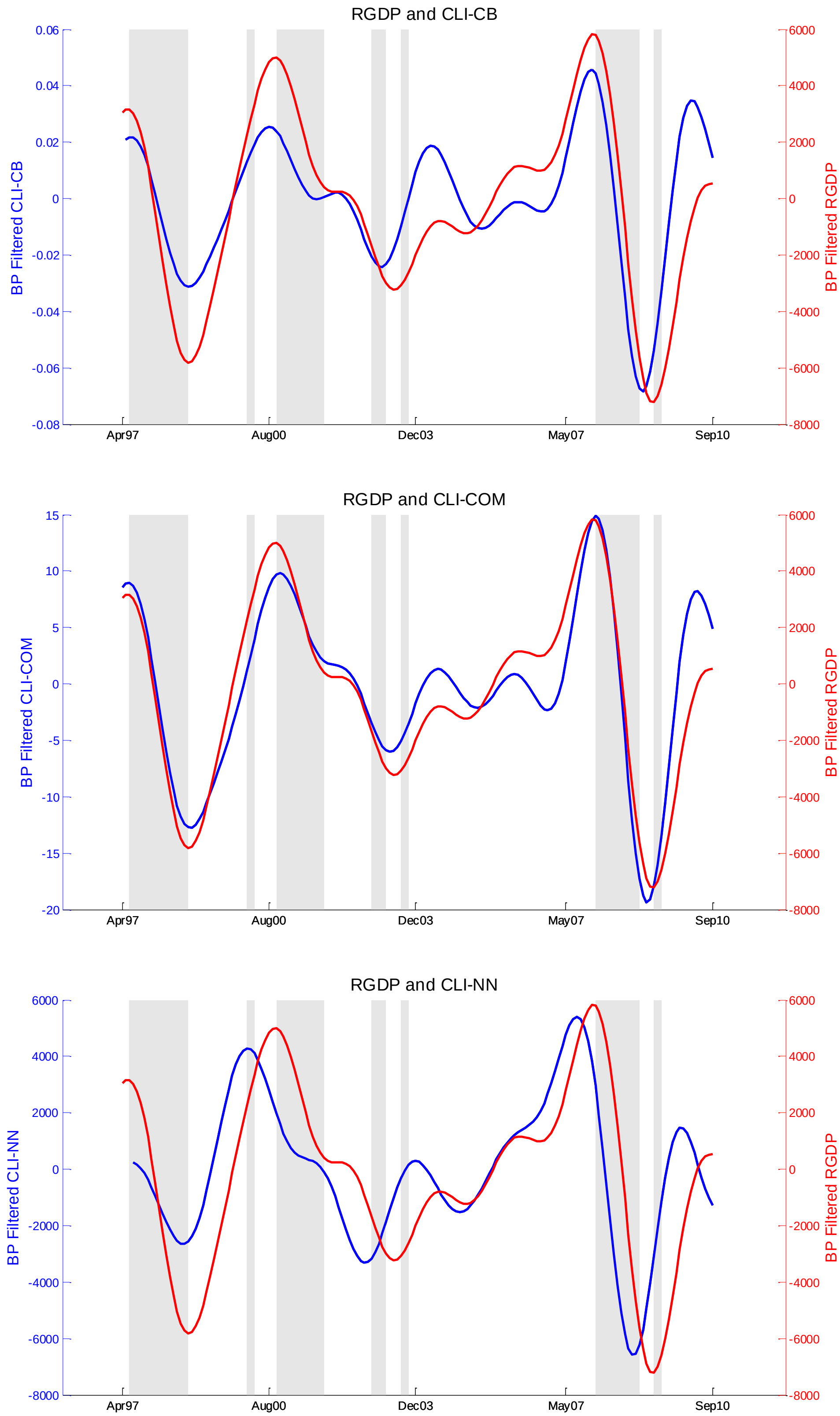
