Essays on business cycles and macroeconomic forecasting

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Essays on Business Cycles and
Macroeconomic Forecasting

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A thesis submitted in partial fulfillment of the requirements
for the degree of

Doctor of Philosophy

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January 2016
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Abstract

This dissertation consists of two essays. The first essay focuses on developing a quantitative theory for a small open economy dynamic stochastic general equilibrium (DSGE) model with a housing sector allowing for both contemporaneous and news shocks. The second essay is an empirical study on the macroeconomic forecasting using both structural and non-structural models.

In the first essay, we develop a DSGE model with a housing sector, which incorporates both contemporaneous and news shocks to domestic and external fundamentals, to explore the kind of and the extent to which different shocks to economic fundamentals matter for driving housing market dynamics in a small open economy. The model is estimated by the Bayesian method, using data from Hong Kong. The quantitative results show that external shocks and news shocks play a significant role in this market. Contemporaneous shock to foreign housing preference, contemporaneous shock to terms of trade, and news shocks to technology in the consumption goods sector explain one-third each of the variance of housing price. Terms of trade contemporaneous shock and consumption technology news shocks also contribute 36% and 59%, respectively, to the variance in housing investment. The simulation results enable policy makers to identify the key driving forces behind the housing market dynamics and the interaction between housing market and the macroeconomy in Hong Kong.

In the second essay, we compare the forecasting performance between structural and non-structural models for a small open economy. The structural model refers to the small open economy DSGE model with the housing sector in the first essay.
In addition, we examine various non-structural models including both Bayesian and classical time-series methods in our forecasting exercises. We also include the information from a large-scale quarterly data series in some models using two approaches to capture the influence of fundamentals: extracting common factors by principal component analysis in a dynamic factor model (DFM), factor-augmented vector autoregression (FAVAR), and Bayesian FAVAR (BFAVAR) or Bayesian shrinkage in a large-scale vector autoregression (BVAR). In this study, we forecast five key macroeconomic variables, namely, output, consumption, employment, housing price inflation, and CPI-based inflation using quarterly data. The results, based on mean absolute error (MAE) and root mean squared error (RMSE) of one to eight quarters ahead out-of-sample forecasts, indicate that the non-structural models outperform the structural model for all variables of interest across all horizons. Among the non-structural models, small-scale BVAR performs better with short forecasting horizons, although DFM shows a similar predictive ability. As the forecasting horizon grows, DFM tends to improve over other models and is better suited in forecasting key macroeconomic variables at longer horizons.
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Chapter 1

Introduction

Over the past decades, real business cycle (RBC) theory has developed rapidly to facilitate exploration of the driving forces behind the macroeconomic dynamics. It has grown substantially and be widely used as an important tools for studies of the macroeconomy at business frequencies. The financial crisis occurred in 2007-08 has aroused interest in studying the role of the housing market in driving business cycles. The housing market in the U.S. at the beginning of the twenty-first century has experienced large fluctuations in housing price and residential investment, which has led many scholars to deem that the dynamics in housing market might be the important driving forces behind the business cycles. Thus, these essays construct a DSGE model with the housing sector, which incorporates both contemporaneous and news shocks to domestic and external fundamentals, to study the driving forces behind housing market dynamics and the macroeconomy in a small open economy. Furthermore, the DSGE model could be used as a prominent tool for forecasting macroeconomic variables. To further examine the predictive ability of structural model, we compare the forecasts generated from the DSGE model with those generated from various non-structural models, including the dynamic factor model (DFM), classical vector autoregressive (VAR) model, large-scale Bayesian VAR (LBVAR), small-scale Bayesian VAR (SBVAR), factor-augmented VAR (FAVAR), and Bayesian FAVAR (BFAVAR). Through the comparison among the seven available models, we want to find out which
model can lead to the best forecasting performance of a typical small open economy, such as Hong Kong.

In the first essay, we document that the fluctuations of housing price have become a prominent characteristics of the macroeconomy. Housing rental expenses and residential mortgage payment contribute to a large portion of household expenditure. In addition, residential investment becomes the dominant source of private wealth accumulation in many countries. Considering Hong Kong as an example, the ratio of housing price to annual household income has increased to 17 according to Annual Demographia International Housing Affordability Survey in 2015. Furthermore, in Hong Kong, homeownership is common, and the bulk of housing expenditure requires financing (Ho and Wong, 2008). Since housing expenditures probably account for the largest proportion of household spending in most, if not all, economies, it is widely believed that house represents a vital role in the wealth accumulation for households and the macroeconomy (Case, 2000; Goodhart and Hofmann, 2003; Edelstein and Lum, 2004; Kim, 2004; Leung, 2004; Phang, 2004; Cutler, 2005; Gerlach and Peng, 2005; Gan, 2010). While it is well noted that housing is an important issue from an individual perspective, the Hong Kong housing market has experienced large fluctuations in housing price in the past years. Hong Kong is an ideal case for the investigation of the relationship between housing market and the aggregate economy. Historical data (Figure 1.1) indicates that there are obvious and large deviations of housing price from its trend, as compared to the real GDP and real consumption between 1985 and 2014. Hong Kong is a typical small open economy and ranking first according to 2015 Index of the economic freedom as the world’s freest
With relative dense population and a dynamic economy, the housing spending in Hong Kong accounts for a significant proportion of the total expenditure and wealth accumulation of the domestic households. Ho and Wong (2006) indicate that the housing market collapse plays an important role in the Asian Financial Crisis in 1998. Given the significant effect of the housing market on the Hong Kong economy, we take Hong Kong as the representative small open economy for analyzing housing market fluctuations.

Current research on the dynamics of the housing market in a small open economy focuses on the role of contemporaneous shocks to some external fundamentals, such as unanticipated changes to terms of trade. In addition, no study has integrated the impact of news shocks to those fundamentals into the analysis of housing market dynamics for small open economies. To fill this gap, the primary contribution of the first essay is to study the quantitative impact of both contemporaneous and news shocks to the domestic and external fundamentals on housing market dynamics of a small open economy. We construct a small open economy model, which merges the elements of the three branches of business cycle models in the literature. First, there are financial frictions in which the collateral constraint of credit-constrained households is tied to housing price and loan-to-value ratio (Iacoviello, 2005; Monacelli, 2009; Iacoviello and Neri, 2010). Second, the business cycles of the small open economy are driven not only by domestic shocks but also by external shocks (Mendoza, 1991, 1995; Blankenau et al., 2001; Kose and Riezman, 2001; Kose, 2002; Gali and Monacelli, 2005; Lubik and Teo, 2005; Neumeyer and Perri, 2005). Domestic shocks contain shocks to sector-specific technology, housing preference, cost-push inflation, and credit constraint (captured by loan-to-value ratio). External shocks include shocks to foreign housing preference, terms of

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1 In 2015 Hong Kong continues to be the top-rated free economy in the index for more than 10 years. (See the Heritage Foundation for details)
trade, foreign interest rate, and foreign demand. Third, the sources of aggregate fluctuations include both contemporaneous and news shocks (Beaudry and Portier, 2004; Jaimovich and Rebelo, 2009; Fujiwara et al., 2011; Khan and Tsoukalas, 2012; Schmitt-Grohe and Uribe, 2012; Born et al., 2013). The error term of each domestic or external shock contains a contemporaneous component and a news component. The news component consists of news announced four and eight periods in advance.

We estimate and simulate the model using the Hong Kong macroeconomic data over the period 1985:Q1–2014:Q1. We find that external shocks and news shocks play an important role in driving the housing market dynamics in a small open economy. Fluctuations in housing price are mainly driven by contemporaneous shock to foreign housing preference, contemporaneous shock to terms of trade, and news shocks to technology in the consumption goods sector. Each of the three shocks accounts for one third of the asymptotic volatility of housing price. As for the cyclical movements in housing investment, terms of trade contemporaneous shock and consumption technology news shocks also exhibit a significant contribution. The former explains 36% of the asymptotic variance in housing investment, while the latter explains 59%. External shocks and news shocks are also important for driving fluctuations in non-housing variables. Their influences, however, are remarkably different at various forecast horizons. Contemporaneous shock to terms of trade contributes more than 98% to the volatility of aggregate output, consumption, and employment at short horizons. By contrast, news shocks to consumption technology account for 62–78% of their asymptotic variance.

In the second essay, we conduct a forecasting experiment to compare the predictive ability of key macroeconomic variables, namely, output, consumption,
employment, housing price inflation, and CPI-based inflation, between structural and non-structural models in a small open economy. Unlike the structural DSGE model, which is estimated using six observables, SBVAR is estimated using 10 data series, and DFM, LBVAR, FAVAR, and BFAVAR exploit information from a large data set including 86 macroeconomic time series over the period 1993Q3 to 2014Q1 in Hong Kong. We use two approaches for extracting information from a large data set; the first involves estimating common factors by principal component analysis, and the second is Bayesian shrinkage. The results, based on MAE and RMSE of one to eight quarters ahead over the period 2006Q1 to 2014Q1 indicate that non-structural models outperform the structural model for all variables of interest across all horizon in terms of out-of-sample forecasting. Among the non-structural models, SBVAR results in better forecasts at short forecasting horizons in most cases, although DFM shows a similar predictive ability. As the forecasting horizon grows, DFM tends to perform better and even improves over other models in forecasting key macroeconomic variables at longer horizons.

Overall, the thesis studies the significance of a small open economy model in explaining housing market dynamics and the forecasting ability of both structural and non-structural models. Since the global financial crisis in 2007–2009 has aroused academic interest to readdress the nexus between the housing market and business cycles, the findings of the first essay could provide insights into identifying the key driving forces behind the housing market dynamics for small open economies for policy makers. Furthermore, macroeconomic forecasting is also important for policy makers and professional agents who make their economic decisions based on the judgement about the future developments of the macroeconomy. Thus, the results of
the second essay could facilitate policy makers with a better understanding of the competitive forecasting performance of various models.

The rest of the dissertation is organized as follows. Chapter 2 presents the first essay, which constructs a small open economy with a housing sector to explore the role of both contemporaneous and news shocks to domestic and external fundamentals in housing market dynamics and the business cycle. Chapter 3, the second essay, compares the forecasting ability of structural and non-structural models in predicting key macroeconomic variables of a small open economy. Chapter 4 concludes the thesis and gives an outlook for further research.

Figure 1.1 Hong Kong housing prices at business cycle frequencies

Notes: in the above graph all series are measured in percentage deviations from trend
Chapter 2

An Analysis of Housing Market Dynamics in Small Open Economies: A Case of Hong Kong

2.1 Introduction

What are the sources of fluctuations in the housing market? This is an important question especially for an economy with high leverage on housing. In a small open economy such as Hong Kong, more than half of all households own residential properties, and the net housing wealth is three times more than the GDP. If there is a substantial collapse in the housing market, the wealth of most households will decrease significantly. This may even lead to negative equity for those households with mortgages and reduce private consumption and investment hereafter. Boom-bust cycles in housing price and the aggregate economy are important issues in both academic and policy analysis. The recent collapse of the housing price and the ensuing financial crisis that occurred in the U.S. starting in December 2007 attracts great attention to the behavior of housing price. The empirical facts about highly volatile housing price over the business cycles and their co-movement with the macroeconomy have led many scholars to consider the developments in the housing market as an important driving forces behind the business cycles, rather than a passive reflection of

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2 According to the Census and Statistics Department of Hong Kong, the home ownership rate in Hong Kong was 51.2% in 2013. The net housing wealth is defined as the market value of private residential housing minus the value of outstanding mortgage loans. In 2013, the ratio of net housing wealth to GDP was 3.2. For comparison, the similar ratio in 2010 was 2.1 for Canada and 1.8 for the U.S. (Wong 2014).
Economists have applied different business cycle models to investigate the driving forces of housing market dynamics and the linkage between the housing market and the macroeconomy. Davis and Heathcote (2005), Monacelli (2009), and Iacoviello and Neri (2010) construct different DSGE models with the inclusion of the housing (durable goods) sector to analyze the determinants of housing market fluctuations. They found that contemporaneous shocks to current fundamentals, including sector-specific productivity, housing preference, and monetary policy, can drive large fluctuations in housing price and the residential investment. However, recent empirical survey studies by Case and Shiller (2003) and Piazzi and Schneider (2009) show that housing price dynamics are also affected by expectations about the future state of the macroeconomy and particularly by optimism about future housing price appreciation. These findings suggest that news shock, defined as information that is useful for predicting future fundamentals but does not affect current fundamentals, might be an important driving force behind the housing market dynamics. The idea is that the optimistic expectation about future housing price appreciation may lead to a boom in the housing market. When such optimistic expectations eventually become unrealized, a bust in the housing market results. Lambertini et al. (2012) incorporate news shocks in the model of Iacoviello and Neri (2010) and evaluate the empirical performance of expectations-driven business cycles for housing market fluctuations. They find that news shocks to productivity, investment cost, housing supply, inflation, and monetary policy could generate housing market booms. However, they find that only expectations about future expansionary monetary policy that fail to realize can result in macroeconomic recessions. Gomes and Mendicino (2012) use a similar model and
find that news shocks to domestic foundations, including primarily, inflation, monetary policy, and housing preference, can explain 40% of housing price fluctuation in the U.S. over the last three decades.

All of the above theoretical models consider the analysis for a closed economy and focus on the role of domestic shocks to various fundamentals in driving housing market dynamics. Some recent studies attempt to address the role of external shocks in driving housing price fluctuation for small open economies. The small open economy acts as a price-taker in the world market, implying that changes from abroad, such as world prices, foreign interest rates, foreign demand, and terms of trade, may exert important influence on the fluctuations of domestic housing price. For example, Bao et al. (2009) show that the interest rate shock has a greater impact on output and inflation for the model with a housing sector. Tomura (2010) finds that contemporaneous shock to terms of trade can generate dynamics in current housing price under the condition that the domestic economy is open to international capital flows. Funke and Paetz (2013) develop a small open economy model with a housing sector and find that domestic housing preference shock is the most important determinant of housing price fluctuations.

To our best knowledge, research on the dynamics of the housing market in a small open economy only focuses on the role of contemporaneous shocks to some external fundamentals, such as unanticipated changes to terms of trade. Furthermore, there is no study integrating the impact of news shocks to those fundamentals into the analysis of housing market dynamics for small open economies. To fill this gap, our analysis combines three main streams of the business cycle models: (i) DSGE model with news shocks, (ii) a structural model with housing and non-housing sectors, and
(iii) DSGE model for a small open economy. Our study contributes to the existing literature by highlighting various factors such as external and news shocks that are important to policy makers in monitoring the behavior of the housing market and thus the macroeconomy.

In this essay, we develop a small open economy business cycle model with a housing sector, and the model is subject to both contemporaneous and news shocks to domestic and external fundamentals. Through estimating the DSGE model, our study attempts to examine the various driving forces behind the housing price fluctuations as well as to understand the interaction between the housing market and the aggregate economy.

Hong Kong is taken as a representative small open economy with the monetary policy of currency board system. The model allows for nominal rigidities, sectoral heterogeneity, and collateral constraints as in Iacoviello and Neri (2010). To quantify the relative importance of various shocks, the model is estimated using the Bayesian approach with Hong Kong data. The simulation results show that our model is able to replicate the key features of the data fairly well. It can match the stylized facts that housing prices are significantly volatile, procyclical, and very sensitive to changes in external fundamentals. The historical shock decomposition also shows that our model explains the long-run behavior of housing and other macroeconomic variables well. Using quarterly data over the period of 1985:Q1-2014:Q1, the model estimation shows that external shocks and news shocks drive the housing market dynamics. The fluctuations of housing price are mainly driven by contemporaneous shocks to foreign housing preference and terms of trade and news shock to productivity in the consumption goods sector. Each of these shocks accounts for around one-third of the
cyclical volatility of housing price. Terms of trade contemporaneous shock and consumption technology news shocks also exhibit a significant role in the cyclical movements of housing investment. The former explains 36% of the asymptotic variance in housing investment, while the latter explains 59%. In addition, shocks to external fundamentals also account for a sizable share of the variance in other macro variables. Terms of trade shock asymptotically account for 21.15% of output volatility, approximately 30% of consumption variance, and 37.67% of employment fluctuation. Moreover, from the conditional variance decomposition analysis, contemporaneous shocks contribute to the business cycles mainly at short horizons, while news shocks become more important in the long run. Contemporaneous shock to terms of trade contributes more than 98% to the volatility of aggregate output, consumption, and employment at short horizons. By contrast, news shocks to consumption technology account for 62–78% of their asymptotic variance. We also find that inflation volatility can be almost attributed to contemporaneous shocks to terms of trade and foreign interest rate. This implies that foreign factors can exert an important influence on both real and nominal variables.

The remainder of the essay is organized as follows. In section 2.2, a comprehensive literature review of recent studies is provided. Section 2.3 introduces a DSGE model that incorporates the housing sector, which is subject to both current changes and expectations on domestic and external fundamentals. The model takes the characteristics of the Hong Kong macroeconomy and housing sector into account. Section 2.4 presents the parameter calibration and estimation results. In section 2.5, we show the quantitative results. Section 2.6 concludes the study.
2.2 Literature Review

2.2.1 Introduction

Most standard business cycle models assume that changes in current fundamentals, such as total factor productivity, are the driving forces behind the economic fluctuations. However, these standard models cannot ascribe the driving force of recession to productivity shocks, since in general there is no technology regress during the "bust" phase of the business cycle. An obvious case is the internet bubble of the late 1990s, representing the U.S. investment boom and the subsequent economic slowdown. Very few scholars regard the recession of the early 21st century as a result of a negative technology shock. A lot of macroeconomists hold the view that the collapse of investment observed in the early 21st century resulted from overly optimistic expectations about the profitability of new investments in the internet industry in the late 1990s and early 2000. Accordingly, the expectation-driven business cycle models point out that, if expectation about output growth driven by the optimism of technological innovation fails to realize, then investment will drop and recession will occur. Experience of the recent financial crisis that occurred in the U.S. indicates that the fluctuation of housing price can exert an influential impact on the macroeconomy. Some scholars have made use of the business cycle theory to analyze the housing market dynamics. Also, in order to extend the framework of business cycle theory into a wider context, the analysis of boom-bust cycles for small open economies are also conducted by macroeconomists.

Over the years, new developments and modifications of the news-driven business cycle model are undergoing a constructive process. This chapter provides a
systematic review of the contemporaneous and news shocks to various fundamentals in driving the dynamics of the macroeconomy. We compact the literature into a narrative representation involving business cycles in the housing sector and for a small open economy. In section 2.2.2, the existing approaches to quantify the role of news shocks in driving business cycles are discussed. Section 2.2.3 presents the role of news and contemporaneous shocks in housing market dynamics. In section 2.2.4, the current business cycle models for small open economies are reviewed. Section 2.2.5 concludes.

