MODELING INFLATION IN SINGAPORE: AN ECONOMETRIC BOTTOM-UP APPROACH

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CONTENTS

SUMMARY

The primary objective of monetary policy in Singapore is to achieve low inflation as a sound basis for sustained economic growth. Modeling inflation, therefore, plays a central role in formulating good monetary policy. This thesis surveys the literature on inflation modeling and employs an econometric disaggregated bottom-up approach to model the inflation in Singapore. It analyzes price behaviors of the various categories of goods and services that make up the aggregate price index by focusing on the common critical factors of labor cost, import prices and oil price, and thus demonstrates the influences of Singapore's international trade pattern and unique labor market on the price behaviors. We also conduct pseudo out-of-sample forecast and develop univariate benchmark to assess the forecasting accuracy. The thesis indicates that in terms of the total CPI the disaggregated bottom up model works better than the univariate model while for the subcategories of CPI the performance of the structural models depends on the specific characteristics of that subcategory.

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Chapter 1 Introduction

Modeling inflation is central to the conduct of monetary policy, since price stability, critical objective of monetary policy in many countries, improves the transparency of the price mechanism which allows people to make well-informed financial decisions and efficient resource allocations. More fundamentally, low inflation contributes to long-term growth of economy by boosting employment and public confidence in economy. Over the last three decades, more than 20 industrialized and non-industrialized countries have introduced inflation target regimes characterized by an explicit numerical inflation target and giving a major role to inflation modeling (Roger and Stone, 2005).

Against the backdrop of growing globalization and international capital flows, Singapore has adopted a unique monetary policy that is centered on managing the exchange rate to promote low inflation as a sound basis for sustained economic growth. In fact, the policy proves to be effective for it has helped the economy achieve a track record of low inflation with prolonged economic growth over recent decades. Figure 1 shows the annual inflation rate from 1965 to 2008, highlighting six major episodes of Singapore's experience with inflation. During the period, the inflation rate of Singapore averaged around 2.73% per year.

The first highly inflationary environment occurred in the first half of the 1970s when the first oil crisis hit in late 1973 with a quadrupling of oil prices. The inflation rate peaked at 28.6% in the first quarter of 1974. In 1980-83, the economy experienced another inflationary pressure and the inflation rate accelerated to 8.5% in 1980. It was mainly due to a confluence of the second world oil shock, high capital inflows and a rise in domestic labor cost.

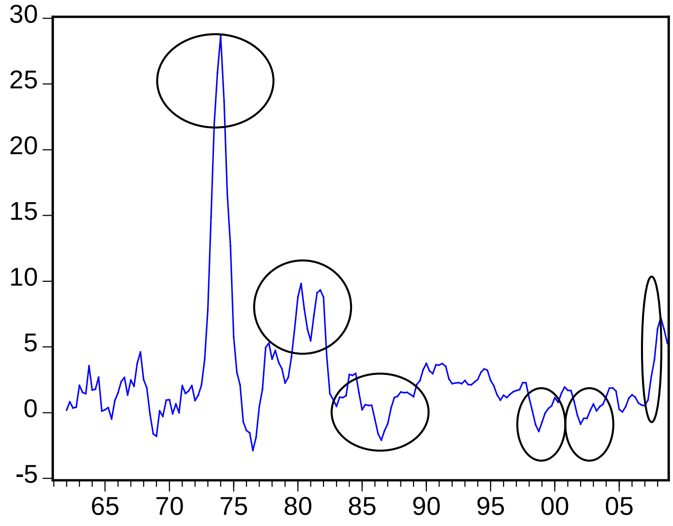


Figure 1: Singapore's Annual Inflation Rate (%)

After that, there were three major recessions, namely the1985-87 slump, the Asian Financial Crisis of 1997-98, and the electronics downturn in 2002-03. The 1985-87 slump is the first recession experienced by independent Singapore. It was partly an imported recession for at that time the marine and petroleum-related industries were struggling worldwide and the economic conditions of its neighboring countries such as Malaysia and Indonesia were worsening dramatically. Besides, by the middle of 1980s, the government slowed down the construction programs and there was a massive oversupply of new buildings, which suppressed domestic property prices. The internal and external factors resulted in a plunge in real GDP growth to -1.6% in 1985, with overall CPI contracting by 1.39% on average in 1986. The next major recession was the well-known Asian Financial Crisis in 1997-98. In 1998, Singapore suffered the economic contraction that the real GDP fell by 0.9% and overall CPI deflated by 0.3%. Soon after recovering from the Asian Financial Crisis, the electronics downturn hit the Singapore economy in 2002-03. As the name shows, the recession was caused by a sharp drop in global electronics demand in

2001-02, while the electronics industry is a key economic engine for the Singapore economy, accounting for 43% of exports in 2003. The economy's real GDP contracted by 1.9% and the inflation rate fell to -0.4% in 2002. In 2007-08 Singapore witnessed again the increases in the prices of goods and services caused by commodities and energy price shocks. The agricultural commodity price surges were largely driven by growing population, bio-fuels production, while the energy price shocks were contributed by increasing energy demand from industrializing countries and market speculation. The inflation rate in 2008 was as high as 6.5%.

In this thesis, we focus on an econometric disaggregated bottom-up approach to model the inflation in Singapore. The approach first analyzes price behaviors of the various categories of goods and services that make up the aggregate price index by developing the econometric models pioneered by Abeysinghe and Choy (2007). We build price determination equations to explain the effects of labor cost, import prices and oil price on the price behaviors of various subcategories of CPI in the long run. We also set up the price adjustment equations to analyze the price mechanisms in the short run.

In the next part of the thesis, we develop the univariate benchmarks and assess the forecasting accuracy of the various models. We not only compare the forecasting accuracy of the univariate model, disaggregated bottom-up model and the aggregated model at aggregating level, but also compare the forecasting ability of univariate models and structural models at the disaggregate level. The thesis concludes that in terms of the total CPI the disaggregated bottom up model works better than the univariate model while for the subcategories of CPI the performance of the structural models depends on the specific characteristics of that subcategory.

The organization of the thesis is as follows. Chapter 2 reviews the history of inflation modeling. Chapter 3 first describes the composition of the CPI and data and terminology, and then analyzes seven categories of CPI and their long-run determinants. After examining the stationarity of each CPI series and the co-integration between explanatory variables, error-correction models (ECM) and autoregressive distributed lag (ADL) models are developed in this Chapter. The economic interpretations of these models are discussed as well. Chapter 5 sets up the univariate benchmark for inflation forecasts. The result is compared with those of the disaggregated bottom-up model and the aggregated model. Chapter 6 concludes. The Appendix documents the mapping from the categories of import price index to the categories of consumer price index.

Chapter 2 Literature Review

The literature on the behavior of inflation places emphasis on both structural and purely statistical models. We start by briefly reviewing the history of Phillips curved-based models, followed by a discussion on the development of univariate benchmarks, and then introduce a practical disaggregated approach widely adopted by central banks and industries. In the end, several inflation models specified for the Singapore economy are discussed in detail.

2.1 Phillips Curve-based Models[1]

Phillips curve has been a building block of empirical macroeconomic modeling for decades. The idea that relates the unemployment rate to a measure of the inflation rate, or some other measure of economic activities, can be traced back to Irving Fisher (1926) who firstly documented a negative statistical relationship between unemployment rate and price changes. Samuelson and Solow (1960) later coined the term "Phillips curve" after the publication of the seminar paper by Phillips (1958).

Modern thinking on the Phillips curve, such as the studies by Phelps (1967) and Friedman (1968), however, is that such a relationship is unstable. Instead, it varies with the public expectation which is determined by changing economic environment, so the long-run Phillips curve must be vertical. The famous claim by Lucas and Sargent (1978) highlighted that the breakdown of the Phillips curve in the 1970s was "econometric failure on a grand scale". As a result, the usefulness of the Phillips curve for modeling and

[1] All the papers discussed in this session concerned the inflation in U.S..

forecasting inflation was threw into a shadow of doubt.

However, modern versions of the Phillips curve are still widely considered as a workhorse for inflation modeling and forecasting, especially the Phillips curve augmented by expectation and supply shocks. As Blinder (1997) argues that, “the empirical Phillips curve has worked amazingly well for decades” and remains the “clean little secret” of macroeconomics. Among the huge amount of research devoted to this topic over the years, we offer a selective review of two major developments in inflation modeling: (i) NAIRU Phillips curve-based models; and (ii) New Keynesian Phillips Curve, since they appear most frequently in the inflation modeling literature.

(i) NAIRU Phillips Curve-based Models

NAIRU (non-accelerating inflation rate of unemployment) specification is an “expectations-augmented” Phillips curve with an adaptive inflation expectation. NAIRU was initially known as the term “natural rate of unemployment” coined by Friedman (1968). It took a prototype form as:

$$\pi_t = \alpha(u_t - \bar{u}_t) + \sum_{i=1}^{N} \beta_i \pi_{t-i} + e_t \qquad (2.1)$$

where inflation π_t is determined by deviations of the unemployment rate from its natural rate $\bar{u}_t$,[2] and adaptive expectation, that is weighted average of recent inflation rates. According to the NAIRU Phillips Curve, unemployment rate in the long run cannot differ from this baseline NAIRU rate at which inflation maintains a stable rate. When unemployment rate is below NAIRU, inflation rate tends to rise, when it is above this rate,

[2] Gordon (1997) used an explicit econometric technique that allowed a time-varying NAIRU to be estimated.

inflation tends to fall. In other words, any attempt to use monetary policy to lower the unemployment below the natural rate on a sustained basis will end in failure. Since the models are based solely on past inflation, they also imply that rapid reduction in inflation require a substantial increase in unemployment.

The "Triangle model" developed by Gordon (1982; 1990; 1997) is a typical NAIRU Phillips curve-based model. It related inflation to three factors - inertia, demand and supply:

$$\pi_{t+1} = \alpha(L)(u_t - \bar{u}_t) + \beta(L)\Delta\pi_t + \gamma(L)z_t + e_{t+1} \tag{2.2}$$

where the past unemployment gap $u_t - \bar{u}_t$ and past supply shocks z_t represented excess demand and supply respectively, while inertia was conveyed by past changes in inflation $\Delta\pi_t$. Although the "Triangle model" with a vertical long-term tradeoff and supply shocks resurrected the Phillips curve, it was criticized for the large statistical uncertainty around NAIRU.[3] Gordon (1997) tried to reject this argument by allowing NAIRU to fluctuate over time as the structure and institution of product and labor market change. Mankiw (2001), however, concluded that "a combination of supply shocks that are hard to measure and structural changes in the labor market that alter the natural rate makes it unlikely that any empirical Phillips curve will ever offer a tight fit."

(ii) New-Keynesian Phillips Curve Models

In recent years there has been an explosion in research on inflation-unemployment dynamics, most of which related to the so called "new Keynesian Phillips curve". These

[3] For example, the paper by Staiger, Stock and Watson (1997) estimated U.S. NAIRU from 5.1 to 7.7 with a 95 percent confidence interval.

models derive the Phillips curve from individual optimization framework with the assumptions of rational expectations and price rigidity. Thus the general NKPC model can be written as[4]:

$$\pi_t = \alpha E_t \pi_{t+1} + \beta\, mc_t \qquad (2.3)$$

where inflation today π_t is a function of expected inflation in the next period $E_t \pi_{t+1}$ and real marginal cost mc_t. Under the assumption that aggregate real marginal cost is proportional to output gap, the model becomes:

$$\pi_t = \alpha E_t \pi_{t+1} + \beta\, y_t \qquad (2.4)$$

where y_t is output gap. In spite of the similarity to Phillips curve models, the NKPC models with forward-looking price setters assume overall price level adjusts slowly to changing economic conditions, while there is inertia in NAIRU models due to lagged values of inflation.

The NKPC models have many virtues, for example, the explicit use of micro foundations through optimization process and the resemblance to the previous Phillips curve-based models. In practice, however, the empirical cases against the NKPC turned out to be quite strong. Fuhrer and Moore (1995) found a significant but negative coefficient on the output gap, indicating it was inappropriate to use detrended output as a measure of output gap. Although Cali and Gertler (1999) tried to overcome the problem by using labor's share of income as a proxy for real marginal cost, Rudd and Whelan (2007) argued that the empirical performance of such labor share models was far from satisfactory. Mankiw (2001) also offered a critique on the grounds that 1) the disinflation

[4] This equation can be derived from many different models of prices rigidity, see Roberts (1995).

booms suggested by the NKPC model (Ball, 1994) contradicted the fact that actual disinflations caused recessions; 2) the NKPC models failed to generate reasonable responses to monetary policy shocks.