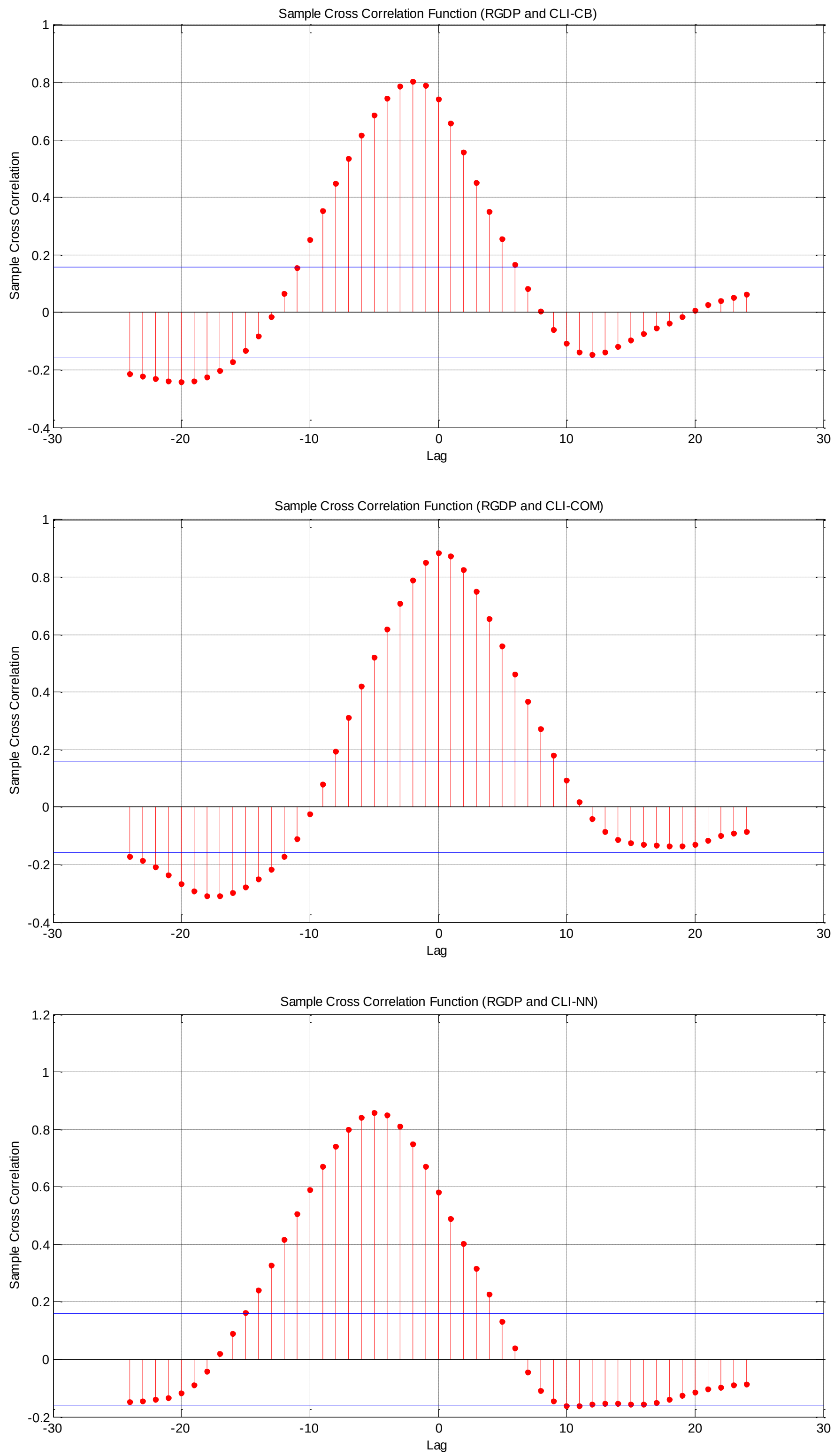