2.2.2 News shocks and business cycles

Following the study of Beautry and Portier (2004), it is widely acknowledged that some combinations of changes in expectations about further fundamentals can be the driving forces of the economic dynamics. We could trace this view back to Pigou (1926), who stated that capital accumulation, generated by optimistic expectation of future increasing demand, could lead to recessions when the expectations do not realize. To be more specific, when agents in the economy hold the expectation that technological improvement will occur in the future, they decide to build up capital contemporaneously, resulting in a macroeconomic boom. If the expectations turn out to be overly optimistic, there will be a reduction of investment and a possible recession. In other words, if good news about future total factor productivity (TFP) or other fundamental variables can generate a boom today, a less favorable realization of the expectations can give rise to a bust, even without any actual decline in fundamental variables. As such, the idea of a news-driven business cycle theory has been reformulated in the framework of DSGE model to estimate the role of news shocks.
2.2.2.1 Whether news shocks can drive business cycles

Beaudry and Portier (2004) construct a simplified three-sector equilibrium business cycle model without some important elements (such as capital adjustment cost, factor utilization rate, and inventories). Their model considers the two productions, and stages includes a consumption good sector, a non-durable goods sector, and a durable goods (or construction) sector. The representative household consumes the final good, and works in both the non-durable goods and construction sectors. Technology grows in a stochastic way only in the non-durable goods sector, but grows deterministically in the durable goods sector. As for the signals about future fundamentals that the agents received, the news received is assumed to be updated every period. In addition, they point out that two important conditions in the model must be satisfied to generate a news-driven business cycle: (a) agents must respond to news shock to future productivity by increasing their current investment demand, and (b) the increase in investment demand must be met through a rise in employment, not a decline in consumption. For condition (a), in order to make sure that investment increases following a signal, news shocks to future productivity must occur in both the capital goods sector and the non-durable goods sector. Moreover, non-durable goods must be complementary to capital in the production technology. If not, agents would not increase investment until the expectation is realized. Then agents would shift the labor force from the non-durable goods sector to the durable goods sector and substitute non-durable goods for capital in their consumption composite. For condition (b), current investment and consumption decisions must be essentially decoupled, which require high labor supply elasticity to favor the emergence of expectation-driven economic
fluctuations. These two conditions are the most significant features that differentiate the three-sector model from the other standard business cycle models. This three-sector model can thus successfully generate business cycle fluctuations and the aggregate co-movement between consumption, investment, and hours of work.

Compared with Beaudry and Portier’s (2004) model, Jaimovich and Rebelo (2009) propose a one-sector model to generate the aggregate co-movement between major macroeconomic variables and a two-sector model to generate sectoral co-movement between output, employment, and investment. These two forms of co-movement are viewed as the central features of business cycles. In addition to news shocks to productivity as Beaudry and Portier (2004), the range of shocks is extended to incorporate aggregate TFP shocks, investment-specific shocks, and sector-specific TFP shocks. Each type of shocks consists of a contemporaneous component and a news component. Unlike Beaudry and Portier’s (2004) model, the authors find three key elements to generate "boom-bust" cycles in the presence of news shocks. These include capital utilization rate that increases the fluctuation of output responding to news shocks, investment adjustment costs that make agents respond immediately to news shocks, and a weak income effect on the labor supply that lead to an increase in hours of work responding to positive news. The authors also find that aggregate co-movement can be generated with moderate labor-supply income effects. Moreover, the assumption of weak income effect of labor supply is essential to generate sectoral co-movement that is robust to the timing and nature of the shocks.
2.2.2.2 The importance of news shocks in business cycles

While news shocks are shown to be able to generate aggregate and sectoral co-movement, the introduction of more shocks into a business cycle model affects the aggregate volatility, depending on the different assumptions adopted.

Unlike Beaudry and Portier (2004) and Jaimovich and Rebelo (2009) who use the calibration method to identify the roles of various shocks, Fujiwara et al. (2011) empirically use the Bayesian method to explore the role of news shocks through a DSGE model proposed by Christiano et al. (2008). They introduce price and wage stickiness, investment adjustment cost, capacity utilization rate, and habit formation in consumption into the model. Their model includes three sets of shocks: (i) an unanticipated TFP shock; (ii) news shocks to TFP with different forecast horizons; and (iii) six other non-TFP shocks with only an unanticipated component. As in Beaudry and Portier (2004), the authors also consider the anticipated component in TFP shocks as a summation of news shocks over periods, implying that agents can revise their received news over time. The estimation results show that the news shocks to TFP have a larger effect than the unanticipated TFP shocks. Also, when the horizon of news grows, the influences of news shocks on nominal factors become larger than that on real factors. This is mainly because the discounted value of leisure becomes smaller at longer forecast horizons, and thus the news shock at longer horizon play a more important role in the volatility of nominal variables. In addition, in order to analyze the response of hours of work to a technology shock, they compare the impacts of the unanticipated and anticipated components of TFP shock respectively. It is found that
the unanticipated technology shock has a negative impact on the hours worked, but the response of hours of work to the anticipated TFP shock is positive.

As with Fujiwara et al. (2011), Schmitt-Grohe and Uribe (2012) also construct a DSGE model using Bayesian approach allowing for both the contemporaneous and news shocks. Their model includes four types of real stickiness: consumption habit formation, adjustment cost in investment, variable utilization rate, and imperfect competition in labor market. Furthermore, as in Jaimovich and Rebelo (2009), they also allow for preference specification, which features a parameter representing the wealth elasticity of labor supply. Unlike other mentioned models, this model assumes that the macroeconomic dynamics are driven by seven structural shocks, namely, stationary and non-stationary shocks to neutral productivity and investment-specific productivity, shocks to government expenditure, wage-markup, and preference. Each type of shock is made up of an unanticipated component and a news component. The Bayesian estimation results indicate that approximately half of the variance of aggregate macro-variables can be attributed to news shocks. For example, wage-markup shock is an important source of aggregate fluctuation, especially regarding hours worked. The dynamics in hours worked and output due to wage-markup shock are virtually ascribed to its anticipated component. Although technology shocks have a large effect on the output growth dynamics, this contribution is due to the unanticipated component of TFP. The minor role of news shock to TFP is because many other shocks are included in the model. If all of the other shocks, except for productivity and government spending shocks, are shut off, then news shock to TFP could play a major role in driving business cycles.
The model by Khan and Tsoukalas (2012) shares some structural features with that of Schmitt-Grohe and Uribe (2012) and those of Jaimovich and Rebelo (2009). The model also considers a rich set of shocks that can be divided into two groups: shocks to technology and non-technology related variables. Technology shocks contain permanent and stationary shocks to TFP and investment. Non-technology shocks include shocks to preference, price and wage markups, government expenditure, and monetary policy. Following Schmitt-Grohe and Uribe (2012), news components in each shock, except for monetary policy shock, are introduced. Unlike the results of Schmitt-Grohe and Uribe (2012), the authors find that the unanticipated shocks have a larger role than news shocks in driving business cycles. The main reason for such results is the nominal rigidities. Nominal frictions lead to a countercyclical response of markups, thus resulting in an increase in the labor demand and supply. Hence, aggregate co-movement is generated. The findings also demonstrate that the contemporaneous shocks dominate in explaining the volatility of real variables, while the news shocks are more important in explaining the dynamics of nominal variables such as inflation. Within the group of news shock, non-technology news shocks prevail over technology news shocks. Furthermore, when the income elasticity of labor supply is restricted to be around zero, unanticipated shocks, especially the unanticipated shock to marginal efficiency of investment, are still the more important driving forces of aggregate co-movement.

Following Jaimovich and Rebelo (2009), Fujiwari et al. (2011), Khan and Tsoukalas (2012), and Schmitt-Grohe and Uribe (2012), Born et al. (2014) construct an estimated DSGE model to investigate the importance of news shocks. Born et al.
(2014) mainly focus on the role of expectations about future fiscal policy, particularly the expectation of tax rate changes, in driving macroeconomic fluctuations. Because fiscal policy are usually widely discussed in advance and are often known to the public prior to being released, anticipated shocks to fiscal policy have long been viewed as an important driving force behind the business cycle. Same as the previous literature, several real and nominal rigidities are introduced and various shocks are believed as important sources of the macroeconomic dynamics. The main innovation of this model is that the authors include a government sector incorporating distortionary labor and capital taxes into the model, and the government releases fiscal policies based on the debt and current economic conditions. The model incorporates both unanticipated and news shocks as Schmitt-Grohe and Uribe (2012). Computing the variance decompositions, the authors find that the fiscal foresight only plays a moderate role in driving business cycles. The news shocks to government spending account for 13% of the fluctuations in output. However, contemporaneous and anticipated shocks to labor and capital tax are not shown much importance in driving the economic dynamics, together contributing only 2% to the output fluctuation. News shocks to tax are only relevant for driving the inflation dynamics. The authors also find that technology shocks play a major role in driving the output fluctuation, which is in line with previous studies (Schmitt-Grohe and Uribe, 2012).

2.2.3 Business cycle models with the inclusion of a housing sector

Housing market dynamics have become an increasingly important factor affecting the business cycles. The recent financial crisis occurred in the U.S. was caused by the burst of the housing bubble, giving rise to the recession of the
macroeconomy. Given the stylized facts about the relationship between the housing market and the aggregate economy, some macroeconomic researchers have argued that the developments in the housing market are among the driving forces of business cycles.

Based on the traditional view that financial factors are key elements of business cycles, Iacoviello (2005) develops a business cycle model to study the interaction between housing price and economic fluctuations. The model captures two main features: nominal debt contracts and financial constraints tied to housing values in terms of both the firm and the household. On the demand side, households are divided into patient and impatient households in terms of heterogeneous discount factors. Both types of households consume, work, and accumulate houses and money. Impatient households discount the future utility more heavily than the patient ones. Impatient households borrow money from the patient ones, ending up facing a binding collateral constraint tied to housing values in equilibrium. On the supply side, entrepreneurs produce intermediate goods, using household labor and real estate. Retailers use the intermediate goods as inputs to produce final goods and act in a monopolistic competitive market. In addition, all debt contracts are set in nominal terms, reflecting the empirical observation in low-inflation countries. Because of the collateral constraints, the rising housing price can increase the borrowing capacity of impatient households, increasing their consumption and investment. Thus the collateral constraint works as a financial accelerator. In the presence of nominal debt, the rise in aggregate price reduces the discounted value of the debt obligations, increasing the debtors' net worth. By introducing shocks to monetary policy, inflation, technology, and housing preference, the model shows that collateral effects on the firm and the household can reflect a positive response of consumption to a housing price shock. The
nominal debt allows the model to replicate the consumption fluctuation to an inflation shock. The transmission mechanism of the model shows that collateral constraint amplifies demand shocks, but nominal debt stabilizes supply shocks. Thus, this mechanism yields an improved output-inflation variance trade-off for the central bank.

Based on the U.S. stylized facts about various macroeconomic variables, Davis and Heathcote (2005) build a neoclassical multi-sector stochastic growth model to study the fluctuations of residential investment. Similar to Iacoviello (2005), the production process consists of two stages. The wholesale firms make use of capital and labor as inputs with three different technologies. Each type of technology produces different intermediate goods, which are defined as construction, manufactures, and services. Unlike the claim by Iacoviello (2005), there are two final-goods sectors. Both final-goods firms use three intermediate goods as inputs with the same technology; one produces the consumption/business investment goods, and the other produces residential structures that are combined with newly available land to produce houses. Moreover, collateral constraints for both firms and households, nominal debt, and price stickiness are excluded. The model is simulated using calibration rather than Bayesian estimation. The simulation results show that the model can reflect two stylized facts. The volatility of residential investment is more than twice as that of the non-residential investment. Furthermore, there are positively co-movements among consumption, nonresidential investment, residential investment, and GDP. The authors also find that construction-intensive residential investment and the slow depreciation rate of residential structures both contribute to the high volatility of residential investment and co-movement. Also, land works as an input for producing houses, thus reducing residential investment volatility and increasing co-movement.
Monacelli (2009) constructs a two-sector model with real and nominal rigidities. On the supply side, this model contains a durable goods sector and a non-durable goods sector. On the demand side, households are also divided into impatient and patient households in terms of their heterogeneous discount rates. In order to introduce credit market imperfections and credit flow between agents as in Iacoviello (2005), the author introduces the borrowing constraint for the impatient households. Unlike Iacoviello (2005), Monacelli only allows for monetary policy shock and calibrates the parameter values. Through the comparison between models with and without credit market frictions, the author shows that an imperfect credit market is an important channel for the transmission of the monetary policy shock on durable and non-durable expenditure. For example, in the presence of collateral constraints on the household side, a monetary policy tightening leads to the decline in the relative price of durable goods and therefore affects the borrowing capacity of households. Consequently, the demand for both durables and durable goods decreases. The rising real interest rate makes patient households substitute consumption inter-temporally, thus reducing the demand for non-durables. As a result, monetary policy can affect the inter-temporal relative price of durable goods as well as the sectoral allocation of demand. Because the price stickiness of durables is assumed to be relatively smaller than that of non-durables, durable spending fluctuations are significantly larger than those of non-durable spending.

Iacoviello and Neri (2010) develop a DSGE model with a housing sector to analyze the driving forces of housing market dynamics. As does Monacelli (2009), they introduce heterogeneity in the discount factors of households and borrowing constraints tied to housing values for households. Thus, credit flow can be introduced between two types of households in the model. In the presence of collateral constraints
tied to housing values, fluctuation in housing price affects the collateral capacity of a fraction of households and the relative profitability of producing new houses. Unlike Davis and Heathcote (2005), the authors include some real and nominal rigidities and a rich set of shocks, such as housing preference shock, monetary policy shock, sectoral technology shock, cost-push shock, investment-specific shock, and so on. Using Bayesian estimation, they find that three main driving forces behind the housing market dynamics. Shocks to housing preference and housing technology together account for about 25% of the fluctuation in housing investment and housing price. The role of monetary policy shock is slightly mild, but its effect becomes more important at the turn of the twenty-first century. In addition, there are large spillover effects from the housing market to the macroeconomy, particularly on consumption instead of business investment. The findings are consistent with the idea that collateral constraint affecting the borrowing capacity of household amplifies the response of non-housing consumption to different types of shocks. Thus, the propagation mechanism is altered.

Bao et al. (2009) construct a small open economy DSGE model with more decision-making agents compared to Iacoviello and Neri (2010). The authors consider consumers, entrepreneurs, bankers, firms, government, and foreigners. Like Iacoviello and Neri (2010), they assume that the households are divided into two types in terms of heterogeneous discount rate: consumers and entrepreneurs. The entrepreneurs are assumed to be real estate specialists and more impatient than consumers. These entrepreneurs provide housing services to consumers, earn rents, and consume goods. Unlike Iacoviello and Neri (2010), entrepreneurs do not directly borrow money from consumers, but from banks. Thus, credit flow can be introduced through the intermediation of banks. Banks accept deposits from consumers, borrow foreign debt
from overseas, and lend to the entrepreneurs for building up housing stock. The risk premium can then be introduced through linking the policy interest rate and the mortgage rate. Unlike other models with the housing sector, the authors do not disaggregate the production of housing from the production of consumption goods. The firms merely employ labor services and import intermediate goods to produce differentiated output under monopolistic competition. In order to apply the analysis in a small open economy, the model incorporates foreigners who lend foreign debt to domestic banks, demand goods through exports, and sell intermediate goods to domestic firms. Adopting the Bayesian estimation, the authors compare the results between the model with and without a housing sector. It is found that the relative flexibility of housing and goods prices plays a major role in driving the dynamics of housing and consumption expenditures. The effects of monetary policy shock on output and inflation are greater for the model with the housing sector.

Compared with Iacoviello and Neri (2010), Tomura (2010) analyzes the housing market dynamics in a wider context, allowing for the influence from the international market. Agents' expectation about future fundamentals is included in the model. Tomura (2010) assumes that households consume and invest in both domestic and foreign markets. The representative firm produces final goods, capital, and residential structure. Like Bao et al. (2009), the independent housing production sector is not introduced. Since an increase in the terms of trade could raise real household income through an increase in the trading value of domestic output, terms of trade shock are used as the proxy for agents' expectation about high income growth and are assumed to be exogenously determined in the international market. To generate boom-bust cycles, Tomura (2010) considers housing price equation as follows:
Current real housing price = imputed rent + expected future real housing price/(1 + real interest rate)

The expectation about high income growth can push up expected future housing price and lead households to save less. Then, less savings lead to an increase in the real interest rate. Thus, the co-movement between expected future housing price and the real interest rate makes current housing price insensitive to changes in household expectations. However, if the economy is open to the international market, international capital flows could offset the shortage of domestic savings due to the high income growth and smooth the fluctuations in the real interest rate. This mechanism makes current housing prices more sensitive to household expectations. Through calibrating the parameter values, the study shows that international capital flows and uncertainty about the duration of high income growth have a large effect in driving the housing market boom-bust cycles.

Like Iacoviello and Neri (2010), Zhang and Hu (2011) establish a general equilibrium model with the housing sector. This mode also features the borrowing constraints tied to housing values. On the supply side, except for the final goods producers, real estate producers are introduced to supply the real estate services using final goods and land without borrowing constraint. Following Iacoviello (2005), the authors introduce a financial accelerator by assuming credit constraints tied to housing values exist among both households and entrepreneurs. As compared to Iacoviello (2005), the difference lies in the demand side. The authors introduce two types of households: homeowner and consumer. Homeowners buy houses subject to their collateral constraints and rent houses to consumers. Consumers who demand nondurable goods and houses consist of normal consumers and Rule-of-Thumb
consumers. Because normal consumers have already own enough wealth, they are able to make standard inter-temporal and intra-temporal decisions; however, Rule-of-Thumb consumers do not have enough wealth to smooth consumption and experience inelastic labor supply. Due to the presence of collateral constraints tied to housing prices, the fluctuation in housing price can affect the agents' borrowing capacity, which in turn affects housing price and investment. The housing price dynamics, on the other hand, can affect borrowing capacity. Thus, a kind of multiplier effect arises. The model estimation and simulation show that the financial acceleration in both sectors amplifies and propagates the dynamics in housing price and the aggregate economy.

Lambertini et al. (2010) and Gomes and Mendicino (2012) extend Iacoviello and Neri's (2010) model by incorporating news shocks over different time horizons to evaluate the empirical performance of news-driven business cycles for housing market dynamics. Unlike Iacoviello and Neri (2010) which only includes contemporaneous shocks to explain the housing market dynamics, these two studies assume that the error term of each shock is made up of an unanticipated and an anticipated component. Lambertini et al. (2010) set the parameter values equal to the posterior mean estimated by Iacoviello and Neri (2010), while Gomes and Mendicino (2012) estimate the parameter values using the Bayesian method. Through analyzing the impulse response functions, Lambertini et al. (2010) find that positive news shocks in different sectors can result in housing market booms, while expectation about future changes of nominal variables, such as monetary policy and inflation, that fails to realize are likely to engender a housing price decrease and also a subsequent economic recession. In addition, Lambertini et al. (2010) investigate the role of the credit market and find that
a lower loan-to-value (LTV) ratio can reduce the volatility of news-driven dynamics and significantly smooth the fluctuations of household debt, consumption, and GDP. Through the variance decomposition, Gomes and Mendicino (2012) find that expectations about cost-push shock is an important factor during the housing market boom in the 1970s, while investment-specific news shocks are more relevant after the 1980s.

Following Jaimovich and Rebelo (2009) and Schmitt-Grohe and Uribe (2012), Tomura (2013) also constructs a business cycle model including news shocks. But there are two innovations in this model. The first is that Tomura (2013) incorporates a housing sector into the model in order to capture the stylized features of housing market dynamics. The second is that the model introduces heterogeneous household beliefs about the accuracy of public signals, which differs from the standard assumption in the previous literature that all households share same expectations from public signals. In detail, the author introduces two types of households with different discount factors as Iacoviello and Neri (2010), but assumes that only the credit-constrained mortgage borrowers form over-optimism about the future technological progress and savers do not share their optimism. Different from the other literature which applies the Bayesian method to estimate the model, Tomura (2013) uses calibration to assign values to the model parameters. The author shows that over-optimistic expectation about future technological progress from mortgage borrowers can generate a boom-bust cycle without price stickiness. In the presence of price stickiness and the assumption that the labor supply elasticity of mortgage borrowers is higher than that of savers, the model can still replicate a low interest rate during housing booms, following the monetary policy of Taylor rule.
Like Bao et al. (2009), Funke and Paetz (2013) develop a two-sector small open economy model with a housing sector. Following Iacoviello and Neri (2010), the authors allow for collateral constraints’ tie to housing values and heterogeneous discount rate in two types of households. Unlike Iacoviello and Neri (2010) and Tomura (2010), the study describes a symmetric small open economy framework. On the supply side, the production consists of a housing sector and a consumption goods sector. Both production sectors are open to the international market. On the demand side, two types of households are introduced: patient and impatient households. Both types of households can consume both domestic and foreign goods, and patient households can invest in both domestic and international bonds market. Besides, Hong Kong is taken as the representative small open economy, under a monetary policy of the currency board system. Thus, spillover effects from foreign countries can exert an influential effect on the fluctuation of domestic housing price and other macro-aggregates. Given a rich set of shocks, Bayesian estimation shows that housing preference shock drives the most part of domestic housing price fluctuations and contributes a lot to volatility of output, consumption, and employment in Hong Kong.