To conclude, when modeling inflation, it is wise to use these NKPC models with cautions, considering the debate is still ongoing over the adequacy of the NKPC and its "hybrid" variants that aim to directly address the empirical deficiency of the pure forward-looking models[5],

2.2 Univariate Models[6]

Recently the inflation modeling literature has centered on the question of whether good univariate statistical models forecast more accurately than structural models or whether we should still rely on those structurally based Phillips curve models to forecast inflation (see Stock and Watson, 2008). In this context, this section lays out three prototype examples of univariate models. It should be kept in mind, however, that a purely statistical model is expected to fit better than a structural model in short run.

(i) Autoregressive moving-average (ARMA) models

The direct ARMA models are the simplest univariate models. Since $\Delta \ln P_t$ is approximately the inflation rate, the quarterly inflation rate is denoted by $\pi_t = \Delta \ln P_t = \ln(P_t / P_{t-1})$. The ARMA models take general form as:

$$\pi_t = \alpha_0 + \varepsilon_t + \sum_{i=1}^{p} \alpha_i \pi_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \tag{2.5}$$

[5] For the discussion on hybrid variants of the NKPC with lagged values of inflation rate, see Rudd and Whelan (2007).
[6] All the papers discussed in this session concerned the inflation in U.S..

where the lag length p and q are determined by the Akaike Information Criterion (AIC) or the Schwartz Baysesian Criterion (SBC).

(ii) Atkeson-Ohanian (2001) model

Atkeson-Ohanian (2001) found from 1984 to 1999 no version of Phillips Curve could make more accurate inflation forecasts than those from a simple univariate model that presumes the forecast of inflation over the next four quarters is equal to the inflation over the previous quarters. Thus Atkeson-Ohanian model is essentially a random walk model:

$$\pi_{t+4}^{4} = \pi_{t}^{4} + \upsilon_{t+4}^{4} \tag{2.6}$$

where π_{t}^{4} is the percentage change in the inflation rate between quarter t-4 and t. After comparing the root mean squared error (RMSE) of different forecasts, AO dramatically demonstrated that over the 1984-1999, their four-quarter random walk forecast outperformed both Phillips curve forecast and Greenbook forecast.

In general, their conclusion was confirmed and extended by other studies. Stock and Watson (2003) added additional activity predictors to AO model and arrived at the same conclusion over 1985-1999. Ang, Bekaert and Wei (2007) also conducted a thorough assessment of different forecasts and confirmed basic AO finding that Phillips curve models fail to improve upon univariate models over the periods of 1985-2002 and 1995-2002. However, whether AO’s claims were accurate depends largely on the chosen periods. For instance, Fisher, Liu and Zhou (2002) showed Phillips curve outperformed the AO benchmark in 1977-1984 using rolling regression with a 15-year window.

As concluded by Stock and Watson (2008) in their comprehensive survey on different models using a consistent data and methodology, Phillips curve-based models are the best among structural models but compared to univariate benchmark their performance is episodic, sometimes better sometimes worse. In this paper, we present basic univariate model as a benchmark for multivariate structural model, comparing these two in respect of forecasting accuracy.

2.3 Disaggregated Bottom-up Approach

One possible way of improving modeling accuracy is to use disaggregated data. Suppose total CPI is the variable of interest and it can be decomposed into n subcategories $CPI_i\,(i=1,2...n)$. Then $CPI=\sum_{i=1}^{n} w_i CPI_i$, where w_i is the given weight associated with each subcategory. Since it uses forecasts from disaggregated data to obtain the forecast for the aggregate, the methodology is called bottom-up approach.

In reality, central banks and industries are likely to employ this approach to model inflation. Bernanke's (2007) speech at the monetary economics workshop of the NBER Summer Institute revealed Federal Reserve Board adopts the bottom-up approach for near-term inflation forecasts. They estimate the aggregate price index by assessing the price changes in subcategories of the index and then aggregates these indices.

There are two advantages to use the disaggregated bottom-up approach. First, it improves fitness of the model by distinguishing the price behaviors of different categories of goods and services. As we know, the prices of food and energy are famous for their volatility while the prices of other categories such as education fees and shelter costs tend to be more persistent. Therefore, the bottom-up approach helps capture idiosyncratic characteristics of each variable by modeling each one individually. Second, it provides an opportunity to examine the particular price mechanism of underlying categories of CPI, which might be useful for trade unions and employers who use them to maintain purchasing power or industrial experts and researchers who are interested in the international comparison of costs.

2.4 Inflation Models for the Singapore Economy

Although Singapore is considered as "a textbook example of a small open economy", few of the literature covered the inflation models specific to the economy. We begin by introducing two Phillips curve related models briefly, and then one latest important work by Abeysinghe and Choy (2007) in detail.

(i) Vincent Low (1994)

Low (1994) summarized the model developed by Singapore's central bank - Monetary Authority of Singapore (MAS). The MAS model used inflation augmented Phillips Curve to set up the wage equation. Based on the data set from 1982 to 1993, the natural rate of unemployment for Singapore was estimated at 3%. Because Singapore is too small to affect world price, MAS adopted a non-standard model to describe the critical role played by foreign prices and exchange rates in determining the domestic prices. The equation for domestic price level was as follows:

$$\text{LnCPI} = 0.70\text{Ln(Import Price)} + 0.21\text{Ln(Unit Labor Cost)} + 0.04\text{Ln(Oil Price)} \qquad (2.7)$$

where the variable of Import Price was exchange rate-adjusted foreign price to distinguish the effects of foreign prices and exchange rates. Since 1% change in foreign prices leads to a 0.7% change increase in CPI, the model concluded that foreign prices dominate in the determination of domestic CPI. However, given the lack of details, it is hard to check the model's fitness to the latest data.

(ii) Eric Parrado (2004)

Parrado (2004) considered NKPC as a viable framework for forecasting Singapore inflation based on real marginal costs. Using quarterly data from 1981Q1 to 2002Q1, the paper adopted the structural estimation by Cali and Gertler (1999), which was a hybrid NKPC model including both forward and backward-looking components for inflation, π_{t-1} and $E_t\pi_{t+1}$ respectively, and the average real marginal cost (domestic supply price index) c_t. The inflation rate was estimated as:

$$\pi_t = 0.4\pi_{t-1} + 0.6E_t\pi_{t+1} + 0.025c_t \tag{2.8}$$

It can be concluded that the backward-looking price setters have been less important than forward-looking ones in influencing the behaviors of inflation in Singapore.

(ii) Abeysinghe and Choy (2007)

The model constructed by Abeysinghe and Choy (2007) actually grew out of their ESU01 model which was the first macro econometric model publicly released in its complete form for the Singapore economy.[7] In the thesis, we follow their framework but pay more attention to the price mechanism of each category composing the overall CPI.

[7] ESU01 model was developed by Abeysinghe and Choy (2001) for the Economic Studies Unit (ESU) of the Department of Economics at National University of Singapore.

The overall price level in their model is composed of tradable and non-tradable prices as follows:

$$CPI_t = (P_t^T)^{\alpha}(P_t^{NT})^{1-\alpha} \tag{2.9}$$

where α and $1-\alpha$ represent the shares of traded and non-traded sectors. By taking logarithms on both sides of the equation which can be transformed into:

$$\ln CPI_t = \alpha \ln P_t^T + (1-\alpha)\ln P_t^{NT} \tag{2.10}$$

After trying different theories and models, for the first time, they incorporated the Balassa-Samuelson effect in the price equation to estimate the above α. The Balassa-Samuelson effect basically asserts that the price differential between traded goods and non-traded goods results from the productivity differential between two sectors under perfect competition and labor mobility, which can be shown as:

$$W_t^T = MP_t^T \cdot P_t^T = MP_t^{NT} \cdot P_t^{NT} = W_t^{NT} \tag{2.11}$$

Substitute (2.11) to (2.10):

$$\ln CPI_t = \ln P_t^T + (1-\alpha)(\ln MP_t^T - \ln MP_t^{NT}) \tag{2.12}$$

where MP is the marginal product. By treating the manufacturing industry as the traded sector and the rest of the economy jointly as the non-traded sector, they resolved the main difficulty in separating the traded and non-traded sectors of the economy. As shown by Figure 2, the rationale behind the method was it made the wage of non-traded sector proportionate to that of traded sector, i.e. $W_t^{NT} = kW_t^T$.

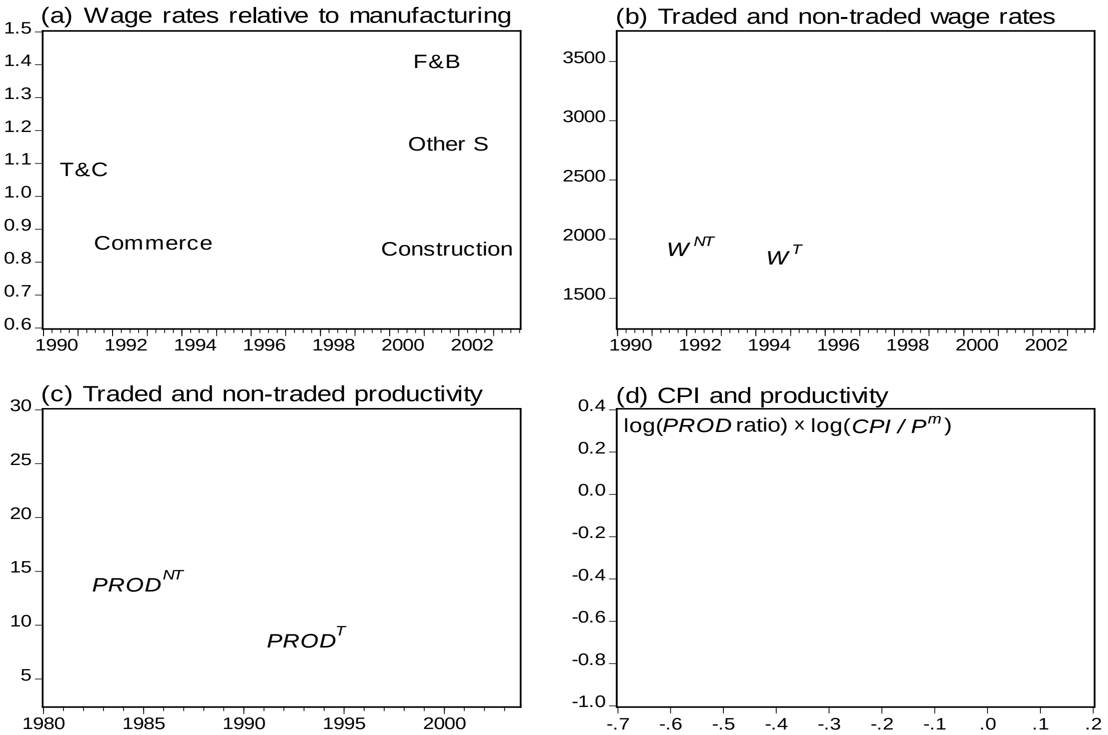


Figure 2: Wages, Productivity and the CPI[8]

Note: (a) plots the nominal wage rates for the major economic sectors relative to manufacturing wages. (b) plots the wages of traded and non-traded sectors defined in the way above. (c) shows the productivity gap between traded and non-traded sectors. (d) shows the residual of CPI after removing the effect of import price and productivity differential between traded and non-traded sector.

The estimation was consistent with the import content of total consumption expenditures according to Singapore's IO tables. A single ECM was used to estimate the price mechanism over 1987Q1 to 2003Q4. The long-term relationship was estimated as:

$$\ln CPI_t = 0.45 \ln IPI_t + 0.55 \ln ULC_t^{NT} \tag{2.13}$$

Where IPI is the import price and ULC_t^{NT} is the unit labor cost of non-traded sector used as the substitution of non-traded price. By calibration the authors find the best coefficients that give the greatest magnitude of the adjustment coefficient of ECM, which are consistent with the Input and Output table of the Singapore economy.

[8] The figure is from Abeysinghe and Choy (2007), pp. 97.

