The Prospects for a Turnaround in Retail Sales

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1. Introduction

1.1. It is common knowledge that Hong Kong's retail sales and private consumption expenditure are highly synchronized. Since the latter takes up a large share of Gross Domestic Product, being able to extract signals from retail sales would allow one to gain insights into the economic condition in advance. The retail performance in recent months has been quite sluggish and it would be of interest to find out if a turnaround is imminent. This paper considers the issue of identifying turning points – peaks and bottoms – in the retail sales figures and evaluates the prospects of their predictability.

1.2. We started with defining turning points and proceeded by reviewing a number of potential predictors. Their relevance is visually and statistically confirmed. This is followed by an evaluation of a few forecasting methods where the focus is placed on assessing the feasibility of implementation and reliability of the results. In general, methods that permit recursive prediction score higher in both respects. Our analysis predicts a continuation of the recent low growth pattern and the chance of a turnaround either way is not large.

2. Turning Points in Retail Sales

2.1. In the economics literature, attempts to identify turning points stemmed mostly from the need to distinguish expansionary and recessionary growth episodes. Common practices include: (i) following dates released by recognized institutions e.g. NBER, (ii) *ad hoc* rules like x consecutive periods of $+/-$ growth, and (iii) statistical identification schemes, see discussion in Pagan and Harding (2011).

Chart 1. Retail Sales – Growth in Value and Volume Similar

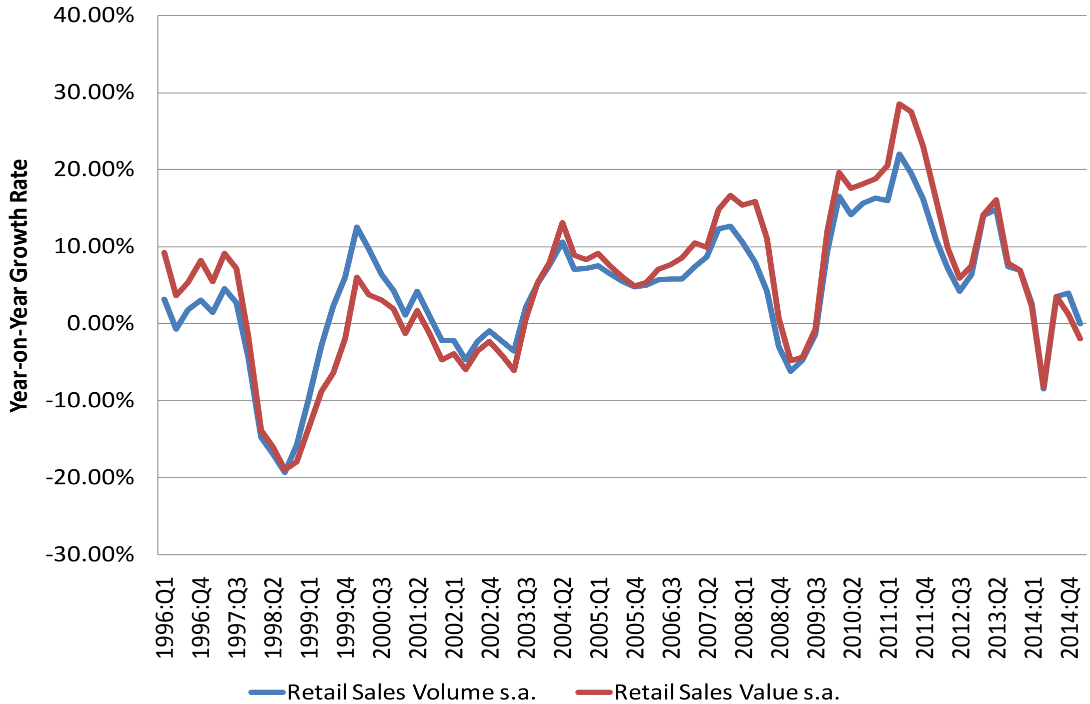
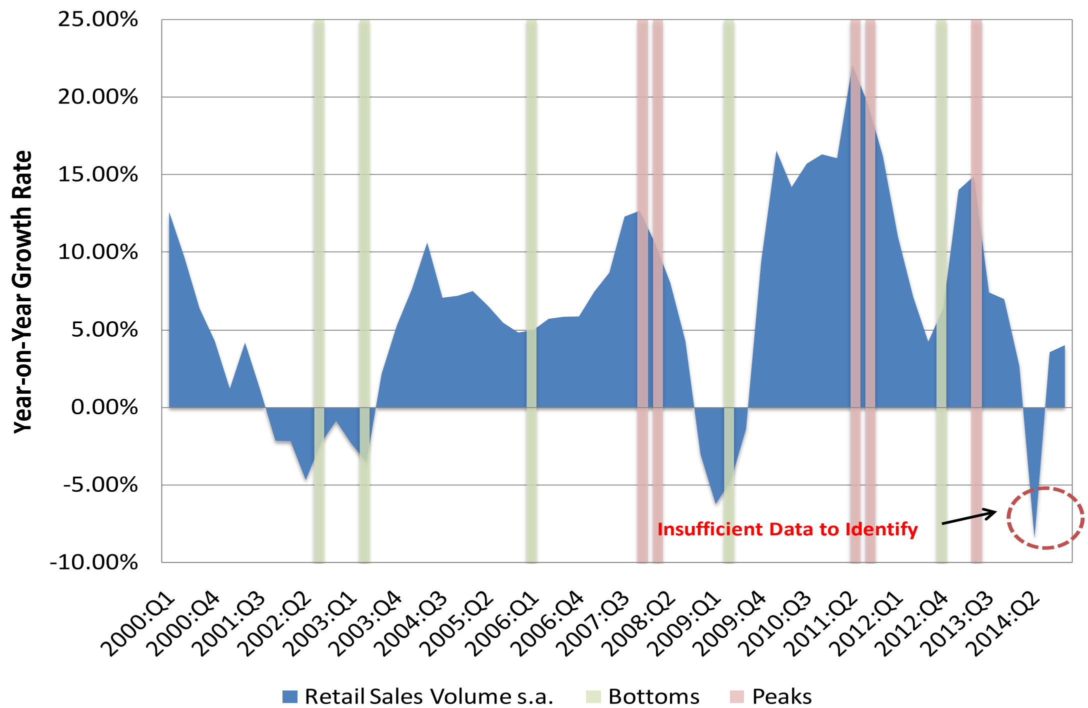