Based on the stylized fact that, during the recent financial crisis, a shrinkage in business investment is in line with a collapse in the land price, Liu et al. (2013) construct a DSGE model to simulate the positive links between land price and business investment and capture the nexus between the housing market and the aggregate economy. In the model, they introduce financial frictions similar to those in Iacoviello and Neri (2010). The authors introduce two types of agents: a representative household and a representative entrepreneur. On the demand side, they introduce the same utility function of households as in Iacoviello and Neri (2010), but the entrepreneur's utility
only depends on consumption. Goods are produced using labor, capital, and land as inputs. Different from Iacoviello and Neri (2010) in which the collateral constraint is tied to the household side, this model assumes that the firms, rather than the households, are budget-constrained. In particular, the authors assume that firms finance investment expenditure by collateral land. Thus, a shock that increases land price could make the borrowing capacity of the firms rise and further generate an expansion in investment and production. Moreover, the household is assumed to be more patient than the entrepreneur. This model contains two separate channels that interact with each other. The first is a collateral channel through which the land price affects macroeconomic variables. A rising land price increases the net worth of the borrower and creates room for an expansion in credit and production. The second is a land reallocation channel through which a positive shock to housing demand generates a higher demand for land. Although the magnitude of land reallocation between constrained and unconstrained agents is ambiguous, the rising demand generates the increase in both the land price and the collateral value. Thus, housing demand shocks exert a broad influence on the aggregate economy through the two channels. To conduct the quantitative analysis of the propagation effects, the authors introduce eight types of structural shocks to different exogenous variables. The Bayesian estimation shows that the shock to housing demand accounts for about 90% of variance of land price, 30-50% of investment, and 20-40% of output. Thus, the model shows that, the existence of credit-constrained firms leads to large fluctuations of the land price due to a housing demand shock and generates the persistent co-movement between the land price and business investment.

Khan and Reza (2014) consider a DSGE model with a housing sector based on
Iavoviello (2005) with an exogenous fixed supply of housing and study the response of housing price to government spending shocks. The authors show that a broad class of DSGE models with a housing sector and collateralized borrowing predict a fall in housing price following a positive government spending shock. By contrast, according to the data, housing price in the U.S. rises persistently after an identified positive government spending shock, using a structural vector autoregression method and accounting for the anticipated effects. The authors argue that the incorrect housing price response is due to a general property of DSGE models. In detail, this counterfactual result is due to the approximately constant shadow value of housing for lenders, defined as the product of the relative price of housing and marginal utility of consumption, which is determined by the expected infinite sum of discounted marginal utility of housing. There are two key features that make the shadow value of housing approximately constant. First, the housing flows do not contribute much to the variation in housing stock and therefore to the marginal utility of housing. Second, temporary government spending shock exerts little influence on future marginal utility of housing. Thus, a positive government spending shock which has a negative wealth effect, causes an increase in the marginal utility of consumption and a fall in the current consumption. Since the shadow value of housing remains approximately constant, it follows that the relative housing price must fall. The authors also find that modifying preferences and production structure does not help in obtaining the correct housing price response. Only when monetary policy strongly accommodates government spending shocks will the effect on housing price be positive. The model, however, does not deliver a persistent rise in housing price as in the data. Thus, the authors conclude that accounting for the empirical evidence on government spending shocks and housing price using a DSGE
model still remains a significant challenge.

2.2.4 **Business cycle models for small open economy**

It is widely believed that changes from the international market, such as terms of trade and foreign interest rate, are important factors to explain the economic fluctuations in a small open economy. According to the estimation of different types of international general equilibrium business cycle models, the effects of these changes can be up to 90% of the shock contribution. These fully specified structural models attempt to solve the inter-temporal optimization problem of economic agents and to identify various types of shocks, especially shocks originated from the international market and their transmission mechanisms.

In early 1990s, Mendoza (1991) extends the business cycle model to a framework of a small open economy. This paper studies the dynamics of savings and investment in which domestic capital and foreign financial assets act as vehicles of savings without any restrictions on international borrowing and lending. Given this novelty, trade in foreign assets finances trade imbalances and plays a crucial role in explaining the fluctuations of savings and investment. Under different specifications such as whether capital adjustment cost is included and whether foreign interest rate shock is allowed, the model replicates many of the stylized facts of business cycles in postwar Canada. These simulations show that the model can generate two key stylized facts in the data. First, savings and investment are positively correlated despite the fact that financial capital could flow frictionlessly across countries. Second, the trade balance and foreign financial assets tend to move against the business cycle. The model also shows that, without capital adjustment cost, the fluctuation of investment becomes
large, because the separation of savings and investment makes physical capital be altered too easily.

Mendoza (1995) constructs a business cycle model with an inter-temporal equilibrium approach to investigate the relationship between terms of trade shocks and business cycles. Unlike his earlier work, Mendoza (1995) constructs a three-sector small open economy model and compares various features of the model-generated business cycles with actual business cycles. In the model, households consume importable, exportable, and non-tradable goods and leisure. Firms produce goods with capital, which is an importable good, and labor. International goods and financial assets markets are competitive, and there are no restrictions on capital or current account flows. Asset trading is limited to one period. Risk-free bonds are measured in units of importable goods. This model captures transmission mechanisms through international capital flow, the cost of imported inputs, and the purchasing power of exports. It also allows for the breakdown of purchasing power parity and real interest rate parity by including non-tradable goods. Furthermore, the model holds the assumption of perfect capital mobility, flexible price, and competitive capital market. With the terms of trade shock and productivity shock, the model can generate aggregate co-movement. The model simulation shows that terms of trade shock could explain nearly 50% of the fluctuations in GDP and real exchange rate. Moreover, impulse response analysis shows that business cycles attributed to terms of trade shock differ significantly from those attributed to productivity shock. In particular, real exchange rate and real interest rate differentials are procyclical to the terms of trade shock, while the productivity shock exerts an opposite impact. Sensitivity analysis shows that the persistence, magnitude, and contemporaneous correlation of terms of trade and productivity shocks
and the substitution elasticity between tradable and non-tradable goods consumption are important factor in driving business cycles. In contrast, labor supply and slight changes in risk aversion are relatively less important.

Standard small open economy models assume that domestic agents can only access to a risk-free bond, and the return rate of the bond is determined exogenously in the international market. Therefore, the steady state of the small open economy depends on initial values, particularly, the initial net foreign asset holding of the corresponding country. As a consequence, transient shocks give the equilibrium dynamics a random walk component which implies an infinite dynamics of endogenous variables, such as asset holdings and consumption, in response to various shocks. Thus, it leads to serious computational difficulty given that all available model-solving methods are only locally valid around a stationary path. To solve the problem, various modifications to the standard models aiming to introduce the stationary equilibrium dynamics have been widely used. Schmitt-Grohe and Uribe (2003) introduce four alternative stationary-inducing specifications for the small open economy business cycle model: a model with an endogenous discount factor, a model with a debt-contingent interest rate premium, a model with portfolio adjustment costs, and a model with a complete asset market. In addition, for purpose of comparison, the authors also study a model without any stationary-inducing features. This study shows that, once all models are calibrated identically, the volatility and impulse response analysis regarding the behavior of key macroeconomic variables, are virtually identical, except that the model with a complete asset market generates less variance of consumption. Thus, computational convenience should be given priority, when introducing stationarity to the non-stationary small open economy business cycle model using different methods.
Neumeyer and Perri (2004) propose a small open economy DSGE model to investigate the quantitative importance of interest rates in driving business cycles. The authors introduce two simple modifications. The first one is that firms have to afford part of the production cost such as wage bills before starting the production process, inducing the demand for working capital. This modification makes the labor demand sensitive to the interest rate. The second one is that labor supply is assumed to be independent of consumption. This modification makes labor supply immune to shocks to interest rate. These two modifications create a transmission mechanism through which real interest rate could play a role in the economic activity. Like Mendoza (1991), the authors construct a one-sector small open economy model in which real frictions are allowed. One important feature of this model lies in the nature of interest rate. The real interest rate consists of an international interest rate component and a country risk component. The international interest rate of small open economies is identified as the rate of return on the U.S. non-investment-grade bonds, which can be viewed as exogenously determined. The country risk spread is constructed as the difference between the domestic interest rate of the small open economy and the international interest rate. Since the variance of country risk spreads are large, changes in country risk are assumed to be driven by some specific shocks, such as productivity shocks. Thus, the fundamental shocks can act as driving forces behind business cycles and country risk spreads at the same time. The quantitative results from the structural model show that fluctuations in real interest rates are caused by fundamental shocks. Furthermore, working capital on the firm side increases the responses of the macroeconomy to those fundamental shocks. The authors also find that eliminating the dynamics in country risk spreads would reduce the GDP fluctuation by approximately
27%, while eliminating the dynamics in international interest rate would reduce the variance of GDP by less than 3%.

Justiniano and Preston (2004) construct a small open economy model, incorporating various specifications to assess the model fit of actual data series from three countries: Australia, Canada, and New Zealand. The model allows for the breakdown of the law of one price and, therefore, create a mechanism for limited pass-through of exchange rate changes to consumer prices through introducing local currency pricing of tradable goods. In addition, the model includes habit formation, prices indexed to past inflation, and a more flexible specification about the motion of the international market. Following Schmitt-Grohe and Uribe (2003) and Khan and Tsoukalas (2012), they also adopt a Bayesian methodology that formally assesses the importance of different specifications. In addition, the analysis uses U.S. data as the proxy for the world economy rather than treating it as unobserved. Given a rich set of shocks, it is found that habit formation is able to increase the variance of consumption and output. Furthermore, for real wages and real marginal costs, higher habit formation could generate higher volatility, especially in response to shocks from abroad.

Under the assumption of real rigidities and the incomplete asset market, as Mendoza (1995), Lubik and Teo (2005) construct a DSGE model to assess the relative importance of shocks to terms of trade and foreign interest rate in driving the business cycles in small open economies. However, this model does not introduce the rich production structure as Mendoza (1995). The authors adopt a one-sector model and use the Bayesian method to estimate the model with data from five small open economies (Australia, Canada, New Zealand, Chile, and Mexico). Thus, structural estimation can take the uncertainty regarding structural parameters into account and make use of the
endogenous cross-equation restrictions to overcome the identification problem. It is shown that world interest rate shock is the most important driving force behind the business cycles, while terms of trade shocks only account for a very small proportion of macroeconomic fluctuations in small open economics. The findings are at odds with that of Mendoza (1995). Because the model assumes that there is a strong wealth effect operating through the accumulation of net foreign assets, agents sizably increase their foreign bond holdings in response to positive world interest rate shocks, simply as a substitution for current consumption towards savings. Meanwhile, domestic households would reduce their investment because the relative return of it has decreased. Terms of trade shocks, however, have only weak inter-temporal substitution effects, given the structure of the model.

Like Lubik and Teo (2005), Gali and Monacelli (2005) construct a small open economy model to investigate the properties and measure the effects of different types of monetary policies on the aggregate economy. The authors model the world economy as a continuum of small open economies represented by the unit interval. Since each economy is of measure zero, the decisions by economic agents in the domestic economy do not have any influence on the rest of the world. Each small open economy is assumed to share identical preferences, technology, and market structure. Given the assumption of complete financial markets and price rigidity, this model can be represented by two first-order equations in terms of domestic inflation and output gap. Unlike Khan and Tsoukalas (2012) which include a rich set of shocks and use Bayesian estimation to estimate the model, this model just allows for productivity shock and world output shock and calibrates the parameters' values. Unlike others, which mainly study the impulse response functions and relative importance of different shocks, this
study mainly analyzes the properties of three different monetary policies for a small open economy: (a) a domestic inflation-based Taylor rule, (b) a CPI-based Taylor rule, and (c) an exchange rate peg rule. Under particular parameterization of households' preferences, it is shown that different monetary policies can be ranked in terms of the associated fluctuations of nominal exchange rate and terms of trade. Based on the analysis of a welfare loss function, a domestic inflation-based Taylor rule is found to be the best monetary policy.

Adolfson et al. (2007) modify the closed economy business cycle model in Christiano et al. (2007) to an open economy framework. In their open economy model, households could consume and invest in composites of domestic and imported goods. And, a rich set of nominal and real rigidities such as price stickiness, wage stickiness, capital utilization rate, investment adjustment costs, and habit formation, are introduced in the model. Moreover, the model includes a working capital channel, which means that firms could borrow money to finance part of the wage they need to pay. Bayesian estimation using Euro data shows that this model is able to replicate the properties of empirical data fairly well. In particular, the model simulation can match both the characteristics of the real exchange rate and the inflation differentials between the Euro area and the rest of the international market, which has been depicted as a difficult task in previous studies (see, Bouakez (2005) for further discussion). Overall, the authors find strong support for the nominal and real rigidities featured in the model. But little evidence about the rate of capital utilization and working capital channel is found to support the conformity between the data and the model.

Following Gali and Monacelli's (2005) small open economy model, Negro and
Schorfheide (2008) develop an econometric framework that relaxes the cross-coefficient restrictions. However, the authors construct a DSGE-VAR model that retains many features of the underlying DSGE model. Since there is a monetary policy change in 1999 that a floating exchange rate policy and full-fledged inflation targeting rule is adopted by the central bank of Chile, the data sample left for the model estimation is relatively short. The DSGE-VAR framework is found to be suitable. This estimation approach extends empirical observations with hypothetical observations, which are generated from the underlying DSGE model, to estimate the coefficients of the VAR. Thus, this approach allows researchers to estimate a VAR system within a short time period. Unlike Gali and Monacelli (2005), who only include productivity shock and foreign output shock, this study allows for more domestic and external shock. The empirical analysis finds that the Chilean Central Bank did not respond significantly to external shocks, such as shocks to exchange rate and terms of trade. Although the cross-equation restrictions implied by the DSGE model are relaxed, the analysis shows that the cross-equation restrictions are helpful in the VAR estimation. In addition, the DSGE-VAR is able to replicate the dynamics of the underlying DSGE model. Finally, the dynamics of the CPI inflation of Chile is mainly driven by domestic shocks, namely technology shock and monetary policy shock, rather than external shocks such as terms of trade shock and foreign inflation shock.

Following Gali and Monacelli (2005), Justiniano and Preston (2010) construct a two-sector DSGE model to quantitatively measure the contribution of foreign disturbances to the macroeconomic dynamics of a small open economy. Similar to Monacelli (2005), this model allows for the breakdown of the law of one price. In addition, the authors consider incomplete asset market and a rich set of shocks,
including technology, preference, labor disutility, monetary policy, and cost-push shocks. Nominal and real rigidities, such as habit formation, price rigidity, and labor market imperfection, are also incorporated. The baseline model assumes that all shocks in the small open economy and foreign countries are independent. Using the Bayesian estimation, it is found that foreign disturbances account for just subtle volatility observed in several small open economy series at all forecast horizons. The cross-country correlations in the benchmark model are virtually zero at all horizons. Extending the baseline framework with shocks that are correlated across countries, each shock in the model is assumed to include two orthogonal components: a disturbance common to the same type of shock in the foreign country and a country-specific disturbance. The estimation results show that the proportion of the variance explained by all foreign shocks is greater than that in the baseline model. The inability to replicate the co-movement in the data is due to the cross-correlation among supposedly orthogonal innovations in the baseline model. Thus, simply allowing for correlation amongst shocks of the same type across countries is not effective to perfectly solve the co-movement problem.

2.2.5 Conclusion

The business cycle theory has gone through decades of development through extensions and modifications. The application of the theory produces a fruitful combination of macroeconomic research direction. The extended DSGE models show that both contemporaneous and news shocks to various real fundamentals play a major role in driving business cycles in a wider context. The models are found to be successful in explaining the macroeconomic fluctuations in the housing sector for small open
economies. With different assumptions about the model and the macroeconomy, the driving forces of economic fluctuation are different. Contemporaneous or news shocks to productivity, interest rate, and preference contribute different proportions to the variance of macroeconomic fluctuation. Based on the insights of the existing works, the present study, as shown in the next chapter, attempts to develop a DSGE model that incorporates both contemporaneous and news shocks and considers the housing sector in a small open economy.
2.3 Model

2.3.1 Introduction

We construct a small open economy DSGE model with a housing sector and integrate news shocks into the systematic model. The small open economy model introduces two types of households with heterogeneous discount factors and two production sectors with two-stage production processes. As in Iacoviello and Neri (2010), our model captures two main characteristics of the housing market.

On the supply side, there are two production sectors; namely, the consumption goods sector and the housing sector. Firms in the two sectors produce consumption goods and houses, respectively. The production process consists of two stages. The outputs of wholesale firms, which acts in a monopolistic competitive market, is used as inputs by retail firms. Retail firms sell the final goods both in domestic and foreign markets. Both sectors only use labor as inputs of production.

On the demand side, there are two types of households, namely, patient (lenders) and impatient (borrowers) households, with heterogeneous discount factors. Impatient households are subject to collateral constraints tied to the housing value. Both types of households work, consume, and accumulate houses. Since impatient households feature a relatively lower discount rate than patient households, there exist credit flows between these two agents. In detail, patient households lend bonds to impatient households and also invest in foreign bonds in the international capital market. Since houses can be used as collateral for loans, impatient households only accumulate the
required net worth to finance the down payment in the houses and face the binding collateral constraint in equilibrium.

To capture the features of the monetary policy for a small open economy like Hong Kong, we adopt the currency board system. The system is adopted as a standard monetary policy by Hong Kong Monetary Authority.

Following Gali and Monacelli (2005), the entire world economy is modelled as a continuum of infinite small open economies represented by the unit interval. Since each economy is of measure zero, any decisions by economic agents in the domestic economy do not have any impact on the rest of the world. Each small open economy is assumed to share identical preferences, technology, and market structure.