In the short-run, the price mechanism was:

$$\underset{}{\Delta \ln cpi_t} = \underset{(4.44)}{0.0025} + \underset{(4.69)}{0.46}\Delta \ln cpi_{t-1} + \underset{(2.41)}{0.05}\Delta \ln ipi_t - \underset{(3.05)}{0.009}D\_98 - \underset{(2.62)}{0.003}D\_01 - \underset{(2.31)}{0.10}EC_{t-1} \quad (2.14)$$

where EC is the error correction term (residuals from Eq.(2.13)), the numbers in parentheses are the t-statistics. D_98 and D_01 are impulse dummies for the period 1998Q1-1998Q4 and 2001Q1-2001Q4 respectively. They concluded that the total CPI is stubbornly persistent because of the small magnitude of the adjustment coefficient. The short run impact of import prices is also smaller and decays with time, while the unit labor costs of the non-traded sector only has lagged effects.

Chapter 3 Modeling Consumer Prices in Singapore

Different models and explanatory variables have been used to understand better the behavior of inflation in Singapore. Figure 3 plots the logarithms of total consumer price index, import price index and oil prices. The Johansen's trace test in Abeysinghe and Choy (2007) shows that the logarithms of total CPI, IPI and labor cost form a sensible co-integrating relationship, which is consistent with the price equation (2.10). Although IPI is expected to capture the effect of oil prices, regression estimates show the presence of a direct effect of oil prices on CPI. Oil prices are likely to play an important role in determining the price level of some categories of CPI, for it not only contributes the costs of goods and services directly, but implicitly links to excess aggregate demand and economic growth as well. Therefore oil prices, together with import prices and labor cost, are considered as explanatory variables for the categories of CPI. It is also interesting to note that log-level total CPI and IPI moved in the opposite direction before 1994, which implies that the import prices did not dominate the price behavior in some periods.

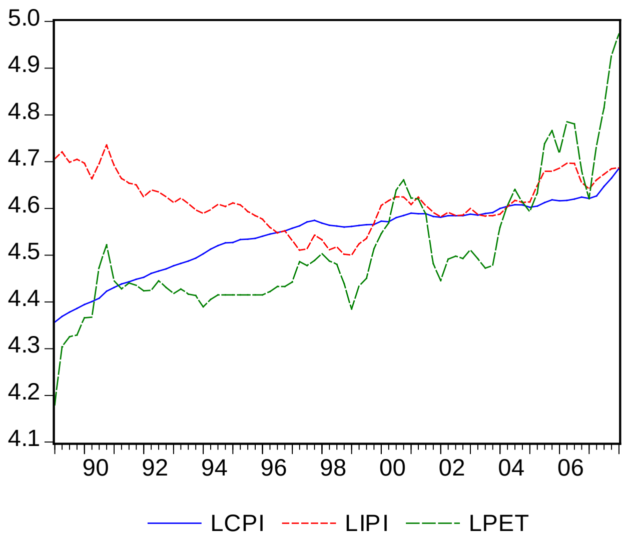


Figure 3: Logarithms of CPI, IPI and Oil Price (PET)

Since the equation incorporated with Balassa-Samulson effect forms a sensible and robust co-integration relationship among independent variables, we follow the framework by Abeysinghe and Choy (2007), and then further employ a disaggregated bottom-up approach that estimates price behavior for the various categories of goods and services. After that, we aggregate these indices according to the weight of each category to obtain the forecast of overall inflation rate. Before moving to the formal models for the seven categories of the CPI, section 3.1 and 3.2 briefly describe the composition of the CPI and the data and terminology used in the thesis. Section 3.3 analyzes the integration of the series and cointegration among them.

3.1 The Composition of the CPI

The CPI measures the change in the price of a fixed basket of goods and services consumed by households. To make sure the representativeness of the index, Singapore's CPI contains seven categories commonly purchased by the majority of the households over time, namely Food, Clothing & Footwear, Housing, Transportation & Communication, Education & Stationary, Health Care and Recreation & Others. The weighting pattern is updated once every five years based on the results of the quinquennial Household Expenditure Survey (HES), showing the relative importance of each item in the basket of goods and services. In the thesis we use the latest 2004 survey-based weighting pattern which was compiled based on the results of the eighth HES conducted from October 2002 to September 2003:

$$\begin{aligned} CPI = {} & 0.2338CPI^{fd} + 0.0357CPI^{cl} + 0.2126CPI^{hous} + 0.2176CPI^{tc} + 0.0819CPI^{edu} \\ & + 0.0525CPI^{hc} + 0.1659CPI^{rec} \end{aligned} \tag{3.1}$$

Since a link factor was derived by the Singapore Department of Statistics to facilitate comparison of price changes over time, it should not be a big problem to use the latest weights to combine all the prices over the years. In effect, the equation (3.1) works as the identity that links all the categories of the CPI.

3.2 Data and Terminology

All data series are available via SingStat Time Series (STS). They are adjusted to 2004-base, spanning 1989Q1-2008Q1. Monthly data are converted to quarterly by computing the average value for the three months in the quarter before any other transformation.

Singapore's consumer price index (CPI) is the series of interest. Price indices of the seven categories are treated as dependent variables in this thesis. Moreover, they are further classified into finer sub-categories. Food category, for example, consists of the sub-categories of Non-Cooked Food and Cooked Food while the sub-category of Non-Cooked Food includes the smaller sections like Rice & Other Cereals, Meat& Poultry, etc. The data are collected via the regular surveys conducted by the department of statistics and the frequency of survey depends on the price behavior of the goods and services.

On the other hand, the Import Price Index (IPI) as one of the explanatory variable tracks changes in the prices of imported goods. The prices are obtained monthly from the selected importers by postal survey, fax or email. Average monthly exchange rates provided by the MAS are used to convert the prices quoted in foreign currencies into Singapore dollars. The coverage and weighting structure of IPI makes sure that the index is representative of the economy's trade pattern. The classification of IPI's categories is based on the Standard International Trade Classification, Revision 3 (SITC, Rev 3), obviously different from those of CPI. Since in this thesis we focus on the seven categories of CPI and try to examine how the corresponding IPI affects each of these categories, we have to map the categories of IPI to those of CPI to get individual import price series for each category of consumer prices. Appendix A shows this mapping in detail.

In terms of unit labor cost of non-traded sector used to represent the non-traded price, it is constructed as $ULC_t^{NT} = \frac{W(1+CPF^{emp})}{PROD_t^{NT}}$, where $W(1+CPF^{emp})$ is economy-wide nominal wage and $PROD_t^{NT}$ is the productivity in the non-tradable sector.[9] For oil price (PET), we use the petrol price index from Price Indices of Selected Consumer Items of STS.

3.3 Integration and Cointegration

This section presents unit-root tests for the variables of interest to determine their orders of integration. Then Johansen's maximum likelihood procedure is applied to test for cointegration among the CPI, unit labor costs, import prices and oil prices.

(i) Integration

Before modeling the total CPI and its categories, it is useful to determine the orders of integration for the variables considered. For a variable x, the augmented Dicky-Fuller statistic ADF(k) is the t ratio on π from the regression:

$$\Delta x_t = \pi x_{t-1} + \sum_{i=1}^{4} \theta_i x_{t-i} + \varepsilon_t$$

[9] We construct the unit labor cost of non-traded sector by following Abeysinghe and Choy (2007), pp.99.

where k is the number of lags on the dependent variable; π and θ_i are coefficients; ε_t is the error term. Given quarterly data, it is natural to perform the fourth-order ADF test to test the order of integration. For a null order, two values are reported – ADF(4) statistic and the estimated coefficient on the lagged variable x_{t-1} (in parentheses). Table 1 lists ADF(4) statistics for the CPI, unit labor costs, import prices and oil prices. Unit-root tests are given for the original variables (all in logs), for the first difference and for the second difference, which permit testing whether a given series is I(1), I(2) or I(3).

Table 1: The CPI: ADF Statistics for Testing for a Unit Root in Various Time Series

	Variable			
Null order	cpi	ulc	ipi	pet
I(1)	2.06	1.44	−0.03	1.60
	(0.00)	(0.00)	(−0.00)	(0.00)
I(2)	−0.61	−2.51*	−4.02	−3.59**
	(−0.06)	(−0.68)	(−0.89)	(−0.92)
I(3)	−4.81**	−5.36**	−6.98**	−5.93**
	(−2.15)	(−3.51)	(−3.20)	(−2.79)

Note: (1) The sample is 1989Q1-2008Q1.

(2) Asterisks * and * * denote rejection at the 5% and 1% critical values

According to the ADF statistics, the unit labor cost and the oil price index seem to be I(1), while CPI and IPI appear to be I(2). However, the point estimates of the characteristic roots in I(2) equation are far from unity, we decide to treat all four variables as I(1) process[10].

Table 2 lists ADF(4) statistics for the CPI's categories and their corresponding IPI (all in log). In terms of the categories of CPI, they are treated as if they are I(1), although some variables appear to be integrated of order 2. In terms of import prices, except the IPI series of Housing and Education & Stationery, all of them are I(1). Therefore all seven IPI are treated as I(1), although it is recognized that some caveats may apply.

[10] It may be valuable to investigate the cointegration properties of the series, assuming that they maybe I(2), but doing so is beyond the scope of this thesis.

Table 2: The Categories: ADF Statistics for Testing for a Unit Root in CPI & IPI

cpi	Categories of CPI						
Null order	fd	cl	hous	tran	edu	hc	rec
I(1)	1.46	1.43	2.07	1.44	2.25	3.33	2.62
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(2)	−0.41	−2.96	−2.17*	−2.68	−1.11	−1.63*	−1.59
	(−0.07)	(−0.75)	(−0.42)	(−0.52)	(−0.11)	(−0.21)	(−0.24)
I(3)	−4.09**	−6.74**	−3.46**	−5.98**	−6.22**	−5.73**	−7.10**
	(−2.34)	(−4.09)	(−1.74)	(−3.00)	(−3.75)	(−2.80)	(−3.79)

ipi	Categories of IPI						
Null order	fd	cl	hous	tran	edu	hc	rec
I(1)	1.40	−1.98	−3.42*	−2.14	−3.55*	0.44	1.03
	(0.00)	(−0.00)	(−0.00)	(−0.00)	(−0.00)	(0.00)	(0.00)
I(2)	−2.75**	−2.71**	−2.55**	−1.56**	−2.48**	−4.13**	−3.36**
	(−0.55)	(−0.73)	(−0.54)	(−0.27)	(−0.51)	(−1.27)	(−0.94)
I(3)	−4.99**	−6.46**	−6.04**	−6.02**	−6.54**	−5.67**	−5.88**
	(−2.45)	(−3.78)	(−3.55)	(−3.29)	(−2.88)	(−3.39)	(−3.16)

Note: (1) The sample is 1989Q1-2008Q1.

(2) Asterisks * and * * denote rejection at the 5% and 1% critical values

(ii) Cointegration

Next step is to clarify the long-run relationships between integrated variables through cointegration analysis. We use Johansen' s procedure which is a maximum likelihood for a finite-order vector autoregression (VAR). To ensure reasonable power of the Johansen procedure, we also test lag order of the VAR before identifying the number of cointegration. If there is a conflict between AIC and SC, we use SC for the benefit of parsimony. The maximal eigenvalue and trace eigenvalue statistics are used to identify the number of cointegrating vectors. Appendix B reports the standard statistics and estimates for Johansen's procedure for the total CPI and its seven categories. The details for each category are discussed in the following sessions.

3.4 Price Behavior of Food

The food prices of Singapore are composed of Non-cooked Food prices and Cooked Food prices. Although Food's weight in the total CPI expenditure fell by 5 percent from 28% in 1998 to 23% in 2004, it still accounts for the largest proportion of the total household expenditure. Singapore is not spared from the general increase in global food prices, its food inflation has remained low by international standards, according to a survey of cooked and uncooked food prices worldwide.[11] The Trade and Industry Ministry (MTI) of Singapore reported in 2008 that the survey of 14 countries from 2005 to 2007 showed Singapore had one of the lowest rates of food inflation for all three years. It is largely due to Singapore's open and competitive environment. Because of a wider range of options, the consumers are able to switch to cheaper alternatives which keep the increases in food prices less pronounced than most countries. For example, while Singapore has traditionally sourced vegetables from Malaysia and China, the country is now getting them from Vietnam and Indonesia as well. On the other hand, businesses have also played a role in moderating the pace of increases by not passing on the full extent of price increases in their inputs immediately. For example, according to the Department of Statistic, recent cooked food price increases have been smaller than those for non-cooked food, which is an indication that hawkers and restaurants have not passed on all the increases in raw food prices to consumers.