Chart 2. Identified Turning Points in Retail Sales



2.2. There is no authoritative identification rule and the reliability of a scheme depends on the particular data series being studied. Chart 1 shows the year on year growth in retail sales in value and in volume terms. The two are similar by nature, and the gap indicates the implicit retail price inflation. Note that we plotted the figures by quarters although the official statistics are released monthly. In our analysis, we allow real wage to play a part. Since the wage figures are reported only quarterly, a common frequency has to be chosen. We focus on the growth in seasonally adjusted retail sales volume in this paper.

2.3. Denote retail sales by RS. Our identifying schemes are symmetric to upturns and downturns. A period t is regarded as:

1) a peak if:
   - $RS_t > \sum_{i=1}^{4} RS_{t-i}/4$,
   - $\sum_{i=1}^{4} RS_{t-i}/4 > \sum_{i=1}^{4} RS_{t+i}/4$.

2) a bottom if:
   - $RS_t < \sum_{i=1}^{4} RS_{t-i}/4$,
   - $\sum_{i=1}^{4} RS_{t-i}/4 < \sum_{i=1}^{4} RS_{t+i}/4$.

2.4. Essentially, we compare the current value with the averages of past 4 quarters and those of the next 4 quarters. The 4-quarter window is obtained after various trials and this choice captures the major twists and turns in retail sales, see Chart 2. In the diagram, the dip observed in 2014:Q2 is unclassified because there is insufficient data to perform the assessment specified above (need data up to 2015:Q2 to assess).

2.5. Whichever method we use to forecast the turning points, it should be capable of detecting those points in advance. **Our evaluation criterion is therefore to check if a model manages to detect a turning point in the forthcoming 4 quarters**.

3. The Predictors

3.1. Next, we proceed to find the variables that could aid our modeling and forecasting of the turning points. Unlike trade figures, retail sales concern transactions of goods and services carried out within the geographical confines of Hong Kong. As a result, it seems that domestic factors are more relevant in explaining their changes. We resort to simple economic principles – consumption theory to be precise – to identify the crucial determinants. Employment, labor income and financial wealth are particular indigenous factors considered. Since Hong Kong is a world-renowned shopping center, including tourism related variables looks inevitable. We take into account also the amount of incoming tourists and their aggregate purchasing power, measured by the change in our trade-weighted effective exchange rate.

3.2. Many of the variables mentioned are measured in index form and their values are not economically meaningful *per se*. In addition, constant rebasing of the indices means that a larger sample can be obtained if we convert the figures into growth rate terms. We seasonally adjusted the raw data and calculated quarterly averages from monthly data before working out the growth rates.

3.3. Chart 3-7 compare retail sales growth with those of the explanatory variables. Chart 3 shows that peaks in retail sales growth lead the peaks in inflation by a few quarters. The price effect is thus not intact. Quite the contrary, it seems that declines in consumption leads to lower prices. Chart 4 indicates that employment growth and wage growth move largely in line with retail sales growth and is thus in support of the income effect. In Chart 5, we proxy wealth effect by the changes in stock prices as measured by the Hang Seng Index. Again, the correlation looks positive giving a correct sign for the wealth effect.