2.3.2 Households

Households are divided into \((1 - \omega)\) patient and \(\omega\) impatient. Impatient households (or borrowers) are denoted as \(b\), and patient households (or savers) are denoted as \(s\). The parameter \(\omega\) represents the relative wage share, which is assumed to be constant through production function with a unit substitution elasticity.\(^3\)

The utility function for patient households is as follows:

\[
E_0 \sum_{t=0}^{\infty} \beta_t^b \left[ \frac{1}{1-\sigma} (X^b_t)^{1-\sigma} - \frac{1}{1+\varphi} (N_{C,t}^b)^{1+\varphi} - \frac{1}{1+\varphi} (N_{D,t}^b)^{1+\varphi} \right]
\]

(2.1)

\(^3\) This assumption implies that \(C_t = \omega C^b_t + (1 - \omega) C^s_t\) and \(D_t = \omega D^b_t + (1 - \omega) D^s_t\). \(C_t\) and \(D_t\) represent the aggregate consumption and housing, respectively, for both patient and impatient households.
where $E_0$ is the conditional expectation operator evaluated at period 0, $\beta_s$ is the discount factor, $\sigma$ represents the inter-temporal elasticity of substitution with respect to total expenditure, and $\varphi$ denotes the inverse of the inter-temporal elasticity of labor supply, $N_{C,t}^s$ and $N_{D,t}^s$ denote labor supply in the consumption goods and housing sector respectively. The index of consumption composite $X_t^s$ is the weighted average of consumption goods expenditure and the stock of houses. That is,

$$X_t^s \equiv (\tilde{C}_t^s)^{1-\gamma} (D_t^s)^{\gamma}$$

where $\tilde{C}_t^s \equiv C_t^s - h_t C_{t-1}^s$, $h_t$ captures the consumption habit formation and $\gamma$ is the relative share of housing in expenditure. $C_t^s$ is a composite consumption index defined by

$$C_t^s \equiv [(1-\alpha_c)^{1/h_c} C_{H,t}^s (j) \eta_{-1}^{1/h_c} \alpha_c^{1/h_c} C_{F,t}^s (j) \eta_{-1}^{1/h_c}]^{1/h_c}$$

where $\eta_c$ represents the intra-temporal substitution elasticity between domestic and foreign goods, and $\alpha_c$ represents the degree of openness (or the share of imported goods in domestic consumption). Since each type of goods consists of a continuum of units, $C_{H,t}^s$ represents the domestic consumption goods given by

$$C_{H,t}^s \equiv \int_0^1 C_{H,t}^s (k) \frac{\mu_c}{\mu_c} dk \frac{\mu_c}{\mu_c-1}$$

where $k \in [0,1]$ represents one unit of goods produced within one country. $C_{F,t}^s$ is an index of foreign goods given by

$$C_{F,t}^s \equiv \int_0^1 C_{F,t}^s (k) \frac{\mu_c}{\mu_c} dk \frac{\mu_c}{\mu_c-1}.$$
where \( C_{i,t}^s \) is an index of differentiated goods imported from country \( i \) and is defined as:

\[
(2.5) \quad C_{i,t}^s \equiv \left[ \int_0^1 C_{i,t}^{s_k} \frac{\tilde{\sigma}_s}{\tilde{\sigma}_s} \, di \right]^\frac{\mu_s}{\mu_s - 1},
\]

Since houses cannot be traded between countries, we don’t allow for the degree of openness in the housing market.\(^4\) \( D_i^t \) denotes the housing given by

\[
(2.6) \quad D_i^t \equiv \left[ \int_0^1 D_i^t(k) \frac{\mu_D}{\mu_D - 1} \, dk \right]^\frac{\mu_D}{\mu_D - 1}
\]

Notice that \( \mu_c \) and \( \mu_D \) symbolize the intra-temporal elasticity of substitution between differentiated goods in the consumption goods sector and housing sector, respectively. \( \tilde{\sigma}_s \) denotes the intra-temporal substitution elasticity between differentiated consumption goods produced in foreign countries. \( \epsilon_i^D \) is the housing preference shock, following

\[
(2.7) \quad \ln \epsilon_i^D = \rho_D \ln \epsilon_{i-1}^D + \epsilon_i^D
\]

where \( \epsilon_i^D \) is an independently and identically distributed (i.i.d) process. Housing preference shock affects the marginal rate of substitution between the two sectors. As mentioned by Iacoviello and Neri (2010), this shock captures cyclical variation in the

\[4\] This assumption makes sense because, in general, the Law of One Price cannot hold in the housing sector. Housing prices are obviously different in different countries, even after being adjusted for exchange rates and taxes.
availability of resources used to purchase houses or other social and institutional changes that affect housing demand.

Since we assume that domestic households can purchase non-durable goods from both domestic and foreign markets, the optimal allocation of expenditures between domestic and foreign consumption goods is given by

\[
C^t_{H,t} = (1 - \alpha_c) \left( \frac{P_{C,H,t}}{P_{C,t}} \right)^{\eta_c} C^t_{C,t}; C^t_{F,t} = \alpha_c \left( \frac{P_{C,F,t}}{P_{C,t}} \right)^{\eta_c} C^t_{C,t}
\]

where \( P_{C,t} = [(1 - \alpha_c) P_{C,H,t}^{1 - \eta_c} + \alpha_c P_{C,F,t}^{1 - \eta_c}]^{1/\eta_c} \) is the consumer price index (CPI). \( P_{C,H,t} \) and \( P_{C,F,t} \) are the aggregate price indices for domestic and foreign consumption goods, respectively. Consequently, the consumption expenditures is

\[
P_{H,t} C^t_{H,t} + P_{F,t} C^t_{F,t} = P_t C^t_t. \]

Patient households maximize their utility subject to:

\[
C^t_t + P_{D/C,t} I^t_{D,t} - B^t_{H,t} - \Xi B^t_{F,t} = \frac{W^t_{C,t} N^t_{C,t}}{P_{C,t}} + \frac{W^t_{D,t} N^t_{D,t}}{P_{C,t}} - R_{t-1} \frac{B^t_{H,t}}{\Pi_{C,t}} - \frac{R^*_{t-1,1} B^t_{F,t-1}}{\Pi_{C,t}}
\]

\[
I^t_{D,t} = D^t_t - (1 - \delta) D^t_{t-1}
\]

\( I^t_{D,t} \) denotes housing investment for patient households. \( W^t_{C,t} \) and \( W^t_{D,t} \) represent the wages in the consumption and housing sectors, respectively. \( \delta \) represents the depreciation rate of housing, and \( P_{D/C,t} \) represents the relative price index of housing to consumption goods. \( B^t_{H,t} \) represents the domestic bond which is denominated with the domestic consumption price index. With the assumption that patient households can invest in the international credit market, \( B^t_{F,t} \) is introduced to represent the foreign bond holdings. \( R_t \) denotes the domestic nominal interest rate, and \( R^*_t \) represents the foreign interest rate ( * denotes the foreign variables).
\[ \Pi_{c,t} = \frac{P_{c,t}}{P_{c,t-1}} \]

is the gross CPI-based inflation rate, and \( \mathfrak{Z}_t \) represents the nominal exchange rate. Since we consider a cashless economy in which money balance is a negligible part of financial assets, money does not appear in either the budget constraint or the utility function.

The patient households maximize equation (2.1) subject to equation (2.10). The first-order conditions for this optimization problem are expressed as follows:

(2.11) \[ \frac{W_{j,t}^s}{P_{c,t}} = \frac{(X_j^s)^\sigma (N_{j,t}^s)^\rho (\tilde{C}_j^s)^{\gamma e_0}}{(1 - \gamma e_i^D) (D_j^s)^{\gamma e_0}}, \quad j = C, D \]

(2.12) \[ P_{d/c,t} = \left( \frac{\gamma e_i^D}{1 - \gamma e_i^D} \right) \frac{\tilde{C}_t^s}{D_t^s} + \beta (1 - \delta) E_t \left[ \left( \frac{1 - \gamma e_i^D}{1 - \gamma e_i^D} \right) \frac{X_{t+1}^s}{X_t^s} \left( \frac{D_t^s}{\tilde{C}_t^s} \right)^{\gamma e_0} \left( \frac{\tilde{C}_t^s}{D_t^s} \right)^{\gamma e_0} P_{d/c,t+1} \right] \]

(2.13) \[ 1 = \beta E_t \left[ \left( \frac{1 - \gamma e_i^D}{1 - \gamma e_i^D} \right) \frac{X_{t+1}^s}{X_t^s} \left( \frac{D_t^s}{\tilde{C}_t^s} \right)^{\gamma e_0} \left( \frac{\tilde{C}_t^s}{D_t^s} \right)^{\gamma e_0} R_t \left( \frac{\mathfrak{Z}_t}{\Pi_{c,t+1}} \right) \right] \]

(2.14) \[ 1 = \beta E_t \left[ \left( \frac{1 - \gamma e_i^D}{1 - \gamma e_i^D} \right) \frac{X_{t+1}^s}{X_t^s} \left( \frac{D_t^s}{\tilde{C}_t^s} \right)^{\gamma e_0} \left( \frac{\tilde{C}_t^s}{D_t^s} \right)^{\gamma e_0} \frac{\mathfrak{Z}_{t+1}}{\mathfrak{Z}_t} \left( \frac{\Pi_{c,t+1}}{\Pi_{c,t+1}} \right) R_t \right] \]

Equation (2.11) is a standard labor-leisure trade-off condition, linking the real wage to the lender's marginal rate of substitution between consumption and leisure. Equation (2.12) equates the real housing price to the marginal rate of substitution between housing and consumption goods, plus the expected resale value. Equation (2.13) is an Euler equation, which is adjusted for housing in the expenditure index. Equation (2.14) can be viewed as the optimal condition for international traded bonds. Together with equation (2.13), the uncovered interest rate parity is implied by these two equations:
Impatient households are assumed to make inter-temporal decisions through the infinite lifetime. The utility function for impatient households, similar to patient households, is expressed as:

\[
E_0 \sum_{t=0}^{\infty} \beta^t \left[ \frac{1}{1-\sigma} (X^b_t)^{1-\sigma} - \frac{1}{1+\varphi} (N^b_{C,t})^{1+\varphi} - \frac{1}{1+\varphi} (N^b_{D,t})^{1+\varphi} \right]
\]

Impatient households choose the amount of consumption goods and housing, borrow from patient households through trading nominal riskless domestic bond, and receive wage income. Following Tomura (2013), impatient households cannot take advantage of the international credit market to finance their expenditures. Thus, impatient households maximize their utility subject to:

\[
C_t + P_{D/C,t} I^b_{D,t} - B^b_{H,t} = \left( \frac{W_{C,t} N^b_{C,t}}{P_{C,t}} + \frac{W_{D,t} N^b_{D,t}}{P_{C,t}} - R_{t-1} \right) \frac{B^b_{H,t-1}}{\prod_{C,t}}.
\]

All the variables are defined similar to patient households. Given that impatient households face a relatively higher discount factor. Impatient households can only borrow up to a fraction of the expected discounted value of next-period value of their houses. Thus, they face the following borrowing constraint:

\[
R_t B^b_{H,t} \leq (1-\chi)(1-\delta) E_t [P_{D/C,t+1} \prod_{C,t+1}] e^{LTV}
\]

---

5 Through equations (2.13) and (2.14) we cannot directly derive equation (2.15). But our model is linearized. It makes sense to log-linearize the interest rate parity condition based on equation (2.15).

6 We abstract from modeling borrowing abroad explicitly since in practice it is not common for domestic residents to borrow mortgage from overseas. A similar assumption has been made by Funke and Paetz (2013).
where \( \chi \) represents the fraction of housing, which cannot be used as collateral for a loan, \((1 - \chi)\) represents the loan-to-value ratio, and \( \varepsilon_{it}^{LTV} \) can be viewed as the variations in the loan-to-value. The borrowing constraint equation demonstrates that the maximum possible amount that a borrower can get cannot exceed the expected future value of the housing stock. Given the difference in the discount factor, the borrowing constraints hold with equality at the optimum. The assumption \( \beta_b < \beta_s \) implies that impatient households discount wealth quickly enough to some lower bound, and for small shocks, the lower bond is binding.\(^7\) Patient households own and accumulate all capital, while impatient households only accumulate houses and borrow the maximum amount against their borrowing constraints. Through equation (2.18), fluctuations in housing values affect the spending capacity of impatient households along the equilibrium path. Thus, the dynamic interaction between borrowing capacity and the housing price could work as a transmission mechanism by which the effects of shocks could persist, amplify and spillover to the macroeconomy. Easing the collateral constraint could weaken the leverage effect, reducing the fluctuation of the endogenous variables, such as output, consumption, but the contemporaneous response of the economy might become more persistent (Kiyotaki and Moore, 1997).\(^8\) Furthermore, one feature which makes our model different from others is that we assume the shock to loan-to-value ratio, \( \varepsilon_{it}^{LTV} \), as

\(^7\) The extent to which the borrowing constraint is always binding in the steady state is mostly determined by the difference between the discount factors of the two types of households and by the variance of the shocks that hit the economy. Iacoviello and Neri (2010) have shown that impatient households are always arbitrarily close to the borrowing constraint, given the fact that discount rate differentials of the magnitude are assumed here.

\(^8\) Changes in the LTV ratio also affect the collateral constraints. Lambertini et al. (2012) indicate that lower LTV ratio could significantly reduce the volatility of the aggregate economy.
The loan-to-value has been widely used as a macro-prudential policy tool to smooth the housing market fluctuations in Hong Kong. We therefore assume that the loan-to-value ratio not only responds to its own previous value, but also actively responds to the real housing price in the last period.

Since impatient households' optimization problem is similar to that of the patient households, we refrain from presenting here the first-order conditions. For details, please refer to the supplementary material in Appendix A.

### 2.3.3 Relationship among inflation, terms of trade, and exchange rate

We introduce several assumptions and definitions before conducting the analysis of the equilibrium. We also derive some useful identities that are extensively referred to in subsequent sections.

The terms of trade between domestic and foreign countries can be given by

$$S_{C,t} = \frac{P_{C,F,t}}{P_{C,H,t}}.$$  

Approximately, in log terms, we have

$$s_{c,t} = p_{c,f,t} - p_{c,h,t}.$$  

By log-linearizing the CPI formula around the steady state and satisfying the PPP, the CPI inflation is as follows:

$$\pi_{c,t} = \pi_{c,h,t} + \alpha_c \Delta \hat{s}_{c,t}.$$  

---

9 Following standard notation, lower-case letters denote logs, and hats denote percentage deviations from the steady state ($\hat{X} = \log \left( \frac{X_t}{X} \right)$), unless we explicitly mention a different convention.

10 For the log-linearized equations of the model, please refer to Appendix B.
Equation (2.20) states that inflation rate in a small open economy is proportional to the percentage change in terms of trade and degree of openness $\alpha_c$.

Based on the Law of One Price (at product level) and identical preferences without a home bias,\(^{11}\) we can derive $P_{C,F,t} = \Xi_f P_{C,F,t}^*, P_{C,H,t} = \Xi_h P_{C,H,t}^*, P_{C,t} = \Xi_t P_{C,t}^*$. $P_{C,H,t}^*$ and $P_{C,F,t}^*$ represent, respectively, the domestic and foreign Producer Price Index (PPI) of consumption goods measured by units of foreign currency. After log-linearizing $P_{C,F,t}$ around the steady state, we have

\[
(2.21) \quad \hat{p}_{c,t} = \int_0^t (\hat{\epsilon}_{c,t} + \hat{p}_{c,t}) dt = \hat{\epsilon}_t + \hat{p}_{c,t}^*
\]

where $\hat{p}_{c,t}^*$ represents the log-linearized international price index\(^{12}\) and $\hat{\epsilon}_t$ represents the percentage deviations from the equilibrium value of $\Xi_t$. Combining with the definition of terms of trade, we obtain

\[
(2.22) \quad \hat{s}_{c,t} = \hat{\epsilon}_t + \hat{p}_{c,t}^* - \hat{p}_{c,H,t}
\]

Based on the Law of One Price, we can define the real exchange rate as

$\hat{r}_{C,t} = \frac{\Xi_f P_{C,F,t}^*}{P_{C,H,t}}$. With the log-linearization around the steady state, we derive the relationship between the real exchange rate and terms of trade as:

\[
(2.23) \quad \hat{q}_{c,t} = (1-\alpha_c)\hat{s}_{c,t}
\]

---

\(^{11}\) Given that the Law of One Price can only hold in the consumption goods sector, our assumption that the housing market is closed makes sense.

\(^{12}\) Foreign CPI and PPI are the same, because we assume that each individual economy is of measure zero.
where \( \hat{q}_{c,t} = \log \mathcal{R}_{c,t} \).

2.3.4 International risk sharing

Households in foreign countries have identical preference as households in the domestic economy. Patient households are able to share country-specific risks by way of trading foreign bonds in the complete credit market. Thus, the Euler equation for the representative household in any foreign country is analogous to that the household in the domestic economy. We can combine the domestic and foreign Euler equations for consumption, resulting in

\[
(2.24) \quad \frac{1 - \gamma}{1 - \gamma} \frac{X^s}{X^s_t} \left( \frac{\hat{C}^{s, e_i}}{\hat{C}^{s, e_i}_t} \right)^{-\sigma} \left( \frac{D^{s, e_i}}{D^{s, e_i}_t} \right)^\gamma = \mathcal{R}_{c,t}
\]

where \( \varepsilon'_i \) represents the foreign housing preference shock following an AR(1) process as equation (2.8), and \( \hat{C}^{s, s}_t \) represents the foreign demand in domestic market for the consumption goods sector. Unlike Funke and Paetz (2013), we assume that housing cannot be traded between countries, and thus \( D^{s, s}_t \) represents the foreign demand in the foreign market for housing sector. Together with equation (2.23), equation (2.24) implies a relationship linking domestic expenditure with world expenditure and the terms of trade. Together with equation (2.20), we can find that terms of trade can have an impact on the domestic economy through the above channel. The terms of trade shock can be an important driving force behind the business cycle for a small open economy, as suggested by Mendoza (1995) and Tomura (2010). The shock is expressed as:
\ln S_{c,t} = \rho_{s,t} \ln S_{c,t-1} + \varepsilon^s_{c,t},

where \( \varepsilon^s_{c,t} \) is an i.i.d. shock process.

Since domestic households are assumed to be able to purchase goods from both domestic market and abroad, demand shocks from foreign countries are important to explain the dynamics of housing sector in small open economies. We introduce foreign demand shock in consumption and housing sectors, respectively, as:

\[ \ln C^*_t = \rho^*_t \ln C^*_{t-1} + \varepsilon^*_t \]

\[ \ln I^*_t = \rho^*_t \ln I^*_{t-1} + \varepsilon^d_t \]

where \( \varepsilon^*_t \) and \( \varepsilon^d_t \) follow the i.i.d. process. \( I^*_t \) represents the housing investment in the representative foreign country, which is defined same as the housing investment of the domestic economy.

2.3.5 Firms

To introduce nominal stickiness in the consumption goods sector, we introduce two-stage production processes. Wholesale firms produce intermediate goods which are used as inputs to produce final goods. Retail firms produce final goods and sell their output in the market. The retail firms operate according to a CES technology.

For retail firms, final goods in both sectors are produced by a continuum of intermediate goods according to a CES function:

\[ Y_{j,t} = \left( \int_0^1 Y_{j,t}^{1+\mu/j}(k) dk \right)^{1/1+\mu/j}, j = C, D \]
where $Y_{j,t}$ denotes the sector-specific output and $Y_{j,t}(k)$ represents the intermediate good $k$. $\mu^j_t$ denotes the sector-specific price mark up over marginal cost for wholesale firms following an AR(1) process as:

$$\ln \mu^j_t = \rho_{\mu,j} \ln \mu^j_{t-1} + \epsilon^\mu_{t,j}$$

where $\epsilon^\mu_{t,j}$ represents sector-specific cost-push shock affecting changes in the price markup.

There is a continuum of intermediate goods producers (wholesale firms). Production of each firm follows a stochastic constant return to scale production function:

(2.26) $Y_{j,t}(k) = A_{j,t} N_{j,t}(k)$

where $N_{j,t}$ denotes the labor input. $A_{j,t} = \exp(a_{j,t})$ represents the sector-specific productivity following:

$$\ln A_{j,t} = \rho_{a,j} \ln A_{j,t-1} + \epsilon^a_{t,j}$$

where $\epsilon^a_{t,j}$ is an i.i.d. process representing the sector-specific TFP shock.

We can derive sector-specific real marginal cost as $(W_{j,t}/P_{j,t,t})/MPN_{j,t}$, where $MPN_{j,t}$ denotes the sector-specific marginal product of labor supply. Aggregating two types of households' optimality labor-leisure decision, we can derive the real marginal cost in both sectors as:
2.3.6 Price setting

Following Iacoviello and Neri (2010), we introduce price stickiness only in the consumption goods sector and rule out price stickiness in the housing sector.\(^{13}\) We assume that retail firms operate in a perfectly competitive market. For wholesale firms, they operate under monopolistic competition following a Calvo-type mechanism. Hence, only a fraction \(1 - \theta_c\) of wholesale firms can re-optimize the prices freely each period, while the remaining fraction of \(\theta_c\) firms cannot do so.

We can derive the log-linearized form of the optimal price-setting rule in period \(t\) as:

\[
\ln \prod_{C,H,t} - \ln \prod_{C,H,t+1} = \beta \left( E_t \ln \prod_{C,H,t+1} - \ln \prod_{C,H,t} \right) - (1 - \theta_c)(1 - \beta \theta_c) / \theta_c \ln (MC) + \ln \mu_{c,t}
\]

As shown, firms that are not able to change prices in any period would set the price indexed to the previous period inflation rate.