[11] For details, see "Singapore's food inflation remains low by international standards", Channel NewsAsia, 3 February 2008

Figure 4(a) plots the quarterly rate of food inflation at an annualized rate, i.e. $\pi_t = 400\ln(CPI_t / CPI_{t-1})$. Compared to the prices of other categories, it clearly shows that the price of food category tends to be more volatile. Figure 4(b) shows the log-level food CPI and corresponding food IPI. After 1993, CPI and IPI of food share the same upward trend which implies that food inflation in Singapore is mainly driven by external factors such as adverse weather in supplier countries. Therefore, in the long run, the import prices of food, together with oil prices and unit labor cost for non-traded sector are expected to affect the domestic food prices.

After checking the co-integration among variables, we find food prices, food import prices and unit labor cost for non-traded sector form a sensible co-integrating relationship. Given $\ln CPI_t^{fd} = \alpha \ln IPI_t^{fd} + (1-\alpha)\ln ULC_t^{NT}$, we find the best α that gives the greatest magnitude of the adjustment coefficient of ECM by calibration. The long-run equation for food price is:

$$\ln CPI_t^{fd} = 0.78\ln IPI_t^{fd} + 0.22\ln ULC_t^{NT} \qquad (3.2)$$

In the short-run, incorporating (3.2) into an ECM and following the method of general to specific modeling, we obtain a parsimonious, economically interpretable and statistically acceptable model:

$$\underset{}{\Delta\ln CPI_t^{fd}} = \underset{(7.09)}{0.0044} + \underset{(4.15)}{0.14}\Delta\ln IPI_t^{fd} - \underset{(3.67)}{0.01}D\_98 - \underset{(5.12)}{0.10}EC_{t-1}^{fd} \qquad (3.3)$$

R^2=0.35 SE=0.005 DW=1.99

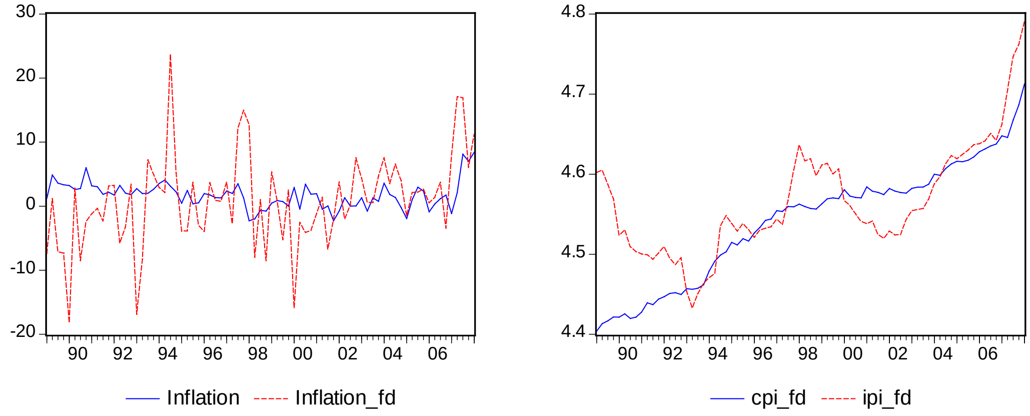


Figure 4: (a) Quarterly Rate of Food Inflation (b) Log-level Food CPI and Food IPI

where EC is the error correction term (residuals from Eq.(3.2)), the numbers in parentheses are the t-statistics, DW is the co-integrating regression Durbin-Watson statistic and D_98 is an impulse dummy for the period 1998Q1-1998Q4. The magnitude of the adjustment coefficient is small, implying food prices are persistent. Besides, the short-run impact of food import prices is small and the unit labor cost of non-traded sector does not have an immediate impact on food prices.

3.5 Price Behavior of Clothing & Footwear

The Clothing & Footwear expenditure only accounts for 3.37% of the total CPI basket in Singapore. The category consists of four subcategories, namely Ready-made Clothing & Accessories, Clothing Materials, Tailoring & Haberdasheries and Footwear. As shown by figure 5(a), the price level of clothing and footwear in Singapore was rising up slowly and smoothly over the years, which can be explained by the increasing demand and supply in the sector. The surging demand, in part, was due to the country's sustained economic growth and the resultant increase in consumer disposable incomes. At the same time, increasingly sophisticated and well-heeled consumers were expected to place a greater emphasis on looking good by wearing designer labels, and many of them did not hesitate to pay premium prices. On the supply side, the prices are suppressed because more and more locally made wares and china-made products were available in Singapore market, which drove up the supply. As a result, the prices of clothing and footwear did not change much for the latest two decades.

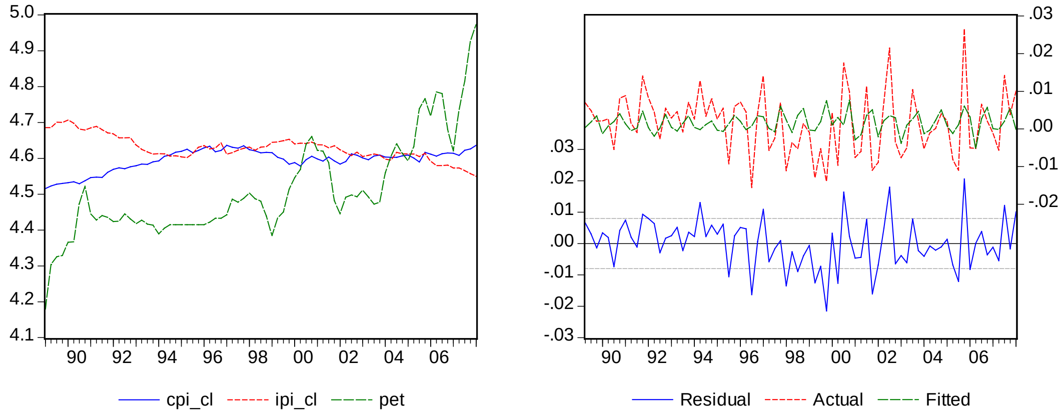


Figure 5: (a) Log-levels of the Series (b) Residual, Actual and Fitted Graph for Clothing & Footwear CPI

Unfortunately, after checking the co-integration among variables, we find no combination of the explanatory variables can form a sensible and robust co-integrating relationship. Therefore, we have to be content with an Autoregressive Distributed Lag (ADL) model to explain the Clothing & Footwear in the short run:

$$\Delta \ln CPI_t^{cl} = \underset{(1.81)}{0.0017} - \underset{(1.72)}{0.149}\Delta \ln CPI_{t-2}^{cl} + \underset{(2.02)}{0.015}\Delta \ln ULC_t^{NT} \tag{3.4}$$

$\mathrm{R}^2 = 0.09 \quad \mathrm{SE} = 0.008 \quad \mathrm{DW} = 2.17$

Although the model is far from satisfactory regarding the insignificant coefficients and low R^2, the graph of residual, actual and fitted value in Figure 5(b) shows that at least the model catches most of the turning points. Besides, since the weight of this category in CPI is quite low, it should not cause problems when combined with other categories of total CPI.

3.6 Price Behavior of Housing

The Housing prices accounts for 21.26% of the total CPI expenditure in Singapore, consisting of three subcategories: Accommodation, Fuel & Utilities and Household Durables. Figure 6(a) plots the log-level housing CPI and corresponding housing IPI, oil prices and labor costs.

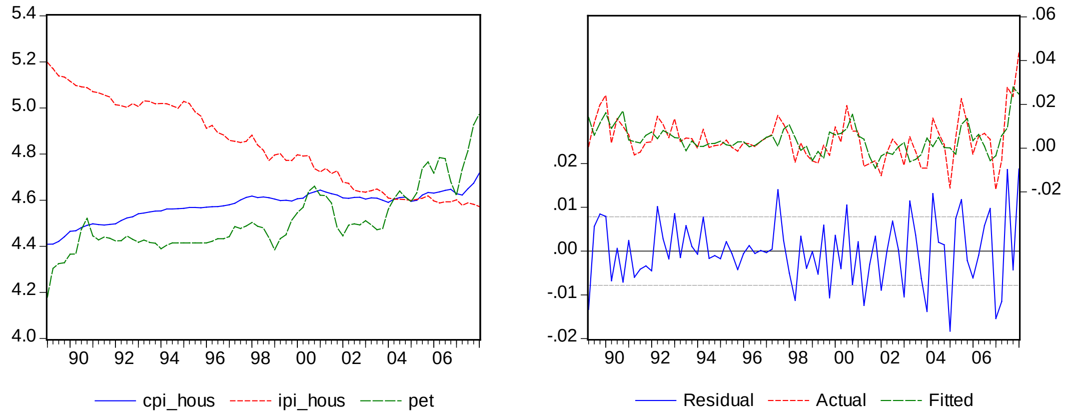


Figure 6: (a) Log-levels of the Series (b) Residual, Actual and Fitted Graph for Housing CPI

Within the subcategory of accommodation, the owner-occupied accommodation, the largest contributor (52%) to the housing CPI, is the most important component. However, the treatment of this component is a difficult issue for it actually measures the opportunity cost of occupying a dwelling instead of renting out. In this context, to compute owner-occupied accommodation index, the Singapore Department of Statistics adopts the rental equivalence method which measures the shelter cost in terms of the expected rental the owner have to pay if he were a tenant of the premise. Although import prices, oil prices and labor cost can not directly explain the movement of this imputed price, they have critical effects on the macro-economy, thus indirectly affecting the rental market. The other two components of fuel & utilities and household durables are obviously influenced by the oil prices and import prices, therefore it is reasonable to include them with labor cost in the long-run model for the housing sector.

After checking the co-integration among variables and find that housing prices, we find the related import prices and unit labor cost for non-traded sector form a sensible co-integrating relationship. We also find out the best coefficients that give the greatest magnitude of the adjustment coefficient of ECM by calibration. The long-run equation for housing price is:

$$\ln CPI_t^{hous} = 0.29 \ln IPI_t^{hous} + 0.38 \ln ULC_t^{NT} + 0.33 \ln PET_t \tag{3.5}$$

In the short-run, incorporating (3.5) into an ECM and following the method of general to specific modeling, we obtain a parsimonious, economically interpretable and statistically acceptable model:

$$\begin{aligned} \Delta \ln CPI_t^{hous} = {} & \underset{(1.63)}{0.0016} + \underset{(2.90)}{0.34} \Delta \ln CPI_{t-1}^{hous} + \underset{(2.09)}{0.020} \Delta \ln ULC_t^{nt} \\ & + \underset{(5.22)}{0.11} \Delta \ln PET_t - \underset{(3.12)}{0.11} EC_{t-1}^{hous} \end{aligned} \tag{3.6}$$

$R^2 = 0.43 \quad SE = 0.008 \quad DW = 2.29$

The magnitude of the adjustment coefficient is small, implying housing price is quite sticky. Besides, it is reasonable to find that the related import prices do not have a short run effect, for only the price of small-weighted household durables is directly affected by it. Without surprise, oil prices have a small but immediate effect on housing price which can be contributed by its direct effect on fuel & utilities and indirect link to the price index of owner-occupied accommodation. Figure 6(b) shows the short-run model fits the data quite well.

3.7 Price Behavior of Transport & Communication

The Transport & Communication category accounts for 21.76% of the total CPI expenditure in Singapore. Transport, the main component of the category, can be further grouped into Private Road Transport, Public Road Transport and Other Travel & Transport. Within the Private Road Transport, the Purchase of Vehicles has the highest weight, accounting for 39% of this category. The other part of the category is the communication prices dominated by telephone & internet access. Figure 7(a) plots the log-level transport & communication CPI and corresponding IPI, oil prices and labor cost, which clearly shows the co-movement between oil price and transport & communication CPI.