3.4. Chart 6 and 7 concern patrons from foreign countries. 6(a) shows the trends of all foreign and mainland visitors and 6(b) shows the data in growth rates. The co-trending (number of) all foreign and Chinese visitors means that including both in our exercise might contaminate the estimation, so we choose to work with total visitors and the share of Chinese visitors among all visitors.

Chart 3. Retail Sales and Inflation – Inflation Contemporarily and Positive Correlated with Retail Sales – Non-intuitive Price Effect

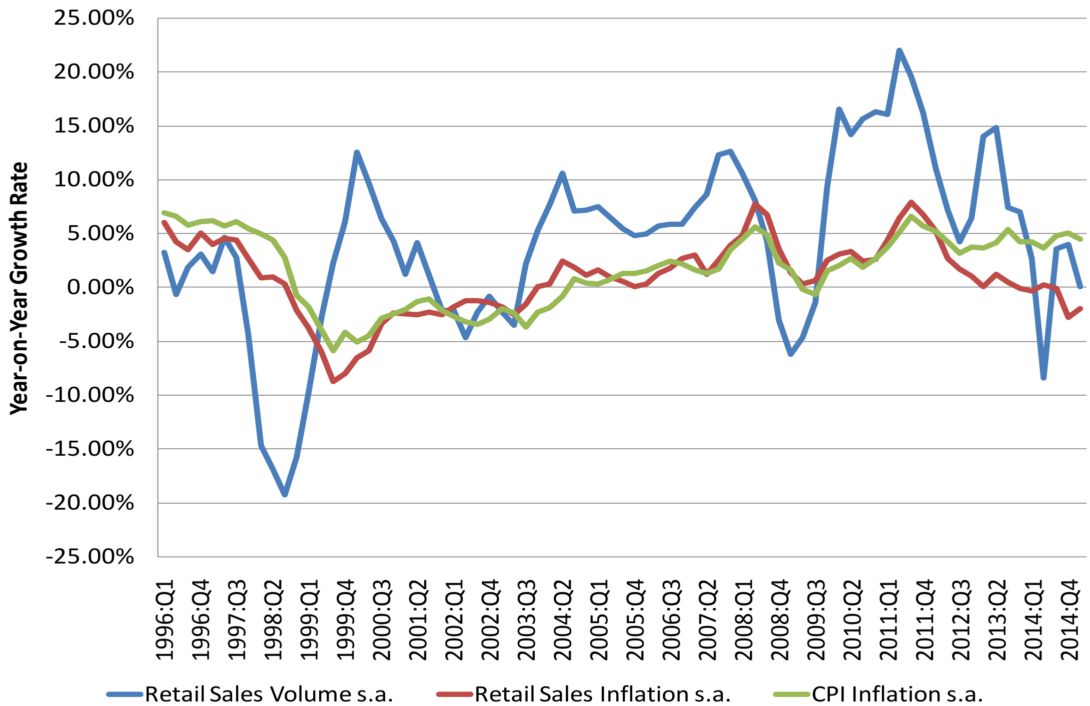


Chart 4. Retail Sales vs. Income Prospects – Seemingly Positive Income Effect

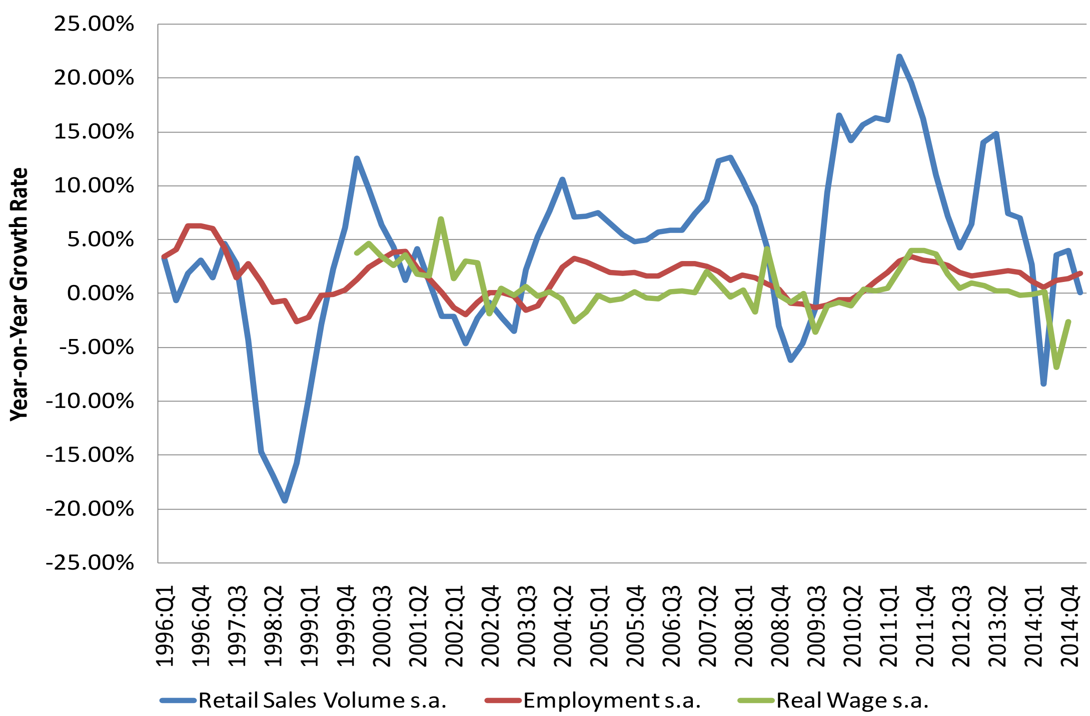