Figure 4: Cross Correlations of Annual Growth Rates of RGDP and CLIs



Once the structure is defined, an algorithm is programmed to "train" and validate the ANN. As in Qi's paper, the Levenberg-Marquardt algorithm[4] is used together with the criterion of minimizing mean squared errors. The parameters are set at: $N_1 = 21, N_2 = 4$. Unlike standard regression models, focus will not be on the interpretation of these interlocking weights, but on how well the generated output $f(X)$ matches the reference series y. The CLI obtained from this approach is denoted CLI-NN.

A major difference between the neural network CLI here and Qi's is that we attempt to match $f(X_{t-6})$ to y_t instead of matching contemporary values. In a way, we use brute force to amplify any leading property the *X*s may have. As in the case of the common factor approach, a 3-month exponentially weighted moving average is applied to CLI-NN before use. Figure 2 illustrates the resulting CLIs as compared to RGDP.

4. Performance Evaluation

4.1 Forecast Accuracy

As mentioned in the previous paper, forecasting is not the prime objective of constructing leading indicators. The methods discussed above do not guarantee the magnitudes or the shapes of the CLIs to resemble those of RGDP. Typically, it is the month-on-month changes or annual growth rates of the CLIs that shed light on the pulse of the economy. So functionally, it serves pretty much like a diffusion index.

If a forecast is what one desires, an extra model has to be devised to serve the purpose. We use a simple VAR(6) here, i.e., the vector of RGDP and CLI is regressed on it own lag values. Forecast performance is measured and compared using the Theil's U statistic which is the ratio of root mean square forecast errors of a certain model to that of a benchmark forecast. This measure is commonly adopted for forecasting exercises, and has the advantage of being a unit-free indicator that facilitates comparison of forecasts defined in different scales. Specifically,

$$U = \sqrt{\frac{1}{T-T_0}\sum_{t=T_0}^{T}\left(y_{t+h} - \hat{y}_{t,h}\right)^2} \Bigg/ \sqrt{\frac{1}{T-T_0}\sum_{t=T_0}^{T}\left(y_{t+h} - b_{t,h}\right)^2},$$

where T is the full sample size, T_0 the first out of sample observation, *h* the forecast horizon (e.g. 1-step ahead), *y* the actual value of the forecast subject in the out-sample, $\hat{y}$ the forecast value, and *b* the predicted value of the subject using a benchmark method.

[4] This is a hybrid form of optimization technique which interpolates between the Gauss-Newton and the gradient descent methods.

Obviously, if $U < 1$ the particular model beats the benchmark, and the opposite is true for $U > 1$. In this paper, the benchmark model is an order-6 univariate autoregression. Table 2 stipulates the values of the Theil's Us.

Among the three approaches, the NN based leading indicator generates the most accurate predictions over medium to long hauls. The OECD approach ranks second, and the common factor approach last. From a forecasting perspective, however, none of these three approaches deliver CLIs that can edge past simple univariate AR forecasting.

Table 2: Theil's U statistics of various CLIs

Models / Horizons	CLI-CB	CLI-COM	CLI-NN
1	1.1295	1.1097	1.0407
2	1.1556	1.2023	1.1260
3	1.1073	1.2067	1.1114
4	1.0536	1.1785	1.0540
5	1.0036	1.2042	0.9930
6	0.9552	1.3284	0.9667

4.2 Turning Point Analysis with *Ad Hoc* Rules

A crucial function of leading indicators is to detect turning points of economic activities. There are *ad hoc* detection methods as well as model-based detection methods that serve this purpose. We present below observations from some of these assessments. The reference contraction periods are derived from the Harding-Pagan (2002) algorithm using deseasonalized and disaggregated RGDP. Table 3 shows the peaks (red) and troughs (blue) of these cycles and the performance of the three CLIs using two *ad hoc* rules. The first is a conventional three month rule – 3 consecutive monthly declines in the CLI signify an economic downturn. The other is a 4/7 rule – 4 monthly declines in the past 7 months. This latter rule allows the screening out of false signals popped up at times.

In the table, a '1' in the column marked "recessions (Harding-Pagan)" signifies a slowdown after hitting a peak, and a '0' indicates periods of up-trends. For columns corresponding to the 3-month rule, a '1' marks a negative monthly change in the CLI and a '0' the otherwise. Finally, the column corresponding to the 4/7 rule shows the total number of negative monthly changes for the CLI concerned from time t to time t-6. So, a value smaller than 4 does not warrant concern. A string of numbers with values 4 or larger indicates an economic downturn.