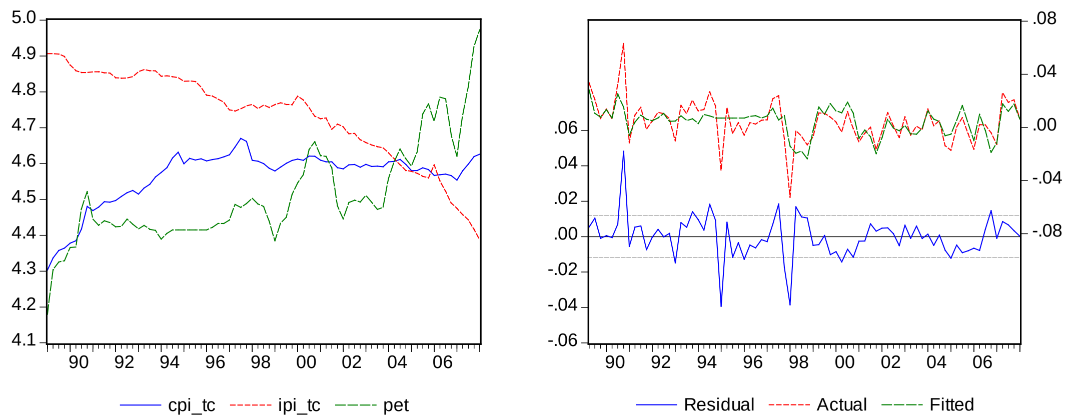


Figure 7: (a) Log-levels of the Series (b) Residual, Actual and Fitted Graph for Transport & Communication CPI

Singapore's transport market has many unique features. In terms of private road transport, for example, Certificate of Entitlement (COE) system requires residents of

Singapore to bid for the right to buy a motor vehicle, with the number of certificates deliberately restricted. The Quota Premium (i.e. bid certificate prices) belongs to other running costs of the category. ERP (Electronic Road Pricings) scheme is another example, for it is an electronic toll collection scheme adopted in Singapore to manage traffic by road pricing. In terms of public road transport, government intervention has been particularly important. For example, the Public Transport Council (PTC) established in 1987 is responsible for approving and regulating bus services, public transport fares and ticket payment services. Therefore it can be concluded that transport & communication prices are subject to the public policies to a large extent.

Since there was no combination of the explanatory variables that can form a sensible and robust co-integration relationship for transport & communication sector, we use an Autoregressive Distributed Lag (ADL) model to depict the data:

$$\Delta \ln CPI_t^{tc} = \underset{(3.89)}{0.007} - \underset{(3.15)}{0.009} D\_02 - \underset{(3.86)}{0.024} D\_98 + \underset{(6.46)}{0.17} \ln \Delta PET_t \tag{3.7}$$

$\mathrm{R}^2 = 0.44 \quad \mathrm{SE} = 0.012 \quad \mathrm{DW} = 1.84$

where D_98 and D_02 are impulse dummies for the year 1998 and 2002 respectively. Given our previous discussion, it is reasonable to find only oil price has a relatively big short-run effect on transportation & communication prices for it directly affects the cost of transport and explicitly links to the economic cycles. As shown by Figure 7(b), the fitness of the ADL model is satisfactory.

3.8 Price Behavior of Education & Stationery

The Education & Stationery category only accounts for 8.19% of the total CPI expenditure in Singapore. It can be further grouped into three subcategories, namely School/Tuition & Other Fees, School Textbooks & Stationery, and Newspapers, Magazines & Books. Among the subcategories, School/Tuition & Other Fees has the highest weight, accounting for 73% of the category. Figure 8(a) plots the log-level education & stationery CPI and corresponding IPI, oil prices and labor cost. We find the education prices keep going up with declining import prices and increasing oil price.

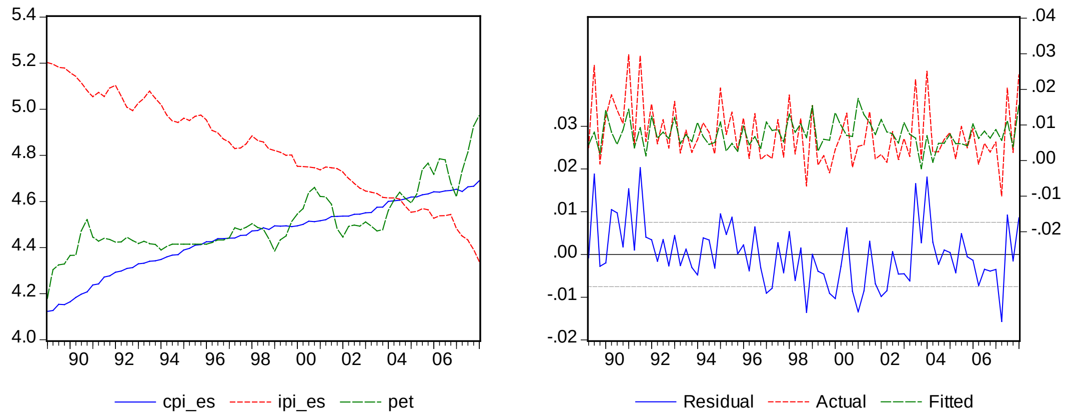


Figure 8: (a) Log-levels of the Series Education & Stationery CPI

(b) Residual, Actual and Fitted Graph for

After checking the co-integration among variables, we find education & stationery prices, corresponding import prices and unit labor cost for non-traded sector form a sensible co-integrating relationship. Later, the coefficients of the long run equation indicate that as a labor intensive service sector Education & Stationery is largely determined by unit labor cost for non-traded sector. Through calibration, the long-run equation for Education & Stationery is:

$$\ln CPI_t^{edu} = 0.08 \ln IPI_t^{edu} + 0.42 \ln ULC_t^{NT} + 0.50 \ln PET_t \tag{3.8}$$

In the short-run, incorporating (3.8) into an ECM and following the method of general to specific modeling, we obtain a parsimonious, economically interpretable and statistically acceptable model:

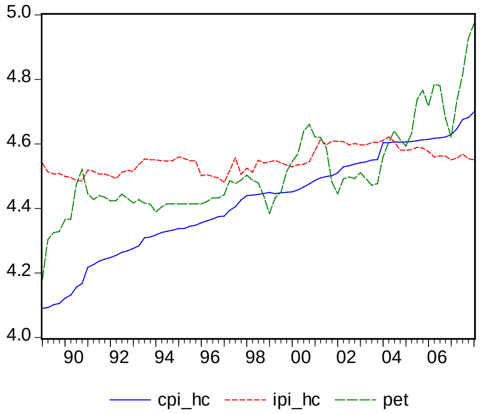
$$\Delta \ln CPI_t^{edu} = \underset{(8.28)}{0.0096} - \underset{(2.62)}{0.28} \ln \Delta CPI_{t-1}^{edu} - \underset{(3.16)}{0.05} EC_{t-1}^{edu} \tag{3.9}$$

$R^2 = 0.20 \quad SE = 0.008 \quad DW = 1.70$

In this model, the magnitude of the adjustment coefficient is small, implying education prices are also persistent. Besides, the corresponding import prices and the unit labor cost have no impacts on Education & Stationery prices in the short run. As shown by Figure 8(b), the fitness of the EC model is satisfactory.

3.9 Price Behavior of Health Care

The Health Care category has the smallest weight and only accounts for 5.25% of the total CPI expenditure in Singapore. It can be further grouped into three subcategories, namely Medical Treatment, Proprietary Medicines & Supplies, and Medical/Health Insurance. Among them Medical Treatment gains the highest weight (65%) and includes the labor-intensive components such as Hospitalization Fees and Nursing Services. Therefore it is natural to expect that labor cost for non-traded sector plays an important role in determining the price level of this category. The corresponding import prices, on the other hand, largely affect the subcategory of Proprietary Medicines & Supplies. Figure 9(a) plots the log-level education & stationery CPI and corresponding IPI, oil prices and labor cost.



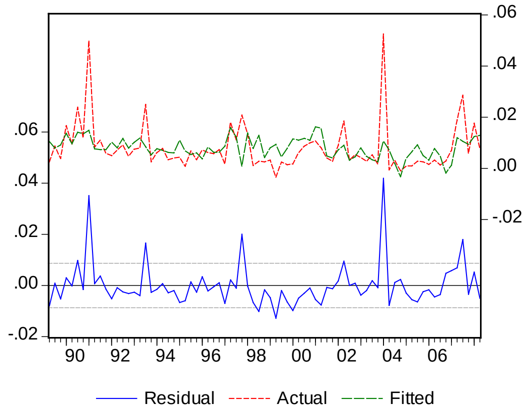


Figure 9: (a) Log-levels of the Series (b) Residual, Actual and Fitted Graph for Health Care CPI

After checking the co-integration among variables, we find health care prices, corresponding import prices and unit labor cost for non-traded sector form a sensible co-integrating relationship. We also find out the best coefficients that give the greatest magnitude of the adjustment coefficient of ECM by calibration. The long-run equation for Health Care is:

$$\ln CPI_t^{hc} = 0.17\ln IPI_t^{hc} + 0.40\ln ULC_t^{NT} + 0.43\ln PET_t \tag{3.10}$$

In the short-run, incorporating (3.10) into an ECM and following the method of general to specific modeling, we obtain a parsimonious, economically interpretable and statistically acceptable model:

$$\underset{(7.14)}{\Delta\ln CPI_t^{hc} = 0.0073} + \underset{(2.13)}{0.14}\Delta\ln IPI_t^{hc} + \underset{(2.63)}{0.06}\Delta\ln PET_t - \underset{(2.67)}{0.05}EC_{t-1}^{hc} \tag{3.11}$$

$R^2 = 0.18 \quad SE = 0.009 \quad DW = 1.98$

In this model, the magnitude of the adjustment coefficient is small, implying health care prices are also persistent. Besides, the corresponding import prices have a bigger impact on health care prices in the short run than oil prices. As shown by Figure 9(b), the EC model fits the data well.

3.10 Price Behavior of Recreation & Others

The Health Care category accounts for 16.59% of the total CPI expenditure in Singapore. It can be further grouped into eight subcategories, namely Recreation & Entertainment, Alcoholic Drinks & Tobacco, Personal Care, Household Services, Non-Durable Household Goods, Personal Effects, Holiday Expenses, and Hobbies & Others. With large component of consumer services, recreation prices are increasing over the years.

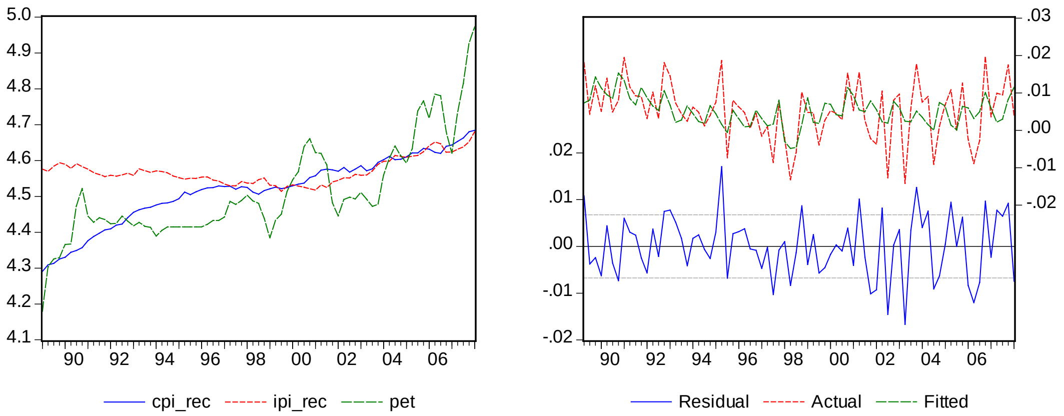


Figure 10: (a) Log-levels of the Series (b) Residual, Actual and Fitted Graph for Recreation & Others CPI

After checking the co-integration among variables, we find recreation & others prices, corresponding import prices and unit labor cost for non-traded sector form a sensible co-integrating relationship. We also find out the best coefficients that give the greatest magnitude of the adjustment coefficient of ECM by calibration. The long-run equation for Recreation & Others is:

$$\ln CPI_t^{rec} = 0.51 \ln IPI_t^{rec} + 0.35 \ln ULC_t^{NT} + 0.14 \ln PET_t \qquad (3.12)$$

In the short-run, incorporating (3.12) into an ECM and following the method of general to specific modeling, we obtain a parsimonious, economically interpretable and statistically acceptable model:

$$\Delta \ln CPI_t^{rec} = 0.0056 + 0.025 \Delta \ln ULC^{nt} - 0.01 D\_98 - 0.10 EC_{t-1}^{rec} \qquad (3.13)$$

(7.05) (3.52) (3.48) (4.07)

$R^2 = 0.27 \quad SE = 0.007 \quad DW = 2.06$

where the numbers in parentheses are the t-statistics, DW is the co-integrating regression Durbin-Watson statistic. In this model, the magnitude of the adjustment coefficient is small, implying sticky recreation & others prices. Besides, unit labor cost for non-traded sector has effect on recreation & others prices in the short run, which is reasonable for the category with a large component of consumer services. As shown by Figure 10(b), the EC model fits the data well.