Chart 5. Retail Sales vs. Stock Market – Wealth Effects Seems to be Present

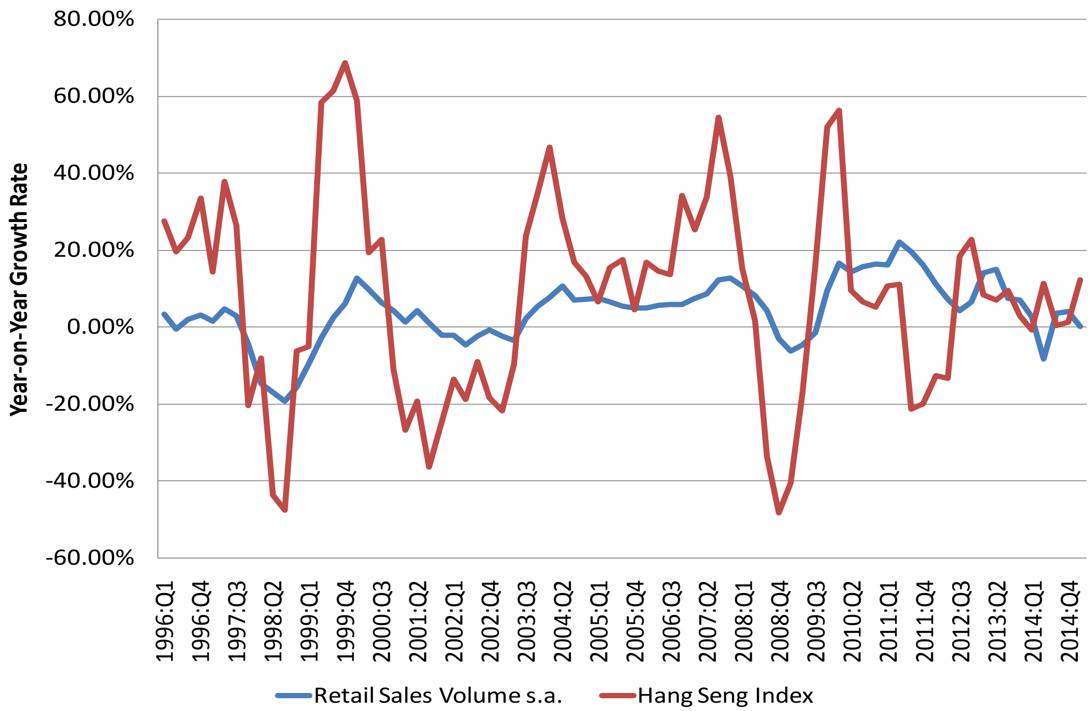


Chart 6(a). More Tourists and an Increasing Share of Mainland Visitors

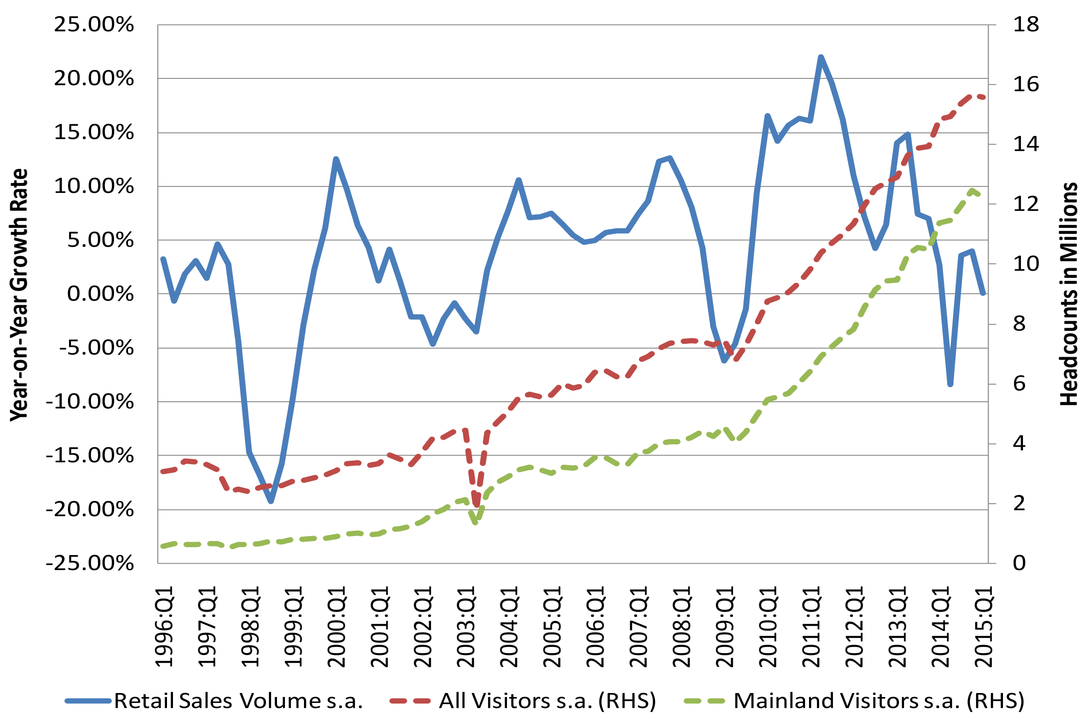


Chart 6(b). Foreign Visitors Not a Conspicuous Factor in Growth Rate Terms

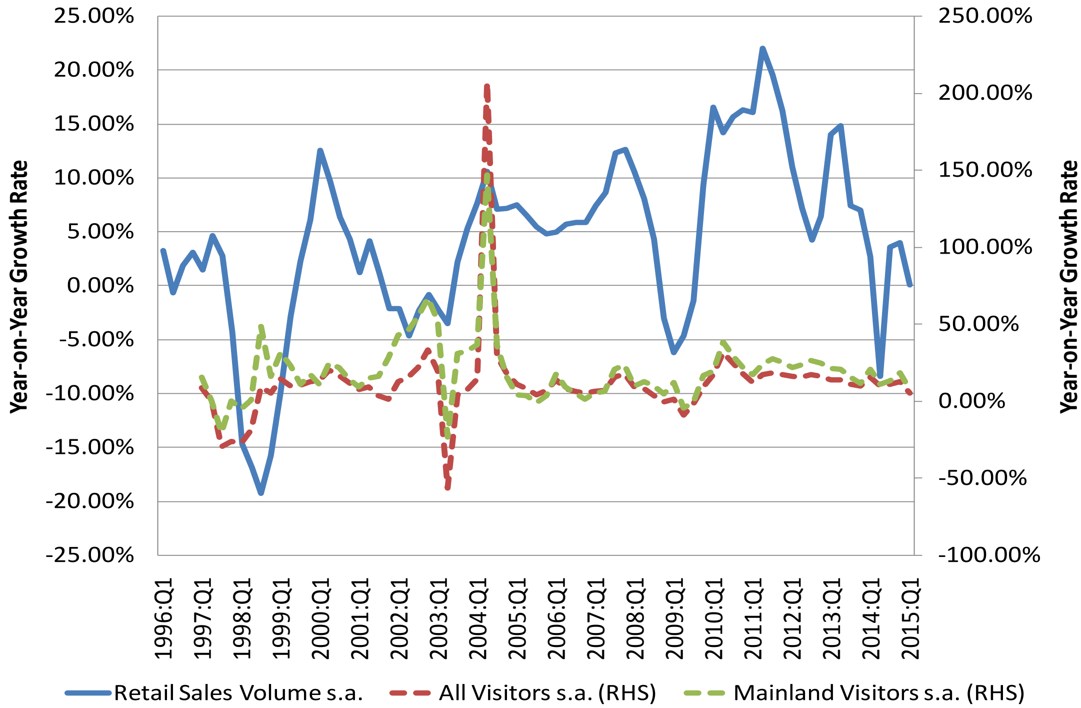
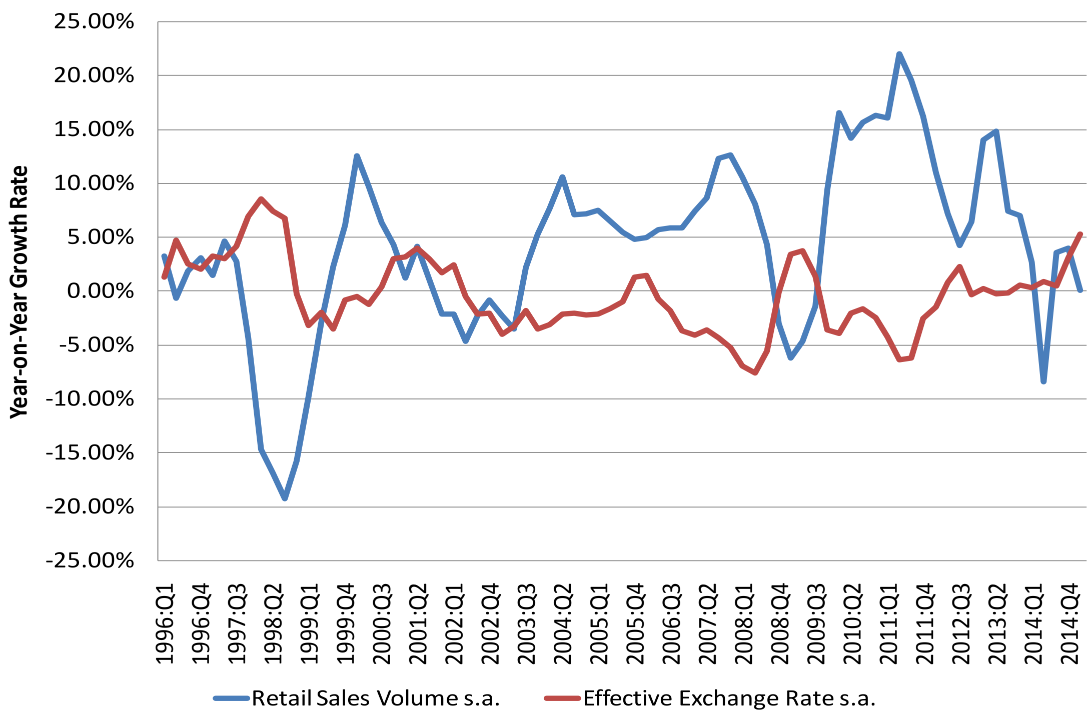