Table 3: Turning Points Predictions of various CLIs using Ad Hoc Rules

		RGDP	RGDP Annual Chg %	Recession (Harding-Pagan)	CLI_CB (3 mo rule)	CLI_CB (4/7 rule)	CLI_COM (3 mo rule)	CLI_COM (4/7 rule)	CLI_NN (3 mo rule)	CLI_NN (4/7 rule)
1997	4	94508.47		0						
	5	95052.24		0	0		0		0	
	6	95504.79		0	0		0		0	
	7	95600.01		0	0		0		1	
	8	95433.89		1	1		1		1	
	9	94985.50		1	0		1		1	
	10	94117.09		1	1		1		1	
	11	93110.56		1	1	3	1	4	1	5
	12	92093.65		1	1	4	1	5	1	6
1998	1	91040.33		1	1	5	1	6	0	6
	2	90294.89		1	0	5	0	6	1	6
	3	89896.28		1	0	4	1	6	0	5
	4	89578.65	-5.22	1	1	5	0	5	1	5
	5	89280.40	-6.07	1	1	5	1	5	1	5
	6	88895.95	-6.92	1	1	5	1	5	1	5
	7	88276.29	-7.66	1	1	5	1	5	1	5
	8	87731.44	-8.07	1	1	5	0	4	1	6
	9	87351.57	-8.04	1	0	5	1	5	0	5
	10	87007.32	-7.55	1	0	5	1	5	0	5
	11	86843.85	-6.73	1	0	4	0	5	0	4
	12	86882.24	-5.66	0	0	3	0	4	0	3
1999	1	87019.54	-4.42	0	1	3	1	4	0	2
	2	87517.64	-3.08	0	0	2	1	4	0	1
	3	88352.11	-1.72	0	0	1	0	4	0	0
	4	89212.01	-0.41	0	0	1	0	3	0	0
	5	89992.38	0.80	0	1	2	1	3	0	0
	6	90588.21	1.90	0	0	2	0	3	0	0
	7	90893.84	2.97	0	0	2	0	3	0	0
	8	91308.19	4.08	0	0	1	0	2	0	0
	9	91975.77	5.29	0	0	1	0	1	0	0
	10	92785.87	6.64	0	0	1	0	1	0	0
	11	93885.79	8.11	0	0	1	0	1	0	0
	12	95153.34	9.52	0	0	0	0	0	0	0
2000	1	96195.90	10.55	0	0	0	0	0	0	0
	2	96877.89	10.70	0	1	1	1	1	0	0
	3	97129.91	9.94	0	0	1	0	1	1	1
	4	96947.84	8.67	1	1	2	1	2	0	1
	5	96936.02	7.72	1	1	3	0	2	0	1
	6	97299.94	7.41	0	0	3	0	2	0	1
	7	97845.41	7.65	0	0	3	0	2	0	1

	8	98523.72	7.90	0	0	3	0	2	0	1
	9	99165.57	7.82	0	0	2	0	1	0	1
	10	99480.36	7.21	0	**1**	3	**1**	2	0	0
	11	**99609.73**	6.10	0	**1**	3	**1**	2	**1**	1
	12	99575.61	4.65	**1**	**1**	3	**1**	3	**1**	2
2001	1	99279.75	3.21	**1**	**1**	**4**	**1**	**4**	**1**	3
	2	99063.30	2.26	**1**	0	**4**	0	**4**	0	3
	3	99004.25	1.93	**1**	1	**5**	1	**5**	1	**4**
	4	98917.15	2.03	**1**	1	**6**	1	**6**	0	**4**
	5	98910.41	2.04	**1**	0	**5**	0	**5**	1	**5**
	6	98923.44	1.67	**1**	0	**4**	**1**	**5**	1	**5**
	7	98726.55	0.90	**1**	1	**4**	**1**	**5**	0	**4**
	8	98477.18	**-0.05**	**1**	0	3	**1**	**5**	1	**4**
	9	98196.77	**-0.98**	**1**	1	**4**	0	**5**	1	**5**
	10	97770.69	**-1.72**	**1**	1	**4**	1	**5**	0	**4**
	11	97501.96	**-2.12**	**1**	0	3	0	**4**	0	**4**
	12	**97469.25**	**-2.12**	**1**	1	**4**	**1**	**5**	0	3
2002	1	97526.74	**-1.77**	0	1	**5**	**1**	**5**	0	2
	2	97852.90	**-1.22**	0	0	**4**	**1**	**5**	0	2
	3	98424.85	**-0.59**	0	0	**4**	0	**4**	0	1
	4	99018.24	0.10	0	0	3	0	**4**	0	0
	5	99757.86	0.86	0	0	2	0	3	0	0
	6	100553.20	1.65	0	1	3	0	3	0	0
	7	101098.21	2.40	0	1	3	0	2	0	0
	8	101432.16	3.00	0	0	2	1	2	0	0
	9	101575.24	3.44	0	1	3	1	2	0	0
	10	101528.18	3.84	0	0	3	0	2	0	0
	11	101842.03	4.45	0	1	**4**	1	3	0	0
	12	102475.69	5.14	0	0	**4**	1	**4**	0	0
2003	1	**102795.52**	5.40	0	0	3	0	**4**	0	0
	2	102148.18	4.39	**1**	1	3	**1**	**5**	0	0
	3	100546.70	2.16	**1**	0	3	**1**	**5**	0	0
	4	98669.84	**-0.35**	**1**	1	3	**1**	**5**	0	0
	5	**98434.21**	**-1.33**	**1**	0	3	**1**	**6**	0	0
	6	100331.45	**-0.22**	0	0	2	0	**5**	0	0
	7	103427.42	2.30	0	0	2	0	**4**	0	0
	8	105919.09	4.42	0	0	2	0	**4**	0	0
	9	106935.19	5.28	0	0	1	0	3	0	0
	10	106535.27	4.93	**1**	0	1	0	2	0	0
	11	106301.68	4.38	**1**	1	1	1	2	0	0
	12	106916.95	4.33	0	0	1	0	1	0	0
2004	1	108162.67	5.22	0	0	1	1	2	0	0
	2	109517.83	7.21	0	0	1	0	2	0	0
	3	110569.70	9.97	0	1	2	**1**	3	0	0
	4	111012.58	12.51	0	0	2	**1**	**4**	0	0