---

\(^{13}\) Barsky et al. (2007) find that there is a large incentive for households to negotiate the housing price. This is because housing is relatively expensive on a per-unit basis, and most houses are priced for the first time when they are sold.
Given the assumption that there is no price stickiness in the housing sector, the real marginal cost of the housing sector is equal to the inverse of the price markup, which can be shown as:

\[(2.30) \quad MC_{D,t} = \frac{1}{1 + \mu_{D,t}}\]

### 2.3.7 Equilibrium

Output in the consumption goods sector can be consumed in domestic and foreign markets. The market clearing condition for each good \(k\) in the two sectors of the domestic economy is then given by:

\[(2.31) \quad Y_{C,t}(k) = C_{H,t}^{i}(k) + \int_{0}^{1} C_{H,t}^{i}(k) di\]

\[(2.32) \quad Y_{D,t}(k) = I_{D,t}(k)^{14}\]

where \(C_{H,t}^{i}(k)\) denotes the country \(i\)'s demand for consumption good \(k\) produced in the domestic economy, and \(I_{D,t}(k)\) represents housing investment in the domestic market. Putting equations (2.31) and (2.32) into the definition of aggregate of domestic output, equation (2.25), we can derive the following first-order log-linearize approximation around the steady state:

\[(2.33) \quad \hat{y}_{c,t} = (1 - \alpha_c) \hat{c}_t + \alpha_c \hat{C}_t^* + \alpha_c \theta_c \hat{s}_{c,t}\]

\[(2.34) \quad \hat{y}_{d,t} = \hat{i}_{d,t}\]

where \(\theta_c = \zeta_c + (\eta_c - 1)(1 - \alpha_c)\).

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\(^{14}\)Since we assume that the housing market is closed, the output in the housing sector is only satisfied for domestic demand.
The aggregated real output in both sectors can be defined as 
\[ P_{H,t}Y_t = P_{C,H,t}Y_{C,t} + P_{D,H,t}Y_{D,t} \]. The aggregated price index can be defined as 
\[ P_{H,t} = P_{C,H,t}^{1-\xi_t}P_{D,t}^{\xi_t} \]. \( \xi_t \) denotes the share of the housing sector in the aggregate production being affected by both domestic and foreign housing preference shocks.

\[ (2.35) \quad \dot{y}_t = \frac{P_{D/c}^{-\xi}}{Y} \tilde{y}_{ct} + \frac{\delta P_{D/c}^{1-\xi}}{Y} \tilde{y}_{dt} + \Xi \hat{P}_{D/c,H,t} - \xi_t \ln P_{D/c} (\varepsilon_t^D + \varepsilon_t^*) \]

where 
\[ Y = P_{D/c}^{-\xi}C + \delta P_{D/c}^{1-\xi}D \] ,
\[ \Xi \equiv (1 - \xi_t) \frac{\delta P_{D/c}^{1-\xi}D}{Y} - \xi_t \frac{P_{D/c}^{1-\xi}C}{Y} \]
and 
\[ \hat{P}_{D/c,H,t} = \hat{P}_{D/c,ct} + \alpha_c \hat{s}_{ct} \].

Our study only focuses on the small open economy, thus we do not explicitly model the world economy.

2.3.8 Monetary policy

We adopt a currency board system as the standard formulation of the monetary policy as the case for Hong Kong. This means that the nominal exchange rate of domestic currency for the small open economy is effectively fixed to a representative foreign currency. To be more specific, the deviation from equilibrium of the nominal exchange rate is assumed to be zero. Consequently, the monetary policy is conducted to ensure \( \hat{\varepsilon}_t = 0 \), where \( \hat{\varepsilon}_t \) represents the deviation of the nominal exchange rate from its steady state. By log-linearizing uncovered interest rate parity stated in equation (2.15) around the steady state, we can derive the monetary policy as \( \hat{r}_t = \hat{r}_t^* \). It means that the percentage deviation of the domestic interest rate from its equilibrium value is equal to that of the foreign interest rate and that the percentage deviation of the
domestic CPI-based inflation is equal to that of "the rest of the world". The present study takes Hong Kong as the representative small open economy in the estimation. The exchange rate of the Hong Kong dollar is effectively pegged to the U.S. dollar. After transforming equation (2.21) as \( \hat{\pi}_{c,t} = \hat{\pi}_{c,t}^{*} \), we can model the monetary policy of Hong Kong as a typical Taylor rule:

\[
(2.36) \quad \hat{r}_{t}^{*} = \rho_{r} \hat{r}_{t-1}^{*} + (1 - \rho_{r}) (\rho_{\pi} \hat{\pi}_{c,t}^{*} + \rho_{y} \hat{y}_{t}^{f} ) + \epsilon_{r,t},
\]

where \( \epsilon_{r} \) represents the monetary policy shock and \( y_{t}^{f} \) represent the output gap of the U.S. following an exogenous AR(1) processes as \( \hat{y}_{t}^{f} = \rho_{y} \hat{y}_{t-1}^{f} + \epsilon_{t}^{f} \).

2.3.9 Shocks

In this model, we have a system of shocks. They are the household-specific housing preference shock, sector-specific technology shock, loan-to-value shock, sector-specific cost-push shock, sector-specific foreign demand shock, terms of trade shock, and world interest rate shock.

In order to introduce news shocks into the model, we assume that, except for \( \hat{y}_{t}^{f} \), the error term of each shock \( \epsilon_{x,t} \) process is made up of an unanticipated component \( \epsilon_{x,t}^{0} \) and an anticipated component \( \epsilon_{x,t-n}^{n} \) with \( n = \{4,8\} \). The general structure for each shock is given by \( \epsilon_{x,t} = \epsilon_{x,t}^{0} + \epsilon_{x,t-n}^{n} \). \( \epsilon_{x,t-n}^{n} \) denotes the news received in \( n \) quarters in advance, \( \epsilon_{x,i} \) is i.i.d., and \( x \) represents the different types of shocks. Both components are i.i.d. normal with a mean of zero and uncorrelated across time and horizons. As in Schmitt-Grohe and Uribe (2012), we assume that the anticipated component is only changed and revised four and eight quarters ahead so that the latter
period can always modify the news received previously. If the expectation does not realize, then $e_{x,t-4}^4 = -e_{x,t-8}^8$ or $e_{x,t}^0 = -(e_{x,t-4}^4 + e_{x,t-8}^8)$ and $e_{x,t} = 0$.

2.4 Calibration and Estimation of Parameters

2.4.1 Estimation Approach and Data

We take log-linear approximation of the first-order optimal conditions, budget constraints of households and firms, and the aggregate market equilibrium conditions around the steady state.\(^{15}\) Our estimation strategy follows the Bayesian approach, which is now commonly used in estimating DSGE models. Bayesian estimation is shown to enjoy significant computational efficiency over maximum likelihood methods in large-scale models.\(^{16}\) We begin with fixing some parameter values to match equilibrium values. We then set prior to incorporate the pre-sample information and reduce the problem of dimensionality due to a large number of parameters. Thus, we can maximize the log posterior function to estimate the mode of the posterior distribution. The log posterior function can be derived by combining the prior distribution of the parameters with the likelihood function of the data. For the given parameters, we use the Kalman filter to derive the likelihood function through the state-space representation of the model. Finally, we use the Metropolis-Hastings algorithm to obtain the posterior distribution and to conduction the simulation.\(^{17}\)

\(^{15}\) For details about the steady state, please refer to Appendix C.

\(^{16}\) See Lubik and Schorfheide (2004), Smets and Wouters (2007), and Schmitt-Grohe and Uribe (2010) for early examples.

\(^{17}\) See An and Schorfheide (2007) for details of this methodology. We also test the convergence for the stability of the estimated parameters.
We draw the quantitative analysis with the Hong Kong data. Before fixing the parameter values, we need to transform the data into a suitable form for computing the likelihood function. We use quarterly data for six macroeconomic variables as observables: real GDP per capita \( (Y) \), real consumption per capita \( (C) \), gross CPI based inflation \( (\Pi_C) \), gross property price inflation \( (\Pi_P) \), nominal interest rate \( (R) \), and hours of work \( (N) \).\(^{18}\) All of the data are obtained from the websites of the Census and Statistics Department of Hong Kong, the Rating and Valuation Department of Hong Kong, and Hong Kong Monetary Authority.\(^{19}\) Based on the availability of the data series, the analysis covers the period from 1985:Q1 to 2014:Q1.

Real GDP per capita is measured by the chained (2012) Hong Kong dollar divided by the labor force (the land-based non-institutional population aged 15 and over who satisfy the criteria for being classified as the employed population or unemployed population). Real consumption per capita is derived from private consumption expenditure measured in chained (2012) Hong Kong dollars.\(^{20}\) Hours of work are represented by employment (employed persons aged 15 and over who have been at work for pay or profit during the 7 days before enumeration or have had formal

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\(^{18}\) Following Iacoviello and Neri (2010) and Funke and Paetz (2013) we use per capita data instead of aggregate data. Our model is a stationary model abstracting from population growth, thus per capita data fits the model better.

\(^{19}\) Values of real GDP, Real Consumption, CPI price index and employment are obtained from the website of the Census and Statistics Department of Hong Kong (http://www.censtatd.gov.hk/home/index.jsp). Property price index are obtained from the website of the Rating and Valuation Department of Hong Kong (http://www.rvd.gov.hk/). Nominal interest rate data are obtained from the website of Hong Kong Monetary Authority (http://www.hkma.gov.hk/eng/index.shtml). All the data series are accessed at Jun. 2014.

\(^{20}\) The seasonally adjusted data from the website of Census and Statistics Department of Hong Kong only are available from 1990 and on. In order to consider a relatively longer time period, we use self-prepared seasonally adjusted data.
job attachment). Nominal interest rate is proxied by the 3-month deposit rate on deposits of less than 100,000 HK dollars. Territory-wide residential property prices are chosen to represent domestic property price. Consumer price indices of households in different expenditure ranges are used to measure the CPI-based inflation.

Since DSGE models are typically built to capture variations at business cycle frequency, they are ill-equipped to deal with variation at seasonal frequency. Thus, all the data are seasonally adjusted using the WIN-X13 interface of the U.S. Census Bureau. Because our model does not explicitly specify the trend process and the model variables are assumed to represent stationary concepts, the detrending of the empirical counterparts to those model variables has to take place outside of the model. All real variables are in log-difference, except for inflation rate and nominal interest rate. These two variables are only in log because they are widely believed to be stationary. In order to match the log-linearized model, we also demean the data series. Due to the potential mismeasurement of employment, we allow for measurement error in hours of work. Besides, the housing price index suffers from some measurement problems (see Rappaport (2007) for a survey). Thus, we also allow for measurement error in the housing price inflation.22

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21 Due to the unavailability of quarterly data on hours of work in Hong Kong, we use employment as the proxy for hours of work. For a robust check, we convert the available yearly data of hours of work within a short sample period to quarterly data and estimate the model. It is found that the quantitative results are very similar.

22 Allowing for measurement error poses no problem as long as the parameters which needs to be estimated are identified (See Pfeifer (2013) for details).
2.4.2 Calibrated Parameters

We calibrate some parameters that are difficult to estimate using data at business cycle frequencies by matching the long-run properties of the data. Table 2.1 summarizes our calibration results. We fix the depreciation rate of the housing stock at $\delta = 0.01$, in accordance with an annual rate of 4% as Monacelli (2009). We set the discount factor of patient households as $\beta_s = 0.99$, implying a steady-state annual nominal interest rate of around 3%. We set the discount factor of impatient households $\beta_b = 0.96$, which is standard in the literature. This value has a limited effect on dynamics, but is large enough to guarantee an impatient motive for impatient households to be arbitrarily close to the borrowing limit. Thus, the linearization around the equilibrium value with binding borrowing capacity is accurate.\(^{23}\)

The loan-to-value ratio is difficult to calibrate without data on debt and housing holdings of credit-constraint households. The loan-to-value ratio adopted by the banking industry in Hong Kong in November 1991 is 70%. This ratio is fully endorsed by the Hong Kong Monetary Authority as a prudent measure against over-exposure to the property market. We set the loan-to-value ratio at 70%. Thus, our calibration is meant to capture the typical loan-to-value ratio for the credit-constrained households who are likely borrow the maximum possible against the associated housing values. According to the statistical literacy from the Census and Statistics Department of Hong Kong, housing expenditure accounts for about 33% of the total household

\(^{23}\) See Iacoviello (2005) for details.
expenditure.\textsuperscript{24} We then set the share of housing in the consumption expenditure for a typical household at $\gamma = 0.33$.

The substitution elasticities between domestic and foreign goods $\eta_c$ and those between goods produced in the consumption sector of different foreign countries $\zeta_c$ are difficult to estimate. We just follow Funke and Paetz (2013) and set $\eta_c = \zeta_c = 2$. For the share of the housing sector in the aggregate production, we fix $\xi = 0.1$, which is roughly consistent with the share of the real estate sector in Hong Kong's GDP in general. We set the equilibrium value of the price mark up in both sectors at 0.1, in line with that of Funke and Paetz (2013). For the coefficients of monetary policy rule, we have $\rho_\pi = 1.5$ and $\rho_{yf} = 0.5$ as standard value in the literature on Taylor rules. For the shock process for foreign output gap, we simply set the persistent coefficient $\rho_y = 0.7$. Finally, we normalize the steady-state level of hours of work $N$ at 0.3, which means that each individual agent chooses to work around $1/3$ of his/her time endowment.

2.4.3 Prior Distributions

For the Bayesian estimation, we combine all model parameters into a vector $\Theta$ and derive the prior distribution $p(\Theta | A)$, where $A$ represents the specific model, $p(\bullet)$ represents the probability density function (pdf), such as a normal, gamma, inverse gamma, beta, or uniform function. Then we can estimate the likelihood function

\textsuperscript{24} Details can be found in the website of Census and Statistics Department of Hong Kong (http://www.censtatd.gov.hk/statistical_literacy/educational_materials/statistics_and_you/index.jsp).
using the Kalman filter, where $Y_t$ are the observations up to period $T$. The likelihood function stands for the density of the observed data, given the model and the associated parameters. Using Bayes’ theorem, we can derive the posterior distribution

$$p(\Theta | Y_T, A) \propto p(Y_T | \Theta, A) p(\Theta | A).$$

The posterior distribution incorporates the uncertainty corresponding to the parameter values. We can simulate the posterior distribution with the help of the Metropolis-Hastings algorithm. Finally, we estimate the posterior mean and standard deviation using the empirical distribution.

In general, we set the priors values which are consistent with the existing literature (e.g., Smets and Wouters, 2007; Funke and Paetz, 2013). The priors of the estimated parameters are shown in Table 2.2. The degree of openness in consumption $\alpha_e$ is a beta distribution with the mean of 0.5 and standard deviation of 0.1. For price rigidity parameter $\theta_e$, we assume a beta distribution with a prior mean of 0.75. This value corresponds to a frequency of price adjustment of about four quarters, which is a standard calibration in the recent literature. Regarding consumption habit $h_e$, we use a beta distribution with the mean of 0.5 and standard deviation of 0.1. Following Born et al. (2013), the parameter representing the Frisch elasticity of labor supply $\varphi$ is assumed to follow a gamma distribution with the mean of 2 and standard deviation of 0.7. The prior distribution for the parameter representing the elasticity of substitution with respect to total expenditure $\sigma$ is a normal distribution with mean 1 and standard deviation 0.37. Concerning the share of impatient households $\omega$, we just follow Funke and Paetz (2013) and use a beta distribution with the mean of 0.2 and standard deviation of 0.1.
The priors of shocks are shown in Table 2.3. We use inverse gamma priors for the standard errors of each shock component with prior mean 0.1 and standard deviation 2 (Table 2.3). For the news shocks, we follow Khan and Tsoukalas (2012) and set a prior mean for each news component so that the variance of the unanticipated component of each shock is equal to the sum of the variance of the corresponding news component. This prior implies that the news components taken together are as important as the associated unanticipated shock components. For the persistence, the autoregressive parameters of the shocks are assumed to follow a beta distribution with a prior mean of 0.5 and standard deviation of 0.2 (Table 2.3). Since the LTV shock process is regarded as a macro-prudential tool, the coefficient of real housing price $\rho_p$ is set to follow a normal distribution with a prior mean of -0.5 and a standard deviation of 0.2 (Table 2.3), implying the monetary authority aim to adjust the LTV ratio to reverse the real housing price. The only exceptions are the measurement errors, for which we assume an inverse gamma distribution with prior mean 0.01 and fairly tight standard deviations 0.1 (Table 2.3).

### 2.4.4 Posterior distributions

we use the Metropolis-Hastings algorithm to obtain the draws from posterior distribution of different parameters in the model. Following Schorfheide (2000) and Smets and Wouters (2007), inference is done in two steps. First, we maximize the log of the posterior density and compute an approximation of the inverse of the Hessian matrix at the mode. Second, we choose two parallel chains with 200,000 draws from the posterior distribution using a multivariate jump distribution with covariance matrix proportional to the inverse of the Hessian matrix. The first half of the generated
parameter vectors are neglected as a burn-in sample, and the second half draws are used to simulate posterior distribution. In order to strengthen the validation of the estimation results, we also monitor convergence using the convergence diagnosis proposed by Gelman et al. (1992) and Brooks and Gelman (1998). Convergence is based on the comparison of output obtained by computing recursively the first four moments of the marginal posterior distribution of each parameter. The convergence diagnosis is assessed by looking at the graphs of the draws, in which the within-chain and between-chain variances should stabilize and converge to the same value as a function of the number of draws to verify the convergence.

Tables 2.2 and 2.3 report the posterior mean, standard deviation, and the 90% probability internals for the structural parameters. In addition to the structural parameters, we also estimate the standard deviation of the measurement errors for hours of work and property price inflation. Most of the estimation results are consistent with the previous business cycle research, considering only contemporaneous shocks (e.g., Smets and Wouters, 2007; Funke and Paetz, 2013) and those including both contemporaneous and news shocks (e.g., Khan and Tsoukalas, 2012).

We find a moderate degree of habit formation in consumption and relatively higher inter-temporal elasticity of substitution with respect to total expenditure, as shown by the positive values of $h_c$ and $\sigma$ (Table 2.2). Because houses are relatively expensive on a per-unit basis and usually serve as durable goods and housing prices are highly flexible, households tend to have high inter-temporal substitution elasticity with respect to houses. Although households prefer to smooth their non-durable goods expenditure, the inter-temporal elasticity of substitution with respect to total
expenditure is still high. The share of impatient households $\omega$ in our baseline estimation is small (12.57%), but significantly positive. This number implies a relatively lower share of labor income of the credit-constrained households.\(^{25}\) The labor disutility parameter $\varphi$ is estimated at 5.33, a relatively high value. This represents a fairly inelastic labor supply and is consistent with the estimation results in the existing literature.\(^{26}\) Turning to the nominal rigidity in our model, the estimate of $\theta_c$ (0.27) implies that prices are on average adjusted about every 1.4 quarters. Not surprisingly for a small open economy like Hong Kong, the degree of openness $\alpha_c$ is very high, with an estimate of 0.41. The high value is reasonable due to the fact that, in recent years, millions of tourists from mainland China contribute significantly to the consumption in Hong Kong.

In sum, the data is shown to be informative on the estimation of the stochastic process for the exogenous shocks. The foreign housing preference shock is estimated to be highly persistent, with an AR(1) coefficient of 0.92. The high persistence of the foreign housing preference shock implies that, in the long run, a large proportion of the variance of the real variables could be attributed to this shock. The parameters of the monetary policy are in consistent with previous estimates found in Born et al. (2013). There is a relatively high degree of interest rate smoothing ($\rho_r = 0.81$) and a moderate value for the standard deviation of the foreign interest rate shock.

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\(^{25}\) This value is close to the one proposed by Funke and Paetz (2013).