Chapter 4 Univariate Benchmarks and Forecasting

Although many papers documented poor forecasting performance of Phillips curve-based models and concluded that they have little advantage relative to univariate models in recent years, ambiguities remain because those results largely depend on the sample period and specification. Therefore univariate models are always used as benchmark to compare their forecasting accuracy with structure models. In this chapter we first develop ARIMA models for the seven categories of the CPI and compare them with the results from the previous structural models. Then, we combine all the categories to obtain the disaggregated bottom-up model for the total CPI. In the end, we compare the performance of the univariate benchmark, the aggregated structural model and the disaggregated bottom-up model.

In the simulated forecasting exercises, static forecast is adopted to construct the simulated record of inflation produced by various models starting with 2001Q1 and ending with 2008Q1. It performs all model specifications and estimations using data through date t, making a one-step ahead forecast for date t+1, then moving forward to date t+1 and repeating this through all the sample. In other words, static forecast always uses the actual value of the lagged endogenous variable.

The RMSE (Root mean squared error) for forecasts used to compare different models is:

$$RMSE_{t_1,t_2} = \sqrt{\frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2}(\pi_{t+1} - \pi_{t+1|t})^2} \tag{4.1}$$

where $\pi_{t+1|t}$ is static forecast of π_{t+1} made using data through date t.

4.1 Univariate Models for the categories of the CPI

In this section, we identify and estimate the univariate models for each of the categories of the total CPI. Since all the variables are I(1) based on the unit root tests, we take the first difference of the logarithms to make them stationary. Then, we examine autocorrelation and partial autocorrelation functions of the $\Delta \ln CPI_i$ sequence. The estimated ARIMA equations are presented below and Figure 11-17 shows the forecasting accuracy of the ARIMA models (left panel of the figure) and the structural models for the individual category (right panel of the figure).

Food

$$\underset{}{\Delta \ln CPI_t^{fd}} = \underset{(0.83)}{0.017} + \underset{(17.55)}{0.95}\Delta \ln CPI_{t-4}^{fd} + \varepsilon_t - \underset{(2.80)}{0.33}\varepsilon_{t-2} - \underset{(4.69)}{0.56}\varepsilon_{t-4} \tag{4.2}$$

AIC=-7.51 SBC=-7.39
Q-statistics for the residuals (significance level in parentheses):
Q(8)= 9.3 (0.10) Q(16)=13.80 (0.39) Q(24)=20.67 (0.48)

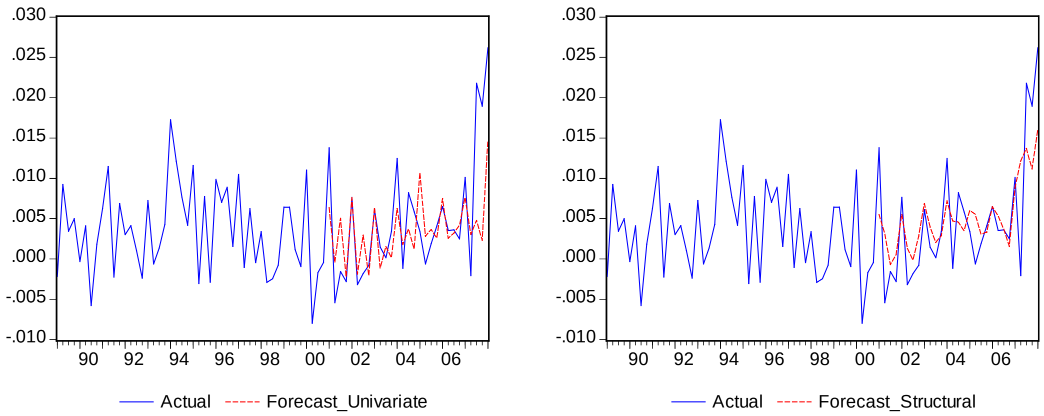


Figure 11: Forecasting Performance of the Univariate Model and the Structural Model for Food

Clothing & Footwear

$$\Delta \ln CPI_t^{cl} = \underset{(0.25)}{0.0002} + \underset{(7.86)}{0.75}\Delta \ln CPI_{t-4}^{cl} + \varepsilon_t - \underset{(2.58)}{0.24}\varepsilon_{t-2} - \underset{(6.00)}{0.66}\varepsilon_{t-4} \tag{4.3}$$

AIC=-6.80 SBC=-6.68

Q-statistics for the residuals (significance level in parentheses):
Q(8)=6.70 (0.24)   Q(16)=10.60 (0.65)   Q(24)=17.96 (0.65)

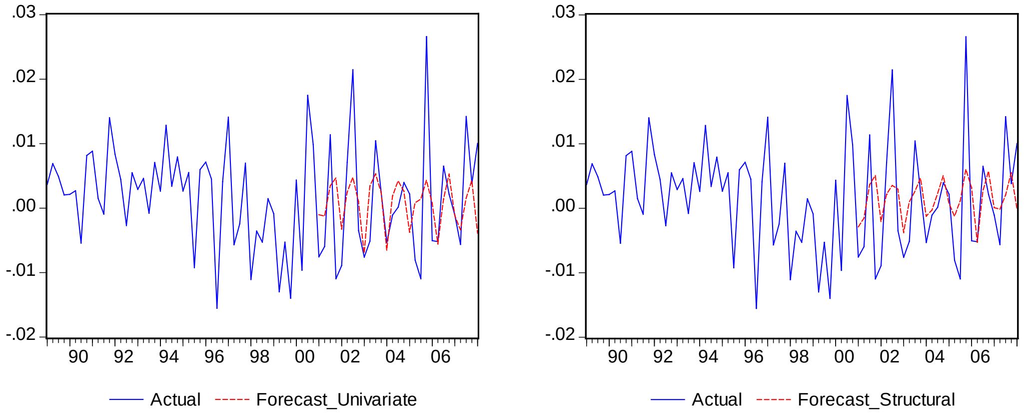


Figure 12: Forecasting Performance of the Univariate Model and the Structural Model for Clothing & Footwear

Housing

$$\Delta \ln CPI_t^{hous} = \underset{(2.24)}{0.0046} + \underset{(4.05)}{0.48}\Delta \ln CPI_{t-1}^{hous} \tag{4.4}$$

AIC=-6.52 SBC=-6.46
Q-statistics for the residuals (significance level in parentheses):
Q(8)=10.25 (0.18)   Q(16)=16.12 (0.37)   Q(24)=24.60 (0.37)

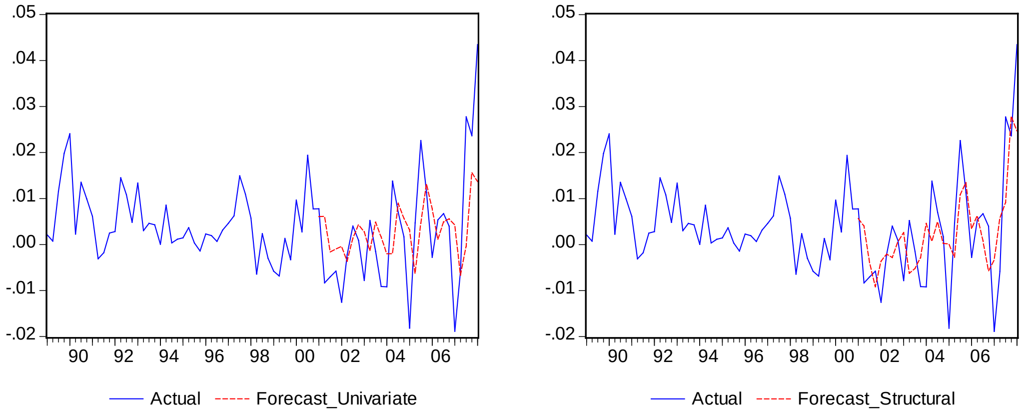


Figure 13: Forecasting Performance of the Univariate Model and the Structural Model for Housing

Transport & Communication

$$\Delta \ln CPI_t^{tc} = \underset{(41.88)}{0.90}\Delta \ln CPI_{t-1}^{tc} + \varepsilon_t - \underset{(65.45)}{0.93}\varepsilon_{t-1} \tag{4.5}$$

AIC=-5.68 SBC=-5.62

Q-statistics for the residuals (significance level in parentheses):
Q(8)=7.69 (0.26)   Q(16)=20.03 (0.32)   Q(24)=34.23 (0.33)

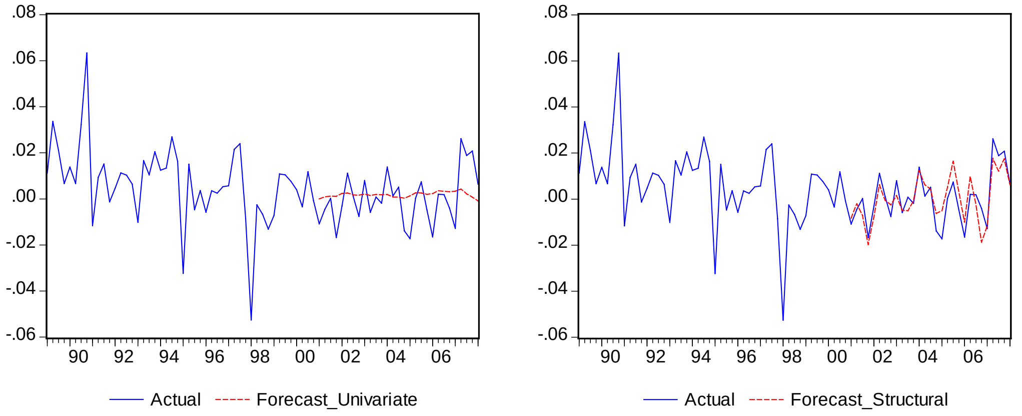


Figure 14: Forecasting Performance of the Univariate Model and the Structural Model for Transportation & Communication

Education & Stationery

$$\Delta \ln CPI_t^{edu} = \underset{(5.53)}{0.007} + \underset{(5.14)}{0.54}\Delta \ln CPI_{t-2}^{edu} + \varepsilon_t - \underset{(2.02)}{0.24}\varepsilon_{t-1} \tag{4.6}$$

AIC=-7.03 SBC=-6.94
Q-statistics for the residuals (significance level in parentheses):

Q(8)=6.48 (0.37)   Q(16)=12.94 (0.53)   Q(24)=18.38 (0.68)

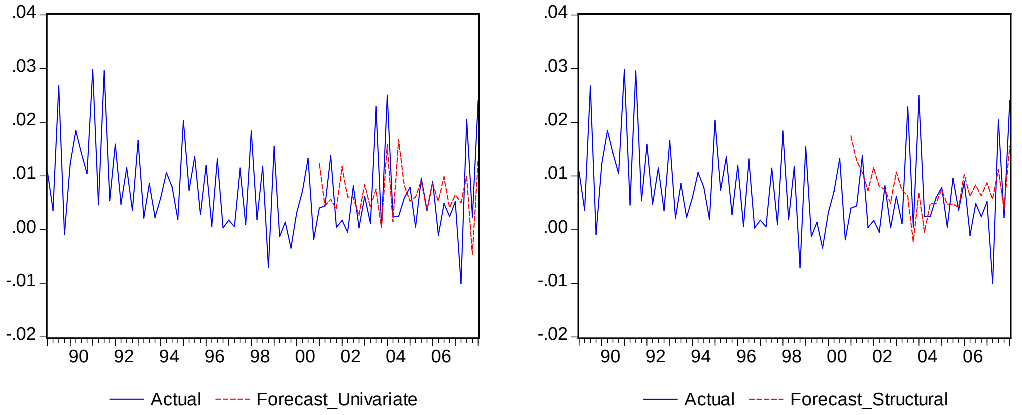


Figure 15: Forecasting Performance of the Univariate Model and the Structural Model for Education & Stationery