	5	111261.98	13.03	0	1	3	1	5	0	0
	6	111518.64	11.15	0	0	2	0	4	0	0
	7	111767.22	8.06	0	1	3	0	4	0	0
	8	112400.87	6.12	0	1	4	1	4	0	0
	9	113403.11	6.05	0	0	4	0	4	0	0
	10	114346.59	7.33	0	0	3	1	4	0	0
	11	115024.60	8.21	0	0	3	0	3	0	0
	12	115342.81	7.88	0	0	2	0	2	0	0
2005	1	115317.87	6.62	0	0	2	0	2	0	0
	2	115722.41	5.67	0	0	1	1	3	0	0
	3	116769.72	5.61	0	1	1	1	3	1	1
	4	118112.34	6.40	0	0	1	0	3	0	1
	5	119492.85	7.40	0	0	1	0	2	0	1
	6	120628.91	8.17	0	0	1	0	2	0	1
	7	121211.86	8.45	0	0	1	1	3	0	1
	8	121576.98	8.16	0	0	1	0	3	0	1
	9	121888.47	7.48	0	0	1	0	2	0	1
	10	122138.03	6.81	0	0	0	0	1	1	1
	11	122827.25	6.78	0	0	0	0	1	0	1
	12	123983.02	7.49	0	0	0	1	2	0	1
2006	1	125156.25	8.53	0	0	0	1	3	0	1
	2	126112.17	8.98	0	0	0	0	2	1	2
	3	126681.18	8.49	0	0	0	0	2	0	2
	4	126757.56	7.32	0	0	0	0	2	0	2
	5	127006.61	6.29	0	0	0	0	2	0	1
	6	127632.94	5.81	0	1	1	1	3	0	1
	7	128379.07	5.91	0	0	1	1	3	0	1
	8	129239.19	6.30	0	0	1	0	2	0	1
	9	130073.63	6.72	0	0	1	0	2	1	1
	10	130607.55	6.93	0	0	1	1	3	0	1
	11	131156.49	6.78	0	0	1	0	3	0	1
	12	131775.75	6.29	0	0	1	0	3	0	1
2007	1	132259.09	5.68	0	1	1	1	3	0	1
	2	132875.33	5.36	0	0	1	0	2	0	1
	3	133642.18	5.49	0	0	1	0	2	0	1
	4	134325.09	5.97	0	0	1	0	2	0	0
	5	135183.69	6.44	0	0	1	0	1	0	0
	6	136191.11	6.71	0	0	1	0	1	0	0
	7	137032.92	6.74	0	1	2	0	1	0	0
	8	137866.79	6.68	0	0	1	0	0	0	0
	9	138678.99	6.62	0	0	1	0	0	0	0
	10	139283.62	6.64	0	0	1	0	0	0	0
	11	140097.30	6.82	0	0	1	0	0	1	1
	12	141106.48	7.08	0	1	2	0	0	0	1
2008	1	141867.01	7.26	0	0	2	0	0	1	2