\(^{26}\) See Funke and Paetz (2013).
2.4.5 Identification in the model

Given the fact that a growing interest is devoted to identification issues in the Bayesian estimation of DSGE models (Canova and Sala, 2009; Komunjer and Ng, 2009; Iskrev, 2010b), we test for local identification both in the model and in the moments. To solve the difficult problem of explicitly deriving the relationships between the deep parameters and the structural properties of the model, we use the local identification approach proposed by Iskrev (2010a). The analysis evaluates the ranks of the Jacobian matrix and can be performed for any equation system representing the linearized model and the associated structural parameters.

Let $J(T)$ be the Jacobian matrix mapping from the structural parameters in the model to the vector containing the parameters that determine the first two moments of the observables used in the model estimation. The Jacobian matrix can be shown as

$$J(T) = \frac{\partial m_\tau}{\partial \tau} \frac{\partial \tau}{\partial \theta},$$

where $m_\tau$ is a function of the deep parameters $\theta$ and $\tau$ represents a vector collecting the reduced-form parameters of the first-order condition of the model.

Thus, $\frac{\partial \tau}{\partial \theta}$ describes the elasticity of $\tau$ to the deep parameters $\theta$, and $\frac{\partial m_\tau}{\partial \tau}$ represents the elasticity of the moments to the reduced-form parameters $\tau$. Suppose that $m_\tau$ is a continuously differentiable function of $\theta$, then a parameter $\theta_i$ is locally identifiable if the Jacobian matrix $\frac{\partial J(T)}{\partial \theta_i}$ has a full column rank at $\theta_i$. Using the identification package developed at the Joint Research Center (JRC) of the European Commission.

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27 See Ratto and Iskrev (2011) for details. This approach is also applied by Schmitt-Grohe and Uribe (2012).
for the DYNARE environment, we find that, in a neighborhood of the posterior mean, all parameters and shocks in the model are locally identified.

2.5 Quantitative Results

2.5.1 Cyclical Properties

Table 2.4 compares some empirical moments from the data to the corresponding moments implied by the model. Overall, the model simulation can match the sample properties fairly well, for both the volatility and correlation of housing and non-housing variables. Our estimated model explains well the cyclicity and volatility of housing price and the patterns of co-movement between housing price and other macro variables. From Table 2.4, we find that housing price inflation is procyclical and more volatile than other macro variables, both in the model and the data. The only exception is that the correlation between housing price inflation and consumption is a bit higher in the data (0.25) than that in the model (0.09).

2.5.2 Variance decomposition

We use the DSGE-based estimation to assess the quantitative importance of various contemporaneous and news shocks in driving the fluctuations in the housing market and the macroeconomy. To this end, we conduct conditional and unconditional variance decomposition for output, consumption, employment, real housing price, and interest rate. Table 2.5 presents the conditional variance decomposition at different forecast horizons. The first row for each variable represents the impact response in the first quarter, while the last row represents the asymptotic decomposition.28

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28 For the shocks whose influence is less than 1%, we indicate the value of 0.
The quantitative analysis shows the following results. First, for housing market dynamics, contemporaneous shocks dominate news shocks. Among contemporaneous shocks, foreign factors contribute most to housing price fluctuation. In detail, foreign housing preference shock $\sigma_{d,*}$ accounts for 41.92% of the volatility of real housing price in the first quarter and more than 30% asymptotically (Table 2.5). This result is consistent with our model expectation that foreign housing preference can affect the domestic market through international risk sharing condition (section 2.3.4). The other important foreign factor is the terms of trade (TOT). TOT shock contributes 50.81% to the real housing price fluctuation at impact, and it still accounts for 32.66% asymptotically. As discussed in section 2.3.3, changes in terms of trade can directly affect domestic CPI-based inflation through equation (2.20). Thus, it can be a driving force behind housing price volatility. These results suggest that Hong Kong as a typical small open economy, its housing market dynamics is primarily driven by contemporaneous foreign shocks.

Second, news shocks also account for a modest share of housing price dynamics. From Table 2.5, we find that influence from news shocks are generated by TFP shock in consumption goods sector ($\sigma_{a,4}$ and $\sigma_{a,8}$). This result is consistent with that in Fujiwara et al. (2011), suggesting that a news shock at longer periods has larger effects on nominal variables. Although TFP news shocks in the consumption goods sector only accounts for nearly 6% at impact, it contributes approximately 33% to the volatility of real housing price asymptotically. News on TFP shocks can affect agents' inter-
temporal consumption and saving decisions.\textsuperscript{29} Thus, it can drive housing price fluctuation, given the fact that a house is included in the total expenditure of households. As for the cyclical movements in housing investment, external shocks and news shocks also exhibit a significant role. Contemporaneous shock to terms of trade explains 93% of the variance in housing investment at impact and 36% asymptotically. News shocks to technology in the consumption goods sector, however, tend to drive fluctuations of housing investment in the long run, explaining 59% of its volatility asymptotically.

Third, for the variance of other macro variables, changes in foreign factors also account for a sizeable share. TOT shock asymptotically accounts for 21.15% of output volatility, approximately 30% of consumption variance, and 37.67% of employment fluctuation (Table 2.5).

Fourth, from the conditional variance decomposition, contemporaneous shocks contribute to the business cycles mainly at short horizons. From Table 2.5, we find that unanticipated shocks account for more than 98% for the variance of output, consumption, and employment and more than 50% for interest rate fluctuation at impact. However, the influence of contemporaneous shocks becomes less at longer horizons. By contrast, news shocks become more important in the long run. For unconditional variance decomposition in Table 2.5, TFP news shock asymptotically accounts for 78.41% of output volatility, 69.03% of consumption variance, and 62.05% of employment fluctuation.

\textsuperscript{29} See Schmitt-Grohe and Uribe (2012) for details.
Fifth, inflation volatility can be almost attributed to contemporaneous shock to terms of trade and foreign interest rate or monetary policy. These two shocks together account for around 90% of interest rate variance at both short and long horizons (Table 2.5). This result implies that foreign factors can exert an important influence on both real and nominal variables.

In sum, the dynamics of both housing price and other macro variables are mostly driven by foreign shocks, particularly contemporaneous shocks to foreign housing preference and terms of trade. News shocks, especially TFP news shock in consumption goods sector, also account for a sizable share in housing market fluctuations and business cycles.

2.5.3 Historical shock decomposition

In Figure 2.1, we illustrate the historical shock decomposition of our estimated model for output, consumption, and real housing price over the sampled period. The graphs illustrate a visual representation of the numerical findings from Table 2.5, verifying the performance of our model. The solid line displays the percentage deviation from the steady state for the corresponding historical data series. The bars of different color denote the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. As shown, during the period 1985-2014, there were three major fluctuations in output, consumption, and real housing price. The first fluctuation was from 1996 to 1999, followed by 2003-2005, and lastly 2007-2013. In the first cycle, due to the Asian financial crisis in 1997, Hong Kong experienced a recession, and real housing prices collapsed. In the second cycle, due to SARS, both GDP and consumption dropped. The Individual Visitor Scheme was first introduced in
July 2003 as well as the liberalization measure under the Closer Economic Partnership Arrangement between Hong Kong and mainland China, at which point real housing price only dropped mildly and then continued to rise afterwards. In the third cycle, the collapse of the housing mortgage market in the U.S. in 2008 caused a serious financial crisis across the world. As a typical small open economy, Hong Kong experienced a slump in output, consumption, and real housing price, but the economy soon recovered. According to Figure 2.1, we find that our model reflects the dynamics of housing market and the macroeconomy as well. In addition, the shock decomposition further confirms the findings in Table 5. The fluctuations of real housing price are mainly driven by shocks to foreign housing preference, terms of trade, and news on TFP in consumption goods sector. Also, shocks to terms of trade and news on TFP in the consumption sector drive the output and consumption volatility.

2.5.4 Impulse responses

Sections 2.5.2 and 2.5.3 document that contemporaneous shocks to foreign housing preference and terms of trade can generate business cycles in both the housing market and the macroeconomy. News shocks to TFP in the consumption goods sector can also be a driving force behind the fluctuation of real housing price and other macro variables. To gain a better understanding of the dynamic effects of these shocks, we analyze their impulse responses. In Figures 2.2 to 2.4, we illustrate the Bayesian impulse response function for contemporaneous shocks to foreign housing preference and terms of trade and the news shock to TFP in the consumption goods sector.
2.5.4.1 Foreign housing preference shock

A housing preference shock can be regarded as a housing demand shock (Iacoviello and Neri 2010), causing real housing price to rise, as shown in Figure 2.2. A positive foreign housing preference shock increases the housing demand in the foreign market. Due to the close relationship between the domestic and world market for a small open economy, domestic housing demand increases as well. This mechanism can be derived from the international risk-sharing condition, as shown in equation (2.24). Due to the Currency Board System, the Hong Kong exchange rate is fixed, implying the co-movement between domestic and foreign sector-specific demand. Furthermore, due to the rising foreign housing demand, the decrease of foreign interest rate can transmit into the domestic economy through the interest rate parity condition of equation (2.15), causing a decrease in the domestic interest rate.

Because households can borrow money at a lower cost, housing demand increases, thus raising the real housing price. Unlike Funke and Paetz (2013), who argue that higher housing demand can lead to an increase in the marginal value of borrowing, we find that the marginal value of borrowing decreases in response to a positive housing demand shock. This result can be due to the macro-prudential policy tool shown in equation (2.19). Policy makers can decrease the loan-to-value ratio to cool the bubbly property market, leading to a decrease in the marginal value of borrowing. In fact, the macro-prudential policy tool reduces the effect of collateral constraint, and in turn, it reduces the sensitivity of borrowing capacity to housing demand shock. The strong

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30 The optimality condition of borrowers with respect to consumption goods is widely interpreted as equating the marginal rate of substitution between durable and non-durable goods expenditure to the "user cost" of durable goods. See Monacelli (2009) for details.
demand in the housing market and the decreasing marginal value of borrowing lead the borrowers to reduce their consumption. However, the increase in real housing price can benefit the lenders, motivating them to increase their consumption. Thus, the aggregate consumption is less sensitive to housing demand shock and decreases slightly. The decrease in consumption in turn generates a downturn of CPI-based inflation rate. Since the consumption sector features the high degree of openness, the decrease in CPI can lead to an improvement in terms of trade, generating an increase in aggregate output and employment.

2.5.4.2 Terms of trade shock

An increase in the terms of trade makes the relative price of domestic goods to foreign goods decrease and stimulates exports. Thus it generates a higher foreign demand for domestic goods, raising the output and employment in consumption goods sector. Furthermore, since we define terms of trade as the ratio of foreign price to domestic price, a positive term of trade shock generates a negative income effect. This would also raise the aggregate output and employment. Because the foreign price for a small open economy is determined in the international market outside the model, a positive term of trade shock implies a decrease in domestic CPI shown in Figure 2.3, resulting in an increase in real housing price.

2.5.4.3 TFP news shock

As shown by the variance decomposition, the importance of TFP shock is mainly ascribed to the news components. The impulse response in Figure 2.4 shows that news shocks about future technological growth in the consumption goods sector
This shock refers to an anticipated increase in TFP in the consumption goods sector eight-period ahead and the expectation realizes eventually. We show that realized news shocks to productivity in the consumption goods sector also generate macroeconomic booms in a small open economy with the housing sector. Figure 2.4 reports the effect of an anticipated increase in TFP in the consumption goods sector, namely an eight-period ahead expected shock to TFP, and realizes eventually. The expectation about future higher productivity induces households to increase their consumption in the future, but merely affects their current consumption. This is due to the high inter-temporal substitution elasticity with respect to the total expenditure estimated in our model. Thus, households tend to wait for the realization of the shock before increasing consumption. When the expectation of high TFP in the consumption goods sector is realized in period 8, the increased TFP leads to an increase of output in the consumption goods sector, even when the employment decreases due to the positive income effect. And the positive income effect also increases consumption. As labor resources are shifted from the housing sector to the consumption goods sector (because of an improvement in consumption technology), housing investment drops, and therefore housing price rises.
2.6 Conclusion

In this paper, we analyze the contribution of both contemporaneous and news shocks to housing market fluctuation and business cycle volatility for a small open economy using an estimated DSGE model with a housing sector. The structure of our model presented above merges three streams of business cycle theory in the literature, namely, small open economy business cycle model, DSGE model with a housing sector, and DSGE model with news shocks. The constructed model incorporates a rich set of shocks and the empirical characteristics of the Hong Kong economy. Our framework bridges the gap between small open economy business cycle models and the housing market research and sheds light on the interactive relationship between housing price fluctuation and business cycles.

Several features are generated from our estimated model. First, at business cycle frequencies, it matched the stylized facts that housing price in Hong Kong is significantly procyclical, volatile, and sensitive to external shocks. Second, over longer horizons, the model explains the fluctuation of housing market over the sample periods and attributes these dynamics to three main factors: contemporaneous shocks to foreign housing preference, terms of trade, and news shock to productivity in the consumption goods sector. Third, through the variance decomposition analysis, we find that each of these three shocks accounts for approximately one third of the variance of real housing price. Cyclical movements in housing investment are also largely influenced by contemporaneous shock to terms of trade and news shocks to technology in the consumption goods sector. The former accounts for 36% of the variance in housing investment, while the latter accounts for 59%. In terms of the variance of non-housing
variables, changes in foreign factors also account for a sizeable share. Terms of trade shock asymptotically accounts for 21.15% of output volatility, approximately 30% of consumption variance, 37.67% of employment fluctuation, and 51.75% of inflation volatility. Fourth, conditional variance decomposition shows that contemporaneous shocks contribute to the business cycles mainly at short horizons. By contrast, news shocks become more important in the long run.

The findings of this paper provide insight for policy makers to identify the key driving forces behind the housing market dynamics and the interaction between housing market and the macroeconomy for small open economies. A better understanding of the sources of housing market fluctuations facilitates policy makers to formulate appropriate policies in a more proactive manner. In light of the 2008-2009 global financial crisis and recovery, it is clear that the analysis of the housing market and the aggregate economy nexus calls for deep empirical and theoretical research. The recent financial crisis highlights the important role of the financial sector in the transmission of business cycles. It might be worthwhile to extend the current model with the inclusion of a financial sector and study the spillover of the housing sector to the financial sector and the resulting impact to the aggregate economy. Furthermore, we may consider floating the exchange rate regime and thus allowing for the law of one price gap. This can enable us to apply our model to other countries with different monetary policies rather than adopting the currency board system in Hong Kong. Further research along this line should be considered.
### Table 2.1 Calibrated Parameters

<table>
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<tr>
<th>Parameter</th>
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<tr>
<td>$\beta_b$</td>
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<tr>
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<tr>
<td>$\gamma$</td>
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### Table 2.2 Prior and Posterior distribution of the structural parameters

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<td>Normal</td>
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<tr>
<td>$\varphi$</td>
<td>Gamma</td>
<td>Mean: 2.000, SD: 0.7</td>
</tr>
<tr>
<td>$\omega$</td>
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<td>Mean: 0.200, SD: 0.1</td>
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<td>Beta</td>
<td>Mean: 0.500, SD: 0.1</td>
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<td>$\alpha_c$</td>
<td>Beta</td>
<td>Mean: 0.500, SD: 0.1</td>
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<td>Parameter</td>
<td>Prior distribution</td>
<td>Prior distribution</td>
</tr>
<tr>
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<td>( \rho_{a_d} )</td>
<td>Beta</td>
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<tr>
<td>( \rho_{\mu_c} )</td>
<td>Beta</td>
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<tr>
<td>( \rho_{\mu_d} )</td>
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<tr>
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<td>Inv.gamma</td>
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<td>Inv.gamma</td>
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Table 2.3  Prior and Posterior distribution of the shock process (continued)

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<th>Posterior distribution</th>
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<td>$\sigma_{a4}$</td>
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Table 2.3  Prior and Posterior distribution of the shock process (continued)

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<th>Parameter</th>
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<tr>
<td>$\sigma_{r8}$</td>
<td>Inv.gamma</td>
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</tr>
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Table 2.4  Model and Data Moments

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<th>Panel A. Standard deviation (percent)</th>
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<td>Employment</td>
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<td>1.26</td>
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<table>
<thead>
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<th>Panel B. Correlations</th>
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<th>Data</th>
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<td>GDP, Housing Price Inflation</td>
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<td>Consumption, Housing Price Inflation</td>
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Table 2.5 Variance decomposition at different horizons

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<th>Variable and Horizon</th>
<th>Forecast Horizon (Quarters)</th>
<th>$\sigma_{a,t}$</th>
<th>$\sigma_{d,t}$</th>
<th>$\sigma_{e,t}$</th>
<th>$\sigma_{r,t}$</th>
<th>$\sigma_{a,t} + \sigma_{a,t,h}$</th>
<th>$\sigma_{d,t} + \sigma_{d,t,h}$</th>
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</table>

Note: The table mainly presents those shocks with large variance contribution. Therefore, the sum of the shock contribution may not add up to 100%.
Figure 2.1  Historical shock decomposition

Real Housing Price

Output

Consumption

Inflation

83
Figure 2.2  Impulse response to unanticipated shock to foreign housing preference

Figure 2.3  Impulse response to unanticipated shock to terms of trade
Figure 2.4  Impulse response to 8-period news shock to TFP in the consumption sector
Chapter 3
Forecasting Macroeconomic Variables In a Small Open Economy: A Comparison Between Structural and Non-structural Models

3.1 Introduction

This paper compares the predictive ability of seven alternative models in forecasting five key macroeconomic variables, namely, output, consumption, employment, housing price inflation, and CPI-based inflation for a small open economy, which in our case happens to be Hong Kong. One of these models is a structural DSGE model with the housing sector in a small open economy. The other models refer to non-structural data-driven models that are estimated as using classical time-series methods or Bayesian techniques. As a part of the forecasting analysis, we also investigate different methods, factor analysis or Bayesian shrinkage, to incorporate information from a large-scale data set into forecasting model.

Both policy makers and academics show great interest in accurate forecasts of economic variables. Some scholars exploit different computational methods to construct structural and non-structural models that can well replicate the empirical features of the data. Thus, large information set proves to be useful in matching the structural economic relationships. Classical time-series models, such as VAR, have difficulty in dealing with large numbers of variables. Thus, the core problem of small-scale models is how to choose the most reliable variables included in the model, in order to avoid the issue of over-parameterization. However, some scholars and policy
makers believe that large information set, which cannot be included simultaneously in a VAR, enjoys great advantages in macroeconomic forecasting exercise.

Bernanke and Boivin (2003) argue that when informing their monetary policy decisions, in practice, central banks usually monitor and analyze thousands of time series variables. Therefore, the associated gains and costs with increasing the amount of variables in the model should be considered by econometricians. The use of various information-extracting methods could overcome the difficulty in dealing with large numbers of variables in the forecasting model. Recent advances in the theory of DFM have shown that, under some suitable restrictions, it is possible to consistently estimate the common factors in an approximate DFM given a large-scale data set (Forni et al. 2000, Stock and Waston 2002b). The various applications of DFM in forecasting exercise can be found in Marcellino et al. (2003) and Forni et al. (2003), which all state that factor models enjoys strong predictive power in forecasting macroeconomic variables. In addition, the Bayesian methods are also gaining popularity in forecasting exercises. Because priors on the parameters in the model provides an effective and consistent way of introducing shrinkage. Banbura et al. (2010) and Koop (2010) have shown that BVAR results in good forecasting results compared to popular alternatives such as factor models. Moreover, factor methods, in which information in the hundreds of variables is represented by a few common factors, could be combined with VAR to formulate FAVAR. This model could also be estimated by the ordinary least square (OLS) or Bayesian methods and be well designed for out-of-sample forecasting.

In addition to the non-structural data-driven model, theory-based models have also been widely used in the forecast exercise. Recently, serious attempts have been made to move the structural model into the field of macroeconomic forecasting. Smets
and Wouters (2004) claim that forecasts generated from a medium-scale DSGE models are superior to unrestricted VAR. Del Negro and Schorfheide (2004) and Del Negro et al. (2007) apply the DSGE priors to the BVAR set up and state that structural models could produce good forecasting results. In addition, a DSGE model with the housing sector may produce reasonable forecasts of housing price inflation. Some studies find that asset prices are helpful in predicting both inflation and output (Forni et al. 2003, Stock and Watson 2003). Since a large proportion of individual wealth is determined by the housing values, housing price is important in signaling inflation and other fundamental variables. As such, the structural DSGE model with the housing sector that forecasts housing price inflation could provide policy makers with a clear picture about the movement of the housing market and the macroeconomy and therefore can serve as a useful tool for policy making.