Health Care

$$\Delta \ln CPI_t^{hc} = \underset{(5.87)}{0.008} + \underset{(2.93)}{0.22}\Delta \ln CPI_{t-2}^{hc} \tag{4.7}$$

AIC=-6.48 SBC=-6.41
Q-statistics for the residuals (significance level in parentheses):
Q(8)=2.09 (0.96) Q(16)=8.31 (0.91) Q(24)=11.04 (0.98)

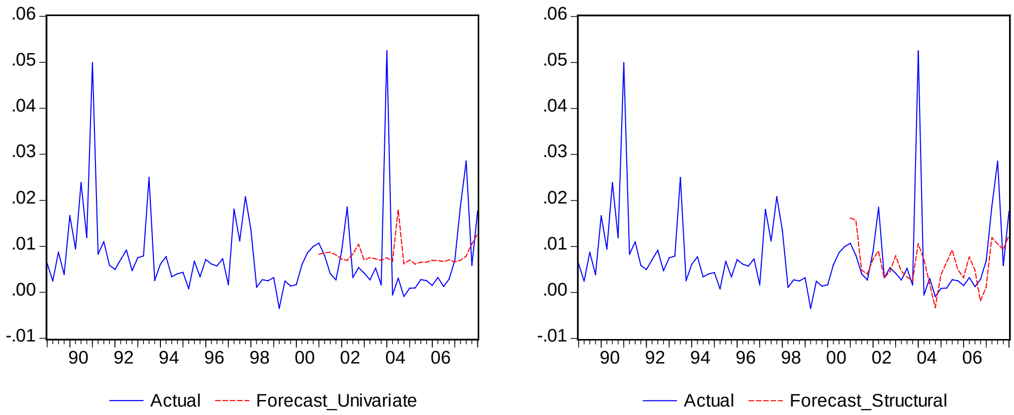


Figure 16: Forecasting Performance of the Univariate Model and the Structural Model for Health Care

Recreation & Others

$$\Delta \ln CPI_t^{rec} = 0.94 \Delta \ln CPI_{t-4}^{rec} + \varepsilon_t - 0.89 \varepsilon_{t-4} \quad (4.8)$$

(20.94) (20.63)

AIC=-7.02 SBC=-6.96
Q-statistics for the residuals (significance level in parentheses):

Q(8)=5.34 (0.50) Q(16)=10.94 (0.61) Q(24)=16.98 (0.77)

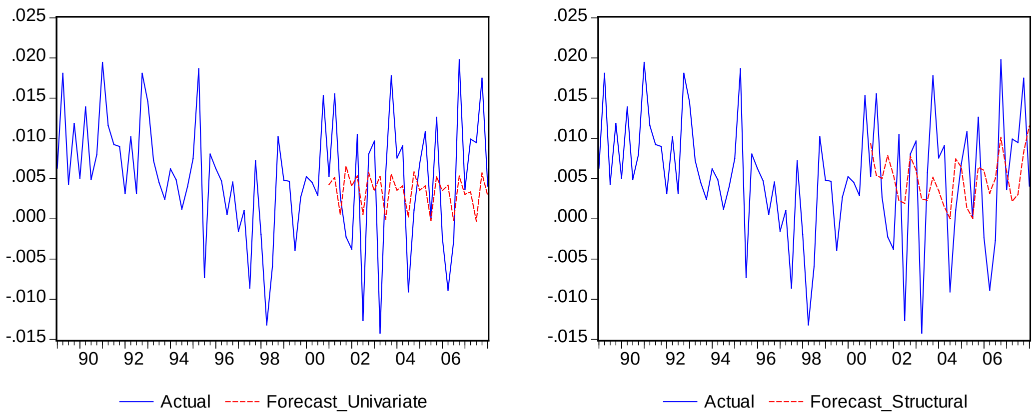


Figure 17: Forecasting Performance of the Univariate Model and the Structural Model for Recreation & Others

As shown by Table 3, the performances of the ARMA models and the structural models depend on the specific characteristics of the specific category. In our case, Food, Clothing & Footwear, Housing, Transport & Communication, Health Care are better forecasted by the structural models while the univariate model works better for Education & Stationery and the performances are almost the same for Recreation & Others. Although the results might be a little bit different when using the data from other periods, the point here is that the structural models are able to forecast more accurately than the univariate models.

Table 3: RMSE of ARIMA Models and Structural Models

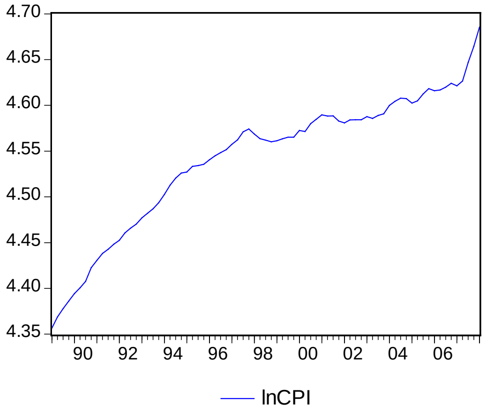
	RMSE						
Categories	fd	cl	hous	tran	edu	hc	rec
ARMA	0.0061	0.0084	0.0123	0.0109	0.0071	0.0109	0.0083
Structural	0.0052	0.0082	0.0097	0.0061	0.0077	0.0065	0.0083

4.2 Univariate Model for the Total CPI

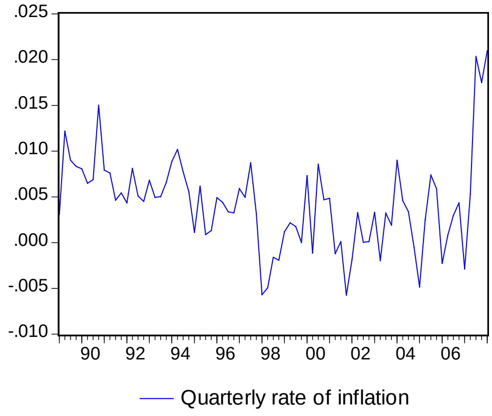
From the Session 3.3, we know the logarithm of the total CPI is I(1) process. It can be shown by Panel (a) of Figure 18 since the series has a positive trend through the period 1989Q1 to 2008Q1. However, after we take the first difference of the logarithm, the series is the most likely candidate to be stationary as shown by Panel (b) of Figure 18. A comparison of the ACF and PACF to the various theoretical ARMA process of the $\Delta \ln CPI$ sequence suggests AR(1) specification is superior to other ARMA models. In Panel (c) and (d), we depict the forecasting performance of the AR(1) model. The estimated AR(1) model is:

$$\underset{}{\Delta \ln CPI_t} = \underset{(3.69)}{0.0048} + \underset{(6.18)}{0.623}\Delta \ln CPI_{t-1} \tag{4.9}$$

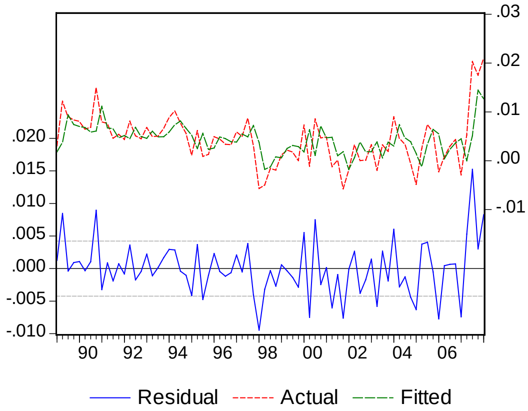
AIC=-8.07 SBC=-8.01
Q-statistics for the residuals (significance level in parentheses):
Q(8)=2.82 (0.90)   Q(16)=11.87 (0.69)   Q(24)=31.19 (0.46)



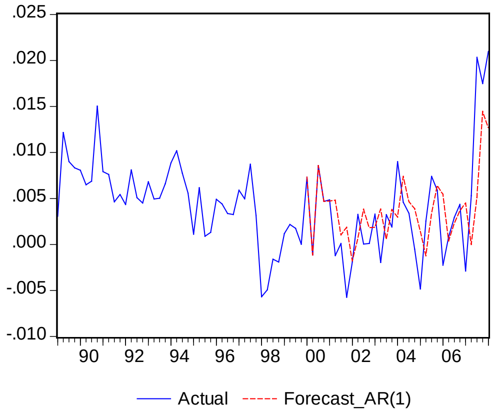
(a)



(b)



(c)



(d)

Figure 18: AR(1) Specification for the Total CPI

4.3 Comparison between Models

To compare the forecasting accuracy of the univariate ARMA model with that of the disaggregated bottom-up model, we should first obtain the forecasting series of the disaggregated bottom-up model by combining all the forecasting values from the seven structural models for the CPI categories based on the identity of 2004-based CPI mentioned before:

$$\begin{aligned} CPI = {} & 0.2338CPI^{fd} + 0.0357CPI^{cl} + 0.2126CPI^{hous} + 0.2176CPI^{tc} + 0.0819CPI^{edu} \\ & + 0.0525CPI^{hc} + 0.1659CPI^{rec} \end{aligned} \tag{4.10}$$

Besides, we also re-estimate the aggregated model following the framework of

Abeysinghe and Choy (2007) to obtain the forecasting accuracy of the aggregated model. The re-estimated model for the total CPI in long run is:

$$\ln CPI_t = 0.43 \ln IPI_t + 0.57 \ln ULC_t^{NT} \tag{4.11}$$

In the short-run, we obtain a parsimonious, economically interpretable and statistically acceptable EC model:

$$\underset{}{\Delta \ln CPI_t} = \underset{(2.89)}{0.002} + \underset{(6.62)}{0.54\Delta \ln CPI_{t-1}} + \underset{(5.41)}{0.05\Delta \ln PET_t} - \underset{(2.35)}{0.013 EC_{t-1}} \tag{4.12}$$

R^2=0.55 SE=0.004 DW=2.35

Table 4: RMSE of the AR(1), the Disaggregated Bottom-up Model and the Aggregated Models for the Total CPI

	AR(1)	Disaggregated Bottom-up Model	Aggregated Model
RMSE	0.0052	0.0038	0.0039

As shown by Table 4, we calculate the RMSEs of the AR(1) model, the disaggregated bottom-up model and the aggregated model respectively. It can be concluded that 1) the disaggregated bottom-up model beats the univariate model, which is good news for structural models. 2) the disaggregated bottom-up model beats the aggregated model marginally, or more prudentially, it forecasts at least as well as the aggregated model. However, considering extra information carried by disaggregated bottom up model for each underlying category of CPI , it is reasonable to conclude that disaggregated model is still preferred. Figure 19 below shows the performance of the disaggregated bottom-up model and the aggregated model.

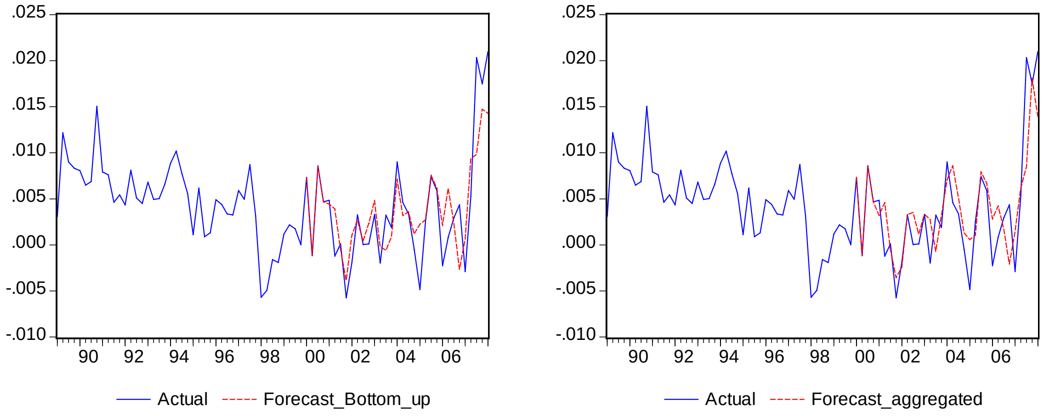


Figure 19: Forecasting Performance of the Disaggregated Bottom-up Model and the Aggregated Model

Chapter 5 Conclusion

In reality, practical inflation modeling is labeled as an art as well as a science. Economists consult a variety of models that differ greatly in details to analyze the price behavior. In this thesis, we reflect the literature on inflation modeling and employ an econometric disaggregated bottom-up approach to model the inflation in Singapore. It analyzes price behaviors of the various categories of goods and services that make up the aggregate price index and focuses on the common critical factors of labor cost, import prices and oil price that demonstrate the influences of Singapore's international trade pattern and unique labor market on the price behaviors.