	2	142292.20	7.09	0	1	2	1	1	1	3
	3	142253.19	6.44	1	1	3	1	2	1	4
	4	141579.00	5.40	1	0	3	1	3	1	5
	5	140856.05	4.20	1	0	3	0	3	1	6
	6	140289.85	3.01	1	1	4	1	4	1	6
	7	139705.34	1.95	1	0	3	0	4	1	7
	8	139339.95	1.07	1	1	4	1	5	1	7
	9	139011.21	0.24	1	1	4	1	5	1	7
	10	138117.37	-0.84	1	1	4	1	5	0	6
	11	136421.80	-2.62	1	1	5	1	5	0	5
	12	134077.92	-4.98	1	0	5	1	6	0	4
2009	1	131629.75	-7.22	1	1	5	1	6	1	4
	2	130778.45	-8.09	1	0	5	0	6	0	3
	3	131913.60	-7.27	0	0	4	1	6	0	2
	4	134113.32	-5.27	0	0	3	0	5	0	1
	5	135883.44	-3.53	0	0	2	0	4	0	1
	6	136487.74	-2.71	0	0	1	0	3	0	1
	7	135947.23	-2.69	1	0	1	0	2	0	1
	8	135801.15	-2.54	1	0	0	0	1	0	0
	9	136638.82	-1.71	0	0	0	0	1	0	0
	10	138097.71	-0.01	0	0	0	0	0	0	0
	11	139626.76	2.35	0	0	0	0	0	1	1
	12	140815.73	5.03	0	0	0	0	0	0	1
2010	1	141391.90	7.42	0	0	0	0	0	0	1
	2	142000.79	8.58	0	0	0	0	0	0	1
	3	142818.41	8.27	0	0	0	0	0	0	1
	4	143546.24	7.03	0	0	0	0	0	0	1
	5	144204.76	6.12	0	1	1	1	1	0	1
	6	144727.30	6.04	0	1	2	1	2	1	1
	7	144953.43	6.62	0	0	2	0	2	0	1
	8	145432.68	7.09	0	0	2	0	2	0	1
	9	146266.48	7.05	0	0	2	1	3	0	1

Of the three CLIs, the CLI-NN exhibits the earliest lead time in generating warning signals overall. It also has the least false signals, but unfortunately, it also missed the mild recession in the SARS period. In those cases when it gives out correct warnings, the signals start either on or before the peak dates[5]. There is much less consistency in the signals generated by the other CLIs as far as the 3-month rule is concerned. Regarding the 4/7 rule, the performances are mixed for the 3 CLIs with no clear winners.

[5] However, according to the 3-month rule, we still need 3 months after the start date to confirm the warning.

If the focus is on detecting back-to-back falls in RGDP growth, all 3 CLIs did reasonably well as there is sufficient lead time between the signal date and the first date of recording negative growth. This is true whether one refers to the 3-month rule of the 4/7 rule.

4.3 Growth Cycle Prediction

This subsection compares the growth cycles implied by the various CLIs and those of RGDP. Growth cycles are deviations from long term growth trend, and are used to measure the momentum of the underlying economy[6]. For leading indicators, it would be most ideal to have procyclical movements between these cycles and those of the reference series, and with a lead time. Figure 3 plots the growth cycles of CLIs and RGDP. They are derived using the bandpass filter, see Christiano and Fitzgerald (2003), tuned to shut down signals of frequency less than 18 months and more than 96 months.

The filtered RGDP is marked in red in these diagrams. It can be seen that there were three peaks in these growth cycles – in mid 1997, in the second half of 2000 and 2007. The growth cycles of all three CLIs have the up- and down-swings largely matched with those of RGDP. However, only CLI-NN shows a clear lead over the RGDP cycle. The same conclusion can be drawn from Figure 4 where the cross-correlations of annual growth rates of RGDP and the CLIs are plotted. Again, CLI-NN has a lead of 5-6 months in growth rate terms over the RGDP. It should be noted that not all these lead time can be exploited as we need 3 months to confirm a signal.

4.4 Forecast for upcoming 6 months

We wrap up the discussion by showing the bottom-line predictions based on the 3 CLIs. Table 4 shows the year on year growth rates of RGDP for 2010:Q4 which is the first upcoming quarter from the end of our sample (Sept, 2010).

Table 4: Predictions of CLIs on economic growth one quarter ahead

Models Horizons (Quarter)	CLI-CB	CLI-COM	CLI-NN	Actual (1st release in Feb 2011)
2010-Q4	6.14%	5.25%	5.95%	6.60%

[6] These may or may not perfectly coincide with actual cycles.

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