Although both structural and non-structural models are widely used in the forecasting exercise, there is, to our knowledge, little literature to conduct a forecasting horse race between these two categories of models for a small open economy. On one hand, the structural DSGE model which is well micro-founded is widely used as an efficient tool for macroeconomic forecasting. On the other hand, the non-structural data driven models have been the subject of various investigation regarding their predictive ability. The main target of this study is to investigate which kind of model(s), structural or non-structural, small-scale or large-scale, is (are) best forecasting model for a small open economy. We conduct a forecasting exercise of a small open economy DSGE model with the housing sector, allowing for both contemporaneous and news shocks. We also examine the predictive ability of data-rich non-structural models, using the DFM or Bayesian shrinkage approach. We totally compare the out-of-sample
forecasting performance of seven models, including DSGE, DFM, FAVAR, classical VAR, and various BVAR. For BVAR, we apply different specifications, including the BFAVAR, small- and large-scale BVAR. Based on MAE and RMSE at one- to eight-quarters horizon, we find that non-structural models outperform the structural model for all variables, and there is no single model which can always dominate at all forecasting horizons. The structural DSGE model does not show any advantage in our forecasting exercise for housing price inflation forecasting, although it can produce reasonable forecasts for real variables such as output and consumption. At short horizons, SBVAR could generate better forecasts than other rival models, although DFM does not lose much advantage and tends to perform better as the forecasting horizon grows. As the forecasting horizon grows over four periods, DFM improves over other models in the long run. We also find that DFM shows the best ability in predicting the turning point of housing price inflation, and SBVAR performs better in predicting the turning point of output. Our results indicate that the advantages of incorporating a large data set are significant only for DFM, especially at longer forecasting horizons.

Against such a backdrop, this study should be viewed as a complete and deep attempt to shed light on the predictive ability of various types of model for a small open economy at different horizons. The rest of the paper is organized as follows: section 3.2 provides a comprehensive literature review of recent studies of the subject matter, section 3.3 discusses various types of models used here, section 3.4 describes the details of data treatment and experimental design, section 3.5 presents the results from our forecasting experiment, section 3.6 discusses the ability of various models in predicting the turning point, and finally section 3.7 concludes.
3.2 Literature review

3.2.1 Introduction

Economic agents who make decisions based on their expectation toward the economic outlook have shown significant interest in macroeconomic forecasting. Over the past two decades, enhancement in computation capacity has fostered sophisticated forecasting methods available, and the role of economic forecasting has become increasingly important. Nevertheless, an interpretation of economic forecasting requires a clear understanding of the corresponding models, their limitations, and awareness of common pitfalls in its application.

Despite the importance of the housing sector in the macroeconomy, relatively few studies have assessed the performance of alternative models that forecast housing prices. Many studies (e.g., Iacoviello, 2005; Case et al., 2005; Leamer, 2007; Pariès and Notarpietro, 2008; Bao et al., 2009; Christensen et al., 2009; Ghent, 2009; Ghent and Owyang, 2009; and Iacoviello and Neri, 2010) claim that housing market is closely linked to the macroeconomy. Forni et al. (2003), Stock and Watson (2003), and Gupta and Das (2010) argue that house-price movements are able to generate economic activity, indicating future direction of economic movements. In addition, there is evidence that housing prices are forecastable to a certain degree (Crawford and Fratantoni, 2003). Models have shown that housing price forecasts can provide policy makers with information on future movements of economic activity and facilitate the formation of policies. Accordingly, it is insightful and meaningful to examine which forecasting models are relatively better with which to capture the future movements of housing prices.
Following Sims (1980) and Litterman (1986a, 1998b), VAR and BVAR become standard methods in forecasting exercises. There are several advantages of VAR and BVAR. They are easy to estimate, and enjoy large flexibility in terms of variable selection, to produce out-of-sample forecasts. In addition, a growing number of studies use factor models in macroeconomic forecasting. The factor models attempt to incorporate economic information from a large data set and, at the same time, are shrunk by extracting only a few number of common factors which could represent the entire economic information set. However, the non-structural forecasting models are not based on (unrestricted VAR) or make little (structural VAR) reference to economic theories.

The alternative approach to purely non-structural forecasting models is structural models. It is grounded on economic theories. For example, firmly based on modern micro-foundations, DSGE models have been of considerable complexity and incorporate several types of nominal and real rigidities emphasized by the New Keynesian literature. Now, DSGE models become a useful technique for policy analysis and the standard tool for macroeconomic forecasting.

With the development of forecasting techniques, various types of structural and non-structural models have been proposed to compare the out-of-sample forecasting performance. Adolfson et al. (2005) find that the open economy DSGE model forecasts are better than time-series forecasting models such as VAR and BVAR. Gupta and Kabundi (2010), on the other hand, find that large-scale BVAR outperforms the small open-economy DSGE model in terms of RMSE. Given the controversy about the forecasting performance between various models, we need to find out an answer to the
question about the abilities of different models to forecast the future state of the housing market and the macroeconomy.

This section provides a literature review about the main methods used in predicting macroeconomic variables and housing price. The focus here will be on the comparison of forecasting performance of different models, including the DSGE model for small open economies, the Bayesian VAR, and the dynamic factor model.

3.2.2 DSGE model based forecasting

DSGE models which are firmly based on the modern macroeconomic theories, are widely used to explain and predict future movements of macroeconomic variables at the business cycle frequencies. The advantage of the DSGE model is that it could provide an internally consistent and logic interpretation of the moving trend of the macroeconomy and generate sound forecasting results.

DSGE models are widely used as forecasting tools by central banks around the world. Bayesian methods are frequently used in the estimation of the DSGE models (e.g., An and Schorfheide, 2007a; Del Negro and Schorfheide, 2010), particularly in the simulation and forecasting macroeconomic variables. The posterior predictive distributions produced by Bayesian estimation could represent the uncertainty embedded in the model.

There is rich literature on putting the forecasting accuracy of DSGE models in comparison with that of VAR or BVAR. Smets and Wouters (2007) show that a structural DSGE model outperforms VAR models in the experiment of macroeconomic forecasting. Following Smets and Wouters (2003) Del Negro et al. (2007) develop a DSGE-VAR model. The authors find that their model shows better forecasting ability than the unrestricted VAR. In another path-breaking study, Adolfson et al. (2007) put
the Smets and Wouters (2003) model into an open-economy framework in order to conduct the Euro-area economy forecasting. Regardless whether point forecasts and the density forecasts are considered, the authors show that the predictive ability of the DSGE model is comparable or even better than that of VAR and BVAR. The recent study conducted by Marcellino and Rychalovska (2014) investigate the empirical validity of restrictions implied by DSGE model through the DSGE-VAR analysis. DSGE model shows superior out-of-sample predictive ability compared to unrestricted VAR and BVAR. Moreover, the structural DSGE model restrictions improve the predictive ability of the standard VAR in forecasting the future state of the labor market, such as wages and unemployment rate.

Comparison between the DSGE model and the dynamic factor model which is mainly data driven, is also found in the literature. Wang (2009) compares predictive ability between the data-driven and DSGE models in a rigorous manner. The author shows that incorporating a large information set in the non-structural model can lead to an improvement in the short-horizon forecasting, while the theory-based DSGE model shows reasonable predictive ability at longer forecasting horizons. Gupta and Kabundi (2010) focus on the forecasting comparison between DSGE model and data-rich model in the framework of a small open economy. Exacting information from a large data set, the author finds that, based on the RMSE, the data-rich large-scale model produces better forecasts than the DSGE model in predicting the key macroeconomic variables.

Some economists compare forecasts generated from DSGE models with those produced by experts, such as the Survey of Professional Forecasts (SPF). Lees et al. (2007) compare the forecasting performance of a small open economy DSGE model
with the Reserve Bank of New Zealand (RBNZ) staff forecasts. Based on the sample period from April 1998 to March 2003, DSGE model shows better ability in predicting GDP growth, whereas models of the RBNZ performs better in predicting nominal variables. Rubaszek and Skrzypczynski (2008) find that a small-scale DSGE model is able to generate better forecasts of the U.S. GDP growth than the SPF, while it shows relatively poor predictive ability in forecasting nominal variables such as inflation and interest rates. Kolasz et al. (2012) show that, although the SPF is able to produce a clear picture of the interest rate forecasts in the short run, the DSGE model is able to generate significantly better GDP forecasts at longer forecasting horizons. From the previous studies, it is found that DSGE models tend to generate better forecasts for real variables, whereas SPF could produce better forecasts for nominal variables. As claimed by Kolasz et al. (2012), the better forecast for nominal variables found in the previous studies can be ascribed to the information advantage of experts, because they are able to obtain the real-time high-frequency data.

Some recent studies provide different story about the forecasting performance of DSGE models. Edge and Gurkaynak (2010) argue that, although DSGE models show some forecasting superiority to statistical and judgmental forecasts, they still have the weakness in the forecasting power the over the period of the Great Moderation, during which the dynamics of the macroeconomy was mainly driven by some structural shocks. Schorfheide et al. (2010) show that a DSGE model is able to predict variables which is not explicitly modeled, such as personal consumption expenditure, inflation, unemployment rate, and housing starts. Herbst and Schorfheide (2011) investigate the ability of DSGE models to forecast co-movements between key macroeconomic variables. The authors find that incorporating more features, such as additional internal
and external propagation mechanisms, into the model by Smets and Wouters (2007) does not improve the density forecasting performance and forecasts of co-movements between key macroeconomic variables.

3.2.3 Bayesian VAR based forecasting

VAR has been widely recognized as a useful tool in macroeconomic forecasting (e.g. Doan et al., 1984 and Litterman, 1986). Different from structural models, VAR does not impose structural restrictions on the parameters in the model and therefore provides a very general representation to capture the relationship between different series of the data. The approach, however, may create some problems that have been widely discussed in the literature. First, this generality leaves a large number of parameters to be estimated, even for models of medium-scale. This leads to the issue of over-parametrization, because the number of unrestricted parameters which can be consistently estimated is relatively limited. As a result, VAR models usually include only a small number of variables, and this may induces a problem of omitted variable which is harmful for the forecasting analysis (e.g., Giannone and Reichlin, 2006). In addition, the issue of over-parametrization is problematic for some studies that require a larger set of variables other than only a few key macroeconomic indicators. Furthermore, in many applications, the VAR coefficients are assumed to remain constant over time. However, in practice, it is often found that the features of the macroeconomy in different periods are also different. For example, in 2008-2009, many economies went through recession due to the financial crisis. Many corresponding policy analysis argue that the parameters in VAR should be changing. This leads to the development of models that allow for changing parameters in the VAR, and a time-varying parameter VAR thus arises.
The challenge that macroeconomists confront is how to build models which are flexible enough to empirically capture key data properties, but are not too flexible to suffer from the over-parameterized. This has initiated the use of Bayesian methods, which have been proved to greatly improve forecasting performance. The Bayesian estimation regards the true population structure as uncertain and does not place too much weight on any particular value of the model parameters. Instead, it takes this opportunity into account in the form of a prior probability distribution over the model parameters. The degree of uncertainty represented by prior distribution can then be altered by the information contained in the data, if the two sources of information are different. As long as the prior information is not too vague, it is altered only by the signal and not by the noise contained in the data set, thus reducing the risk of overfitting. As a result, BVAR is known to produce better forecasts than reduced-form VAR estimated in a classical way and, in some cases, even better than univariate autoregressive moving average processes or structural models.

The choice of a prior distribution summarizing the researcher’s uncertainty over the model parameters is a crucial step in specifying a BVAR. Carriero et al. (2009) forecast exchange rates using a large-scale Bayesian VAR model. The authors show that the BVAR model with a normal-inverted Wishart prior produces systematically better forecasts than a random walk at all forecast horizons. Banbura et al. (2010) construct a medium-scale VAR model including 20 dependent variables and a large-scale VAR model with 130 dependent variables. The authors use a natural conjugate variant of the Minnesota prior developed by Doan et al. (1984) and Litterman (1986). This prior shrinks all VAR coefficients towards zero except for the coefficients on the own lags of each dependent variable. Therefore, forecasts are shrunk towards either a
random walk or white noise with respect to different variables. Besides, the authors set the degree of shrinkage in accordance with the cross-sectional dimension, and show that the predictive ability of small-scale VAR can be improved by including more macroeconomic variables. There are also different methods which impose more restriction on the error covariance matrix than that of Banbura et al. (2010) in the implementation of the Minnesota prior. Gupta and Kabund (2010) also construct a large-scale BVAR using the Minnesota prior. The authors find that, based on RMSE across different forecasting horizons, large-scale BVAR outperforms the unrestricted VAR and small-scale BVAR consistently and significantly.

Moreover, there are alternative methods in setting prior for BVAR. Koop (2010) investigates how stochastic search variable selection (SSVS) methods work with large VAR. The author applies a range of alternative priors and finds that SSVS-based approaches perform best in the forecasting exercise in which relatively small-scale VAR is adequate. However, Minnesota prior-based forecasting performs best with medium-scale or large-scale VAR.

In addition, Koop and Korobilis (2012) indicate that the forecasting model itself can potentially change over time and that the coefficients on the predictors can also change over time. Thus, the authors adopt a method developed by Raftery et al. (2010), which they refer to as dynamic model averaging (DMA). This approach allows the forecasting model to change over time while, and they allow coefficients in each model to evolve over time as well. The authors find that DMA significantly improves the forecasting performance over simple benchmark regressions and other sophisticated approaches such as using time-varying coefficient models. Korobilis (2013) proposes a stochastic search algorithm for variable selection in both linear and nonlinear VAR
using Markov chain Monte Carlo (MCMC) approach. This algorithm will only visit models with the largest probability when the number of models is too large to assess in a deterministic manner. Thus, Bayesian variable selection methods is useful in achieving parsimony. The author shows that this type of variable selection enjoys more advantages in forecasting analysis as the model grows large.

### 3.2.4 DFM based forecasting

In the field of macroeconomic forecasting, a large number of data series are often used to predict a few key economic variables, such as aggregate output or inflation. Yet most multivariate forecasting methods in the literature only allow for incorporation of a limited number of key variables with low dimension.

To circumvent these problems, recent studies have developed a “diffusion index” to impose restrictions on the covariance structure such that the number of parameters is rather limited. The idea is to use factors extracted from a large data set to forecast a few variables of interest, so that the information about the dynamic interrelations contained in a large data set can be represented by a few common factors. Factor models have shown the superiority in forecasting studies (Stock and Watson, 2002a, 2002b; Bernanke and Boivin, 2003; Marcellino et al., 2003; Forni et al., 2003, 2005; Giannone et al., 2004; Boivin and Ng, 2005; D’Agostino and Giannone, 2006).

Although factor models have been proved useful for forecasting purpose, diffusion index forecasts are adopted in various ways. The most two noticeable approaches in the literature are the generalized dynamic factor models of Forni et al. (2005), and the static representation of dynamic factor models of Stock and Watson (2002a). The main differences between these two methods lie in the estimation of the dynamic factors and in the way the projections onto the estimated factors are performed.
In Stock and Watson (2002a), the factors are first estimated by static principal component analysis, then the estimated common factors are directly used to forecast the variables of interest. Different from Stock and Watson (2002a), Forni et al. (2005) estimates the common factors by the generalized principal component analysis, and then imposes the restrictions implied by the dynamic factor structure when the factor space is used in the forecasting exercise.

Previous studies have not yet reached a consensus on which factor model could lead to better forecasts in a finite sample. Using a large set of U.S. data, Boivin and Ng (2005) find that, there is not too much differences about the forecasting ability between these two methods, especially when the time period is short. But Stock and Watson (2002a) performs better with more complicated but realistic error structures. The authors argue that it is because in Stock and Watson (2002a) more flexibility is allowed in the forecasting equation to fit the data, while the dynamic restrictions implied by Forni et al. (2005) may reduce the forecasting accuracy of the model. However, Stock and Watson (2006) find that both methods show similar predictive ability. Schumacher (2007) finds that the forecasts of Forni et al. (2005) are more accurate than that of Stock and Watson (2002a). Agostino and Giannone (2011) propose a nesting procedure to compare the predictive ability of Forni et al. (2005) and Stock and Watson (2002a). The authors find that the two methods have similar predictive ability and their forecasts are highly collinear.

Although the diffusion index methods enjoy great popularity in the forecasting exercise, Bai and Ng (2008) point out that the method does not take the predictive ability of predictors for the variable to be forecasted into account when the factors are estimated. Moreover, the relationship between the predictors and the variables to be
forecasted is restricted to be linear. Thus, the authors adopt the approach of quadratic principal components, which allows for a non-linear relationship between the predictors and the factors. They also estimate the factors used in the forecasting model using a subset of those predictors which have forecasting power for a specific series. The authors find that using fewer but informative predictors could result in significant improvements at all forecasting horizons over the traditional diffusion index forecasts. Allowing for non-linearity can also yield improvement in the forecasting accuracy.

In addition, alternative shrinkage methods have been proposed to improve the predictive ability of DFM, including high-dimensional Bayesian VAR (De Mol et al., 2008; Korobilis, 2008; and Bańbura et al., 2010), Bayesian model averaging (Koop and Potter, 2004), bagging (Inoue and Kilian, 2008), Lasso (Least Absolute Shrinkage and Selection Operator) (Bai and Ng, 2007; De Mol et al., 2008), and boosting (Bai and Ng, 2009). Stock and Watson (2012) empirically compare forecasts from various shrinkage methods to DFM forecasts using a large U.S. macroeconomic data set. The authors find that, in most cases, the DFM forecasts are superior to other shrinkage methods among linear estimators.

Although DFM has been widely discussed in the existing literature, most studies assume that the DFM parameters are stable. Particularly, there are no changes in the coefficients of the factors. However, many macroeconomic forecasting studies have provide broad evidence of time-varying coefficients of the factors. Some recent empirical DFM papers have explicitly allowed for structural breaks. Stock and Watson (2008) provide an empirical study and find considerable structural instability in the

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31 See, for example, Del Negro and Otrok (2008) and Korobilis (2009a).
factor loadings around the 1984 macroeconomic data of the U.S. Despite this structural break, the principal components provide stable estimates of the factors. Bates et al. (2013) find that the principal components estimator and derived DFM forecasts are robust to empirically relevant degrees of temporal instability in the factor loadings.

3.2.5 Factor Augmented VAR based forecasting

As we have discussed before, standard VAR only involves a few variables and this may lead to loss of some important economic information. Simply incorporating a lot of independent variables in a VAR to alleviate the omitted variable problem may present the risk of over-parameterization. Thus, combining factor methods, which extract common factors from a large data set, with VAR approach might be productive. Specifically, if a small number of factors are estimated effectively to represent information about the economy from a large data set, an effective solution to capture the useful information and solve the problem of over-parameterization in VAR analysis is to augment standard VAR with estimated common factors. This is thoroughly investigated in Bernanke et al. (2005).

Bernanke et al. (2005) exploit both a two-step estimation method which means that the common factors are first estimated by principal components before the estimation of the factor-augmented VAR and one-step methods that makes use of Bayesian methods to estimate the factors and the dynamics of VAR simultaneously. Banbura et al. (2010) construct a FAVAR as in Bernanke et al. (2005) to compare the forecasting results of different models. The authors also consider the Bayesian estimation of the FAVAR, given that the factors are estimated by principal components as in Stock and Watson (2002b). These researchers find that the FAVAR and BFAVAR are generally outperformed by the large-scale BVAR at different forecast horizons in
terms of RMSE. Gupta et al. (2011) also exploit two methods for extracting information from a large data set: (1) extracting common factors in a FAVAR or BFAVAR, and (2) Bayesian shrinkage in a large-scale BVAR. After comparing different forecasting models including the DSGE model and classical VAR and BVAR, the authors claim that the small-scale BVAR has better predictive ability than the other models, including the large-scale BVAR in terms of forecasting the U.S. real housing price.