Chart 7. The Purchasing Power of Visitors Seems Crucial



3.5. Finally, Chart 7 shows a plainly negative correlation between the effective exchange rate and retail sales. A weakening HK Dollar favors retail sales while a strengthening HK Dollar serves to deter consumption by foreign visitors.

3.6. How exactly do these variables weigh in on our modeling of retail sales? To answer this, we run a simple regression of the form:

$$RS_t = \mathbf{X}_t\beta + \varepsilon_t \qquad (1)$$

where the matrix $\mathbf{X}$ contains the growth rates of employment, real wage, CPI, the effective exchange rate, total visitors, the Hang Seng Index and the share of Mainland visitors. No intercept is included as it makes little difference to the results obtained. From Table 1, we see that all factors are statistically significant by common standard except for the growth in total visitors which is marginally significant. The signs of the estimates are intuitive, barring that of inflation.

Table 1. Testing the Relevance of the Chosen Factors

Items	Estimates	Statistical Significance
Dependent Variable: Retail Sales Growth		
No. of Observations (quarters)	60	
R^2	0.633	
Independent Variables:		
(i) Employment Growth	1.126	Yes, 1%
(ii) Real Wage Growth	0.729	Yes, 1%
(iii) Exchange Rate Growth	−0.625	Yes, 1%
(iv) CPI Inflation	0.722	Yes, 1%
(v) Growth in Total Visitors	0.034	Yes, 10%
(vi) Share of Chinese Visitors	0.026	Yes, 5%
(vii) Growth in HSI	0.106	Yes, 1%

4. Are the Turning Points Predictable?

4.1. It seems that the variables in Table 1 are useful in general for predicting retail sales. The question is what forecasting model would best deal with the task. It is important to note that our objective is *not* to predict the "level" or the "growth rate" of retail sales, but rather the chance of an upturn or downturn in sales. While even simple regression models can take care of the former, we need methods that can convey probabilistic information in order to predict turning points.

4.2. It is well known that regression models are not good at predicting probabilities, not directly at least. Specifically, future values of the explanatory variables have to be ascertained *a priori*. Consider the simple example of predicting retail sales using model (1). To facilitate forecast, you need either of the following:

1) Explain RS_t by $\mathbf{X}_{t-1}$ so that the next period retail sales can be predicted using variables observed right now;

2) Explain RS_t by $\mathbf{X}_t$ and use other models to forecast $\mathbf{X}_{t+1}$ before running the regression and making the prediction.