Since inflation forecasts are judgmental and no one model can summarize the whole price mechanism, in this thesis, we also conduct pseudo out-of-sample forecast and develop univariate benchmark to assess the forecasting accuracy. By comparing the RMSE of the univariate model, the disaggregated model and the aggregated model, the thesis indicates that in terms of the total CPI the disaggregated bottom up model works better than the univariate model and at least as well as the aggregated model, while for the subcategories of CPI, the performance of the structural models depends on the specific characteristic of that category.

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Appendix A: Mapping of the Categories of IPI to the Categories of CPI[12]

CPI	IPI	Weight(IPI)
Food	food	203
	animal & vegetable oils & fats	15
Clothing & Footwear	textile yarn thread	5
	cotton fabrics, woven	6
	synthetic fabrics, woven	12
	fabrics, knitted or crocheted	9
	special fabrics and products	12
	articles of textile	9
	men's clothing, woven	12
	women's clothing, woven	17
	men's clothing, knitted	10
	women's clothing, knitted	16
	apparel article of textile	49
	other clothing accessories & headgear	5
	footwear	15
Housing	furniture	22
	sanitary, plumbing & heating fixtures & fittings	1
	lighting fixtures	8
	paints & varnishes	24
	household goods	24
	cutlery	8
	television	35
	musical instruments and parts	73
	articles of plastic	47
Transportation & Communication	motor cars	87
	goods motor vehicles	28
	parts for tractors and motor	68

[12] IPI Weights refer to the weight that each subcategory accounts for in the Import Price Index.

	vehicles	
	motorcycles and parts	19
	trailers and parts	4
	telecommunication equipment	628
Education & Stationary	paper and paperboard	32
	articles of paper, paper pulp & cellulose wadding	17
	office supplies	11
	data processing machines	
	office machine	301
	parts for office and data processing	
	printed matter	24
Health Care	medicinal and pharmaceutical products, excl medicaments	49
	medicaments	32
	medical apparatus	46
	measuring instruments	166
Recreation & Others	toys & games	26
	photographic apparatus	29
	photographic supplies	30
	optical goods not elsewhere classified	26
	alcoholic beverages	41
	tobacco	21
	perfumes & cosmetics	50
	soap and cleansing preparations	11
	travel goods	16
	watches and clocks	45
	jewellery	59

Appendix B: Cointegration Tests

1. Cointegration Tests for the CPI

VAR Lag Order Selection Criteria

Sample: 1989Q1 2008Q1
Included observations: 70

Lag	LogL	LR	FPE	AIC	SC	HQ
0	386.8409	NA	2.09e-10	-10.93831	-10.80983	-10.88728
1	699.0271	579.7743	4.41e-14	-19.40077	**-18.75835***	-19.14559
2	723.7905	43.15917	3.45e-14	-19.65116	-18.49479	-19.19183
3	739.7654	26.01615	3.50e-14	-19.65044	-17.98013	-18.98697
4	791.6618	78.58604	1.28e-14	-20.67605	-18.49180	-19.80844
5	833.4068	58.44302*	6.37e-15*	-21.41162*	-18.71343	-20.33987*
6	840.9786	9.735117	8.57e-15	-21.17082	-17.95868	-19.89492
7	858.2094	20.18471	8.96e-15	-21.20598	-17.47991	-19.72594

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.354421	60.42038	54.07904	0.0122
At most 1	0.208987	29.78782	35.19275	0.1703
At most 2	0.133180	13.37697	20.26184	0.3345
At most 3	0.047033	3.372254	9.164546	0.5135

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.354421	30.63255	28.58808	0.0270
At most 1	0.208987	16.41086	22.29962	0.2701
At most 2	0.133180	10.00471	15.89210	0.3339
At most 3	0.047033	3.372254	9.164546	0.5135

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

2. Cointegration Tests for Food

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	363.8617	NA	4.03e-10	-10.28176	-10.15328	-10.23073
1	657.2859	544.9308	1.45e-13	-18.20817	**-17.56574***	-17.95299
2	682.1623	43.35591	1.13e-13	-18.46178	-17.30541	-18.00246
3	704.1790	35.85581	9.66e-14	-18.63369	-16.96338	-17.97022
4	738.8797	52.54678	5.79e-14	-19.16799	-16.98374	-18.30038
5	780.9284	58.86822*	2.85e-14*	-19.91224	-17.21405	-18.84049*
6	797.6519	21.50155	2.95e-14	-19.93291*	-16.72077	-18.65701
7	810.8892	15.50654	3.46e-14	-19.85398	-16.12790	-18.37393

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.289866	38.98454	29.79707	0.0033
At most 1	0.161988	13.65424	15.49471	0.0929
At most 2	0.007764	0.576768	3.841466	0.4476

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.289866	25.33031	21.13162	0.0121
At most 1	0.161988	13.07747	14.26460	0.0763
At most 2	0.007764	0.576768	3.841466	0.4476

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

3. Cointegration Tests for Clothing & Footwear

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	438.8851	NA	4.72e-11	-12.42529	-12.29680	-12.37425
1	667.5015	424.5733	1.09e-13	-18.50004	**-17.85761***	-18.24486
2	688.2857	36.22393	9.52e-14	-18.63673	-17.48037	-18.17741
3	714.1256	42.08217	7.27e-14	-18.91787	-17.24756	-18.25441
4	758.5126	67.21463	3.30e-14	-19.72893	-17.54468	-18.86132
5	797.1249	54.05715*	1.80e-14*	-20.37500*	-17.67680	-19.30324*
6	812.9445	20.33949	1.91e-14	-20.36984	-17.15771	-19.09394
7	822.3675	11.03840	2.50e-14	-20.18193	-16.45585	-18.70189

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.238902	20.20151	27.58434	0.3274
At most 1	0.143013	11.42057	21.13162	0.6053
At most 2	0.098893	7.705698	14.26460	0.4094
At most 3	0.006609	0.490659	3.841466	0.4836

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

4. Cointegration Tests for Housing

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	328.4322	NA	1.11e-09	-9.269491	-9.141005	-9.218455

1	629.2880	558.7322	3.24e-13	-17.40823	-16.76580	-17.15305
2	668.4174	68.19695	1.68e-13	-18.06907	**-16.91270***	-17.60974
3	681.6184	21.49877	1.84e-13	-17.98910	-16.31879	-17.32563
4	725.3342	66.19827	8.53e-14	-18.78098	-16.59672	-17.91337
5	753.7789	39.82256*	6.20e-14*	-19.13654	-16.43835	-18.06478*
6	769.6691	20.43024	6.57e-14	-19.13340	-15.92127	-17.85750
7	787.2316	20.57325	6.81e-14	-19.17805*	-15.45197	-17.69800

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.464437	68.62592	47.85613	0.0002
At most 1	0.199073	22.41767	29.79707	0.2759
At most 2	0.071926	5.990715	15.49471	0.6966
At most 3	0.006292	0.467072	3.841466	0.4943

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.464437	46.20826	27.58434	0.0001
At most 1	0.199073	16.42695	21.13162	0.2009
At most 2	0.071926	5.523643	14.26460	0.6748
At most 3	0.006292	0.467072	3.841466	0.4943

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

5. Cointegration Tests for Transport & Communication

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ

0	314.4180	NA	1.65e-09	-8.869086	-8.740601	-8.818050
1	624.4584	575.7894	3.72e-13	-17.27024	-16.62781	-17.01506
2	642.8150	31.99292	3.49e-13	-17.33757	-16.18120	-16.87825
3	664.7956	35.79692	2.98e-13	-17.50845	-15.83813	-16.84498
4	713.8867	74.33797	1.18e-13	-18.45391	-16.26965	-17.58629
5	762.4182	67.94403*	4.84e-14*	-19.38338*	**-16.68518***	-18.31162*
6	775.6165	16.96932	5.55e-14	-19.30333	-16.09119	-18.02743
7	787.7170	14.17489	6.72e-14	-19.19192	-15.46584	-17.71187

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.262724	22.55464	27.58434	0.1933
At most 1	0.187826	15.39499	21.13162	0.2622
At most 2	0.115552	9.086589	14.26460	0.2790
At most 3 *	0.091894	7.133183	3.841466	0.0076

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

6. Cointegration Tests for Education & Stationery

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	304.3076	NA	2.21e-09	-8.580216	-8.451731	-8.529180
1	618.3440	583.2105	4.43e-13	-17.09554	-16.45312	-16.84036
2	648.0733	51.81401	3.00e-13	-17.48781	-16.33144	-17.02849
3	681.2489	54.02871	1.86e-13	-17.97854	-16.30823	-17.31507
4	718.4401	56.31821	1.04e-13	-18.58400	-16.39975	-17.71639
5	755.6732	52.12628*	5.87e-14*	-19.19066	**-16.49247***	-18.11891*
6	773.4927	22.91073	5.89e-14	-19.24265	-16.03051	-17.96675
7	790.4355	19.84739	6.22e-14	-19.26959*	-15.54351	-17.78954

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.369586	52.94384	47.85613	0.0154
At most 1	0.164234	20.18597	29.79707	0.4103
At most 2	0.074928	7.448086	15.49471	0.5262
At most 3	0.026657	1.918305	3.841466	0.1660

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.369586	32.75787	27.58434	0.0199
At most 1	0.164234	12.73788	21.13162	0.4766
At most 2	0.074928	5.529781	14.26460	0.6740
At most 3	0.026657	1.918305	3.841466	0.1660

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

7. Cointegration Tests for Health Care

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	332.3760	NA	9.90e-10	-9.382170	-9.253685	-9.331134
1	623.4193	540.5090	3.83e-13	-17.24055	**-16.59812***	-16.98537
2	637.8374	25.12869	4.02e-13	-17.19535	-16.03898	-16.73603
3	658.9596	34.39911	3.52e-13	-17.34170	-15.67139	-16.67824
4	706.2542	71.61747	1.47e-13	-18.23583	-16.05158	-17.36822
5	736.0144	41.66430*	1.03e-13*	-18.62898*	-15.93079	-17.55723*
6	751.4010	19.78274	1.11e-13	-18.61146	-15.39932	-17.33556
7	765.6781	16.72462	1.26e-13	-18.56223	-14.83615	-17.08219

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.190900	30.04176	27.85613	0.0368
At most 1	0.122917	19.00165	29.79707	0.4800
At most 2	0.074791	10.689770	15.49471	0.4318
At most 3	0.002399	2.170517	3.841466	0.2796

Trace test indicates 1 cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.190900	29.04011	27.58434	0.0450
At most 1	0.122917	14.311877	21.13162	0.5065
At most 2	0.074791	9.519253	14.26460	0.6753
At most 3	0.002399	2.170517	3.841466	0.3096

Max-eigenvalue test indicates 1 cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

8. Cointegration Tests for Recreation & Others

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	370.5681	NA	3.32e-10	-10.47337	-10.34489	-10.42234
1	682.4894	579.2823	7.08e-14	-18.92827	**-18.28584***	-18.67309
2	704.8645	38.99674	5.93e-14	-19.11042	-17.95405	-18.65109
3	721.6433	27.32546	5.87e-14	-19.13267	-17.46236	-18.46920
4	766.8169	68.40573	2.61e-14	-19.96620	-17.78195	-19.09859
5	808.5185	58.38218*	1.30e-14*	-20.70053*	-18.00233	-19.62877*
6	811.5481	3.895302	1.99e-14	-20.32995	-17.11781	-19.05405
7	827.8012	19.03926	2.14e-14	-20.33718	-16.61110	-18.85713

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.300269	49.63189	47.85613	0.0337
At most 1	0.170505	23.20951	29.79707	0.2359
At most 2	0.084876	9.376043	15.49471	0.3317
At most 3	0.037295	2.812589	3.841466	0.0935

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.300269	28.02237	27.58434	0.0498
At most 1	0.170505	13.83347	21.13162	0.3789
At most 2	0.084876	6.563454	14.26460	0.5420
At most 3	0.037295	2.812589	3.841466	0.0935

Max-eigenvalue test indicates 1 cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values