4.3. Both options are not very applicable in our context. Option 1) can only predict 1-period (one quarter) ahead forecast $\widehat{RS}_{t+1}$, but we need the forecast values of the next 4 periods $\widehat{RS}_{t+1}, \cdots, \widehat{RS}_{t+4}$ to assess the chance of up/down-turns. If we arbitrarily lag the model by 4 quarters (using $\mathbf{X}_{t-4}$), we can arguably make forecasts up to 4-periods ahead but the model fit and predictability could deteriorate drastically by this *ad hoc* lag adjustment. Option 2) seems like a tautology. If there are remarkable ways to predict $\mathbf{X}_{t+1}$, these very methods may well be used to predict RS_{t+1} in the first place. We choose option 1) for our exercise.

4.4. A viable alternative is the probit/logit type models which explain *the odds of an event* using the explanatory variables. Since we differentiate between upturns, downturns, and other non turning point episodes, we have 3 categorical outcomes in this case, and we choose the *ordered probit model* as one of our benchmark:

$$
\begin{aligned}
Y_t^{RS} &= 1, \quad \text{if } t \rightarrow \text{peak within next 4 periods,} \\
Y_t^{RS} &= 2, \quad \text{if } t \rightarrow \text{bottom within next 4 periods,} \\
Y_t^{RS} &= 3, \quad \text{if } t \rightarrow \text{no turning points within next 4 periods,}
\end{aligned}
\tag{2}
$$

where Y_t^{RS} is a categorical variable describing the event associated with period t. The probabilities of occurrence of these events depend on some function of the predictors $\mathbf{X}_t$ [1]. The predicted outcomes of model (2) will be of the form $\mathrm{Prob}(Y_t^{RS} = y)$ with $y = 1,2,$ or 3 which can be interpreted in a straightforward manner.

4.5. The ordered probit model can make prediction of turning points in the forthcoming 4 quarters using current values of the explanatory variables. Any effort to forecast further from that point onwards, say $\widehat{\mathrm{Prob}}(Y_{t+k}^{RS})$ with $k > 4$, requires prior knowledge of $\mathbf{X}_{t+k}$ as would be the case in ordinary regression forecasts.

4.6. Our final benchmark model requires only information up to the present day but can generate forecasts $\widehat{RS}_{t+1}, \cdots, \widehat{RS}_{t+k}$ recursively, even for relatively large k. The problem mentioned in paragraph 4.3 is thus a non-issue. The model is a simple vector autoregression[2]:

$$\begin{bmatrix} RS_t \\ \mathbf{X}_t \end{bmatrix} = \sum_{i=1}^{3} A_i \begin{bmatrix} RS_{t-i} \\ \mathbf{X}_{t-i} \end{bmatrix} + \nu_t \,, \qquad (3)$$

where the square bracket vectorizes the variables inside. Estimation and forecasting of model (3) is somewhat standard.

4.7. The predicted values of (3) will be the *future values* of the variables concerned and we have to find a way to generate probabilistic forecasts of turning points. We take the estimate of the variance matrix of ν_t and do Monte Carlo simulations. These stochastic elements, when added to the unconditional mean predictions, provide multiple sets (1,000 in our exercise) of forecasts over the same future horizon (e.g. 4-periods ahead). We can then assess the counts of turning points realized from these many trials and use them to calculate empirical odds of turning point occurrence.

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[1] In a way, the model breaks down the cumulative normal distribution into a few parts separated by certain cut-off points. Each part or interval represents a different category. The functional aggregate of the predictors are then compared to these thresholds to see which interval a particular observation falls into and which event would be realized as a result.

[2] Since the variables RS and those in $\mathbf{X}$ are either growth rates or percentage points, we ignore the case of cointegration. In addition, the model is used to showcase how turning point forecasts can be made and it should not be regarded as the only way to deliver such kind of forecasts.

4.8. With the outputs of the three benchmark models – regression, ordered probit and vector autoregression – we evaluate their in-sample forecasting performance by checking the ability of predicting turning point occurrence at two different time instances in the sample. We also generate out-of-sample forecasts for the next 4 quarters using the last observations in our sample (2014:Q4). These are summarized in Table 2 below.

Table 2. Summary of Turning Point Forecasts

Date	Actual Retail Sales	Turning Points	Regression Model	Ordered Probit Model	Vector Autoregression
			In-sample Probabilistic Assessment		
Case 1: 2010:Q4					
2011:Q1	20.48%	-	N.A. Point estimate for 2011:Q1 only	Peak Prob. = 30.7% Bottom Prob. = 43.4%	Peak Prob. = 97.0% Bottom Prob. = 0.0%
2011:Q2	28.51%	peak			
2011:Q3	27.51%	peak			
2011:Q4	22.99%	-			
Case 1: 2012:Q4					
2013:Q1	14.08%	-	N.A. Point estimate for 2013:Q1 only	Peak Prob. = 47.8% Bottom Prob. = 35.5%	Peak Prob. = 0.0% Bottom Prob. = 64.5%
2013:Q2	16.09%	peak			
2013:Q3	7.88%	-			
2013:Q4	6.88%	-			
			Out-of-sample Probabilistic Assessment		
Last Observ.: 2014:Q4					
4 quarters in entire 2015	-	-	N.A. Point estimate for 2015:Q1 only	Peak Prob. = 13.6% Bottom Prob. = 26.6%	Peak Prob. = 0.4% Bottom Prob. = 0.0%

5. Interpreting the Results

5.1. As remarked earlier, simple regressions do not deliver probabilistic forecasts in general, except when the independent variables are evaluated at large lags. Ordered probit, by design, gives predicted probabilities of particular events. The table highlights the probabilities of having a peak (hence a downturn) and those of a bottom (hence an upturn), as well as those of "normal times". Since there are three categories of events, their probabilities should add up to 1. In other words,

$$\text{Prob}(normal) = 1 - \text{Prob}(peak) - \text{Prob}(bottom). \qquad (4)$$

Given any two, the equation above can solve for the remaining one easily. The probabilities predicted by the vector autoregression rely on the recursive forecasts the model makes and the *ex post* simulation of random errors. We give a brief discussion of the results shown above.

5.2. Comments of individual model:

1) The regression model:

- The simple regression does not look too useful in making out-of-sample forecast despite that the variables have proven to be statistically significant (see Table 1). The desired probabilities of turning points are not directly obtainable. Our lag 1 specification of the regression did provide a 1-period ahead forecast though. Standing at 2014 year-end, the model predicts the 2015:Q1 retail sales to pick up by 5.4% year-on-year when the actual turnout was -2%.

2) The ordered probit model:

- While the ordered probit gives specific probabilities of upturns, downturns and normal periods, the absolute values of these probabilities are influenced to a large extent by the actual numbers of turning points that have occurred and were spotted in the past. For instance, based on the forecast criterion stated in paragraph 2.5, there is a total of 14 sightings of peaks in retails sales and 17 sightings of bottoms[3].

[3] Note that these numbers are not the actual number of turning points. Imagine the extreme case of only one single turning point in the entire sample, based on the criterion, it will be sighted more than once, e.g. it will be spotted 4 quarters before it occurred, 3 quarters before, and etc..

- The *ex ante* mean probabilities are therefore $\frac{14}{60} = 23.3\%$ and $\frac{17}{60} = 28.3\%$ respectively. From (4), the mean probability of normal times is about 48.4%. These figures are very close to what the model predicts on average regarding the respective events.

- It seems appropriate to pay attention not just to the face values of the predicted probabilities but also to how they change relative to their mean values.

- Regarding the in-sample forecast, the first evaluation (predicted as at 2010:Q4) gives higher than average probabilities of turning points (upturns and downturns regardless) which is true. But with the probability of upturn outweighing that of downturn, this seems to be a false call in a narrow sense. The opposite is true for the second in-sample assessment and the model gives the correct signal.

- By contrast, the model's prediction of retail sales for 2015 is not much of an upturn or downturn. The chance of the coming quarters being "normal" is about 60% which is higher than the sample mean of 48% or so. **The probability of an upturn, in particular, is 13.6% and is much lower than the average figure of 23% in the sample. The result means that an imminent turnaround in retail sales is not a realistic scenario to expect.**

3) The vector autoregression model:

- Unlike the probit model, the vector autoregression model does not take into account the occurrence of turning points in the past. The forecast probabilities depend solely on forecast retails sales growth and can therefore be interpreted directly.

- The model gives an unambiguous signal of a downturn in the first in-sample exercise, which is correct. It misses the forthcoming downturn in the second exercise and gives a false-warning of upturn. Strictly speaking, this is not totally incorrect because growth indeed picked up in the next 2 quarters (2013:1H) but decelerated (not negative growth) in the second half of 2013. It is just that the slowdown from mid-year was regarded as a downturn by our identification scheme.

- **As for the 2015 forecast, the model predicts virtually no chance of upturn or downturn. The predicted probability of "normal time" is over 99%.** In this regard, the conclusions of the vector autoregression model and the ordered probit model coincide. In terms of point forecasts, the vector autoregression model predicts a growth of 2.1% and 7.9% in the first two quarters of 2015.

5.3. This exercise seeks to assess turning points in retail sales growth, although the structure of the study is somewhat experimental. We are sure that other fine-tunings are possible e.g. by resorting to more advanced models. Still, we show how simple models can be used to generate predictions of cyclical upturns and downturns in retail sales.

5.4. The very short time series (and a relatively small number of turning points observed) limited our detailed scrutiny of forecasting performance. For example, with long enough data series, sequential forecasts made consecutively can allow us to smooth the forecast message obtained and reduce the risk of misguidance by false signals.

Reference

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