3.2.6 Housing price forecasting

Forecasting housing price inflation is motivated by some studies in which show that asset prices prove to be helpful in predicting both output and inflation (Forni et al., 2003; Stock and Watson, 2003). Gupta and Das (2008) claim that forecasts of housing price inflation can provide some hints about the trend of CPI inflation and thus are very helpful for policy makers.

Rapach and Strauss (2007, 2009) find that an autoregressive distributed lag (ARDL) model tends to produce better forecast of real housing price inflation than a benchmark AR model. Das et al. (2010) investigate the forecasts of housing price inflation in South Africa using a dynamic factor model and a VAR model including classical and Bayesian specifications. The results indicate that DFM statistically outperforms the VAR model in terms of RMSE for the forecast horizons from one to four quarters. Gupta et al. (2011) also exploit a structural DSGE model and various non-structural time-series models to predict the U.S. real housing price index. The authors find that small-scale BVAR model outperforms other models, including the large-scale BVAR and DSGE models. Balcilar et al. (2012) study the out-of-sample forecasts of the linear and non-linear models of the U.S. regional housing prices. The
authors find that, in terms of point forecast, the non-linear smooth-transition autoregressive model outperforms the linear autoregressive model at longer forecast horizons. The linear autoregressive model, however, dominates the non-linear smooth-transition autoregressive model at short forecasting horizons. The authors do not find major differences for the interval and density forecasts between the linear and non-linear models. Bork and Moller (2012) examine U.S. housing price predictability using a DFM with a large panel of 122 variables. The authors find that a DFM including three factors contains significant out-of-sample forecasting power compared to other models.

3.2.7 Conclusion

Over the last two decades, there has been growing interest among researchers in developing new tools for macroeconomic forecasting. However, given the complexity of the economic system, there is no consensus on which model is the best for out-of-sample forecasting. After all, all forecasting models, no matter how sophisticated they are, provide stylized and simplified ways to capture the complex and rich relationships among macroeconomic variables. In particular, for small open economies, such as Hong Kong, which have more interaction with the international market, the matter gets more complicated. Against such a backdrop, work is expected not only as an investigation to shed light on the type of model that is able to produce better forecasts for a small open economy, but also to check for the validity of various models about housing price forecasting.
3.3 Macroeconomic forecasting models

In this section, we perform the out-of-sample forecasting experiments for different forecasting models. Given a large macroeconomic data set, we focus only on forecasting five key variables: GDP, consumption, employment, housing price inflation, and CPI-based inflation. First, the DSGE model constructed in Chapter 2 is used in forecasting here, and we provide a short description of this small open-economy DSGE model. Second, we describe the Bayesian method used in forecasting. Then, the dynamic factor model and the associated forecasting methods are discussed. Finally, we describe of the FAVAR-based forecasting approach.

3.3.1 DSGE model for small open economy-based forecasting

3.3.1.1 DSGE model specification

In Chapter 2, we show that a modern micro-founded small open-economy DSGE model with the housing sector is able to replicate most properties of the main macroeconomic variables at the business cycle frequencies fairly well. Moreover, a system of optimality and equilibrium conditions can be used to estimate the model using the Bayesian method. Thus, given the sound micro-foundation and theoretically consistent structure, DSGE model could be further used as an important tool for macroeconomic forecasting. We adopt the DSGE model developed in Chapter 2 to investigate how this model performs compared with alternative non-structural models in forecasting macroeconomic variables.

The model assumes that the entire world economy is an infinite continuum of small open economies represented by the unit interval (Gali and Monacelli, 2005). Since each economy is of measure zero, the decisions by domestic agents do not have any influence on the international market. Each economy is assumed to share identical
preference, technology, and market structure. In the small open economy model, there are two types of households with heterogeneous discount factors and two production sectors with two-stage production processes. As in Iacoviello and Neri (2010), our model captures two main features of the houses.

On the supply side, there are two production sectors, namely, the consumption goods sector and the housing sector. Firms in the two sectors produce consumption goods and houses, respectively. The production process consists of two stages. The output of wholesale firms that act in a monopolistic competitive market is used as input by retail firms. Retail firms sell the final goods both in domestic and foreign markets. Both sectors only use labor as inputs of production.

On the demand side, there are two types of households, patient (lenders) and impatient (borrowers) households, with heterogeneous discount factors. Impatient households are subject to credit constraints tied to housing values. Both types of households work, consume, and accumulate houses. Since impatient households feature a relatively lower discount rate than patient households, there exist credit flows between these two agents. In detail, patient households lend bonds to impatient households and also invest in foreign bonds in the international capital market. Since houses can be used as collateral for loans, impatient households only accumulate the required net worth to finance the down payment in the houses and face the binding collateral constraint in equilibrium.

To capture the features of the monetary policy for a small open economy like Hong Kong, we adopt the currency board system. The system is the adopted monetary policy regime in Hong Kong.
In this model, we have a system of shocks that includes the household-specific housing preference shock, sector-specific technology shock, loan-to-value shock, sector-specific cost-push shock, sector-specific foreign demand shock, terms of trade shock, and foreign interest rate shock. These shocks are modelled as autoregressive processes of order one and are assumed to be orthogonal to each other.

In order to introduce news shocks into the model, we assume that, except for $\hat{y}_t$, the error term of each shock $\epsilon_{x,t}$ process is made up of an unanticipated component $\epsilon_{x,t}^0$ and an anticipated component $\epsilon_{x,t-n}^n$ with $n = \{4\}$. The general structure for each shock is given by $\epsilon_{x,t} = \epsilon_{x,t}^0 + \epsilon_{x,t-n}^n$. $\epsilon_{x,t-n}$ denotes the news received $n$ periods in advance, $\epsilon_{x,t}$ is i.i.d., and $x$ represents the different types of shocks. Both components are normal i.i.d. with the mean of zero and uncorrelated across time and horizons. Following Schmitt-Grohe and Uribe (2012), we assume that if the expectation does not realize, then $\epsilon_{x,t}^0 = -\epsilon_{x,t-n}^n$ and $\epsilon_{x,t} = 0$.

### 3.3.1.2 Model estimation and forecasting

As in Smets and Wouters (2007), the model is estimated with Bayesian method using six key macroeconomic variables of Hong Kong: real GDP per capita, real consumption per capita, employment, short-run interest rate, CPI-based inflation, and nominal housing price inflation. Before estimation, all data are seasonally adjusted and transformed to be stationary and demeaned.

Let $\theta$ represent the vector which contains the parameters in the model. We need first to set a prior distribution denoted as $p(\theta)$. Combining the conditional density of the data $Y_{1:T}$ given the parameters $\theta$, the prior can be represented as $p(Y_{1:T}|\theta)$. We can
derive this density function implied by the model. Thus, the posterior distribution is derived as

\[
(3.1) \quad p(\theta | Y_{1:T}) = \frac{p(Y_{1:T} | \theta)}{p(Y_{1:T})}, \quad p(Y_{1:T}) = \int p(Y_{1:T} | \theta) p(\theta) d\theta
\]

where \(p(Y_{1:T})\) represents the marginal likelihood or data density. In order to solve the DSGE model, we use the numerical methods such as MCMC simulation to implement the inference of the posterior distribution. Serially correlated sequences \(\{\theta^{(j)}\}_{j=1}^n\) of \(n\) draws from the density \(p(\theta | Y_{1:T})\) are generated by the MCMC algorithms.

In forecasting exercises, we focus on the predictive distributions, which can be shown as:

\[
(3.2) \quad p(Y_{T+1:T+H} | Y_{1:T}) = \int p(Y_{T+1:T+H} | \theta, Y_{1:T}) p(\theta | Y_{1:T}) d\theta
\]

This decomposition states that we could simulate the DSGE model and then get the draw from the predictive distribution.

We need to first solve the DSGE model using a numerical method prior to the estimation process. The associated law of motion in equilibrium can be written as:

\[
(3.3) \quad s_t = \Phi(s_{t-1}, \epsilon_t; \theta)
\]

where \(s_t\) is a vector stacking the state variables and \(\epsilon_t\) is a vector of the innovations for the structural shocks. Our model can be solved by log-linearization methods:

\[
(3.4) \quad s_t = \Phi_1(\theta)s_{t-1} + \Phi_\epsilon(\theta)\epsilon_t
\]

The system matrices \(\Phi_1\) and \(\Phi_\epsilon\) are functions of the parameters \(\theta\), and \(s_t\) represents the vector of the state variables. And a simple measurement equation can be represented as:

\[
(3.5) \quad y_t = \Psi_0(\theta) + \Psi_1(\theta)t + \Phi_2(\theta)s_t
\]
Equations (3.4) and (3.5) represent the state-space of the linearized DSGE model, which lays the foundation for the forecasting analysis. If the innovation term $e_t$ are Gaussian, then we can evaluate the likelihood function $p(\theta|Y_{1:T})$ using Kalman filter. Therefore, we could estimate the predictive distribution of $Y_{T+1:T+H}$ given $Y_{1:T}$. Then, we could get a point forecast $\hat{y}_{T+h}$ of $y_{T+h}$ and the optimal forecasts is the posterior mean:

\[(3.6) \quad \hat{y}_{T+h|T} = \frac{1}{n} \sum_{j=1}^{n} y^{(j)}_{T+h}\]

which can be estimated by a Monte Carlo simulation.

### 3.3.2 BVAR specification and forecasting

#### 3.3.2.1 Introduction and Notation

Following Sims (1980), the VAR model can be denoted as follows:

\[(3.7) \quad Y_t = c + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t\]

where $Y_t = (y_{1,t} \ y_{2,t} \ldots \ y_{n,t})'$ is a large vector that stacks the random variables, $u_t$ follows a Gaussian white noise of $n$-dimensional with covariance matrix $E u_t u_t' = \Psi$, $A_1, \ldots, A_p$ represent the $n \times n$ autoregressive matrices, and $c = (c_1, \ldots, c_n)'$ is a vector of $n$-dimensional that stacks the constants.

We define write the VAR in matrix form in the way that $Y$ is defined to be a $T \times N$ matrix stacking the $T$ observations on each dependent variable. $u$ and $U$ denote the stacking of the errors corresponding to $y$ and $Y$, respectively. Define $x_t = (1, y'_t, \ldots, y'_{t-p})'$ and

\[(3.8) \quad X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{bmatrix}.\]
Note that, in each equation of the VAR, there are $K = 1 + Np$ coefficients, and then $X$ is a $T \times K$ matrix. If $A = (c A_1 \ldots A_p)'$, we define $\alpha = vec(A)$ which is a $KN \times 1$ vector stacking all the coefficients and the intercepts in the VAR. With all these definitions, the VAR can be written as either:

(3.9) \[ Y = XA + U \]

or

(3.10) \[ y = (I_M \otimes X)\alpha + u, \]

where $u \sim N(0, \Sigma \otimes I_T)$.

From the sampling density $p(y|\alpha, \Sigma)$ we can derive the likelihood function. Thus, we could view the likelihood function as a function of the parameters, which consists of two components: one distribution for $\alpha$ given $\Sigma$ and another in which $\Sigma$ has a normal inverted Wishart distribution. That is,

(3.11) \[ \alpha | \Sigma, y \sim N(\hat{\alpha}, \Sigma \otimes (X'X)^{-1}) \]

and

(3.12) \[ \Sigma | y \sim iW(S, T - K), \]

where $\hat{A} = (X'X)^{-1}X'Y$ estimated by OLS and $\hat{\alpha} = vec(\hat{A})$ and $S = (Y - X\hat{A})'(Y - X\hat{A})$.

### 3.3.2.2 Priors

As discussed in section 3.2, the VAR often confronts with the issue of over-parameterization, which lead to the problem of multicollinearity and loss of degree of freedom, and the VAR-based out-of-sample forecasts tend to be imprecisely estimated. Thus, an approach to solve the problem of over-parameterization, which is the BVAR proposed by Litterman (1981, 1986) and Doan et al. (1984), is to estimate the model
by imposing prior information on the parameters. The prior distributions is set according to the standard practice by Litterman (1986a) and modified by Kadiyala and Karlsson (1997) and Sims and Zha (1998).

The prior of Litterman (1986a) is widely known as the Minnesota prior. The Minnesota prior has gained a great popularity in the field of macroeconomic forecasting. The basic idea is that all the equations in the model are approximated by the random walk process with a drift; i.e., \( Y_t \) can be represented as:

\[
Y_t = c + Y_{t-1} + u_t
\]

This means that the diagonal elements of \( A_1 \) are shrunk toward one and the other coefficients in \( A_1, ..., A_p \) are shrunk toward zero. Instead of eliminating longer lags, the belief incorporated by the priors is that the information contained in the lags become less reliable as the lag length grows and that the own lags represent more reliable of a given variable than the lags of other variables in the model. However, the prior beliefs can be overridden by the data if there is some contradictory information contained in the data set.

The prior distribution can be represented by the following moments of the coefficients:

\[
E[(A_k)_{i,j}] = \begin{cases} 
\delta_{ij}, & i = j, k = 1 \\
o, & otherwise
\end{cases}
\]

\[
\text{Var}[(A_k)_{i,j}] = \begin{cases} 
\frac{\lambda^2}{k^2}, & i = j \\
\frac{\lambda^2 \sigma_i^2}{k^2 \sigma_j^2}, & otherwise
\end{cases}
\]

The coefficients \( A_1, ..., A_p \) are assumed to follow an i.i.d. process. The covariance matrix of the residuals is represented as: \( \Psi = \Sigma \), where \( \Sigma = \text{diag}(\sigma_1^2, ..., \sigma_n^2) \). Finally, the intercept is assumed to be diffuse.
Originally some scholars set $\delta_i = 1$ for all $i$, representing that all of the variables are highly persistent. For the variables which are not very persistent, we set the prior as white noise $\delta_i = 0$.

The overall tightness of the prior distribution is controlled by the hyperparameter $\lambda$, which also represents the relative importance of the prior distribution compared with the information from the data. If $\lambda = 0$, the posterior distribution is identical with the priors and the data does not have any impact on the estimates. If $\lambda = \infty$, however, posterior distribution coincide with the estimates from OLS. Following Banbura et al. (2010), we set the hyperparameter $\lambda$ in accordance with the model size. As the size of the model grows, the parameters are supposed to shrink more in order to avoid over-fitting. This method has been deeply investigated by De Mol et al. (2008). According to De Mol et al. (2008), the factor $1/k^2$ represents decreasing rate of the prior variance as lag length increases, and $\sigma_i^2 / \sigma_j^2$ stands for the different scale and variability of the data set. The coefficient $\vartheta \in (0,1)$ represents the relative importance of the own lags compared with the lags of other variables.

Many different types of the Minnesota prior have been used in some applications, as scholars slightly modify the prior in their particular study. In our forecasting analysis, the possible correlation among the error term of different variables are considered. Consequently, we follow Banbura et al. (2010) and set a prior of normal inverted Wishart distribution. We implement the prior in equation (3.09) and (3.10) by allowing for dummy observations. In this way, adding $T_d$ dummy observations $Y_d$ and $X_d$ to equation (3.9) amounts to setting the normal inverted Wishart prior with $\hat{A} = (X_d'X_d)^{-1}X_d'Y_d$ and $S = (Y_d - X_d\hat{A})'(Y_d - X_d\hat{A})$.
As Banbura et al. (2010), equation (3.9) is augmented with the dummy observations as:

\[
Y_* = X_* A + U_*
\]

where \(T_* = T + T_d\), \(Y_* = (Y', Y_d')'\), \(X_* = (X', X_d')\), and \(U_* = (U', U_d')'\). Then, the posterior can be written as:

\[
\alpha | \sum_y \sim N(\hat{\alpha}, \sum_y \otimes (X_*'X_*)^{-1})
\]

and

\[
\sum_y | \sim iW(\hat{\sum}, T_d + 2 + T - K),
\]

with \(\hat{\alpha} = (X_*'X_*)^{-1}X_d'Y_d\) and \(\hat{\sum} = (Y_* - X_*\hat{A})'(Y_* - X_*\hat{A})\). It can be shown that the posterior distribution of the coefficients is similar to the OLS estimates of regressing \(Y_*\) on \(X_*\). From the view of computation, estimation is feasible for a large data set, because it only requires the inversion of a square matrix with the dimension of \(K = 1 + Np\).

### 3.3.2.3 Forecasting using BVAR

We compare models of different sizes, one for the nine key variables, which are housing price inflation, GDP, consumption, employment, CPI-based inflation, real wages, domestic fixed capital formation, Hang Seng index and terms of trade, and the other one for all the variables in the dataset. Thus, we need to figure out a method to choose the hyperparameter of shrinkage as the model size grows. Consequently, the tightness of the prior is set to make the in-sample fit of all models same as the classical VAR, including five predictors estimated by OLS. Given the constant in-sample fit, the forecasting results generated by alternative models can be compared meaningfully.
With the help of the posterior mean of the parameters, the point forecasts can be computed. Following Banbura et al. (2010), the hyperparameter $\lambda$ is chosen as:

\[
\lambda_m(Fit) = \arg\min_\lambda \left| \text{Fit} - \frac{1}{5} \sum_{i \in I} \frac{msfe_i^{(\lambda,m)}}{msfe_i^0} \right|
\]

where

$I \in \{\text{housing price inflation, GDP, consumption, employment and inflation}\}$

and $msfe_i^{(\lambda,m)}$ represents the in-sample one-step-ahead mean squared forecast error evaluated with the evaluation sample $t = 1, ..., T_o - 1$.\(^{32}\) More precisely:

\[
msfe_i^{(\lambda,m)} = \frac{1}{T_0 - p - 1} \sum_{t = p}^{T_0 - 2} (y_i^{(\lambda,m)}(t) - y_i(t+1))^2
\]

where the sample $t = 1, ..., T_o - 1$ is used to compute the parameter values. We set the baseline fit equal to the one obtained by OLS with order of $p=1$; i.e., for

\[
\text{Fit} = \frac{1}{5} \sum_{i \in I} \frac{msfe_i^{(\lambda,m)}}{msfe_i^0} \bigg|_{\lambda=\infty,m=small}
\]

Finally, as long as the prior beliefs have been specified, the alternative BVAR models, whether based on the only five key variables of interest or all of the 86 variables, can be estimated consistently, and forecasts are computed accordingly.

3.3.3 DFM forecasting

3.3.3.1 Introduction

Following Stock and Watson (2002a, 2002b), different types of factor models have been developed to conduct forecasting exercise. Although different methods associated with the estimation of the dynamics of the underlying factors have been proposed, it still does not reach consensus on which factor specification has the best

\(^{32}\) Following Banbura et al. (2010), the search is performed over a grid for $\lambda$ to obtain the desired magnitude of fit. Division by $msfe_i^0$ represents the differences in scale between the series.
forecasting performance. Forni et al. (2003) find favorable evidence supporting the
dynamic rather than the static factor models, but Boivin and Ng (2005) show little
difference across the different model specifications. Agostino and Giannone (2012)
compare the forecasting performance of the DFM of Stock and Watson (2002a) and
Forni et al. (2005) using U.S. data. The authors conclude that, the two methods show
similar predictive ability and generate highly collinear forecasts. Given the widespread
application in macroeconomic forecasting, we use the DFM of Stock and Watson
(2002a, 2002b) in our forecasting experiment.

3.3.3.2 Model specification

Consider a \( n \times 1 \) vector of \( X_t = (x_{1t}, ..., x_{nt})' \). The premise of a DFM is that a
small number of common factors \( f_t \) drive the dynamics of a large cross-section of time
series variables \( X_t \). The co-movements of the large panel is also affected by a vector
which stacks the idiosyncratic disturbances \( e_t \) with zero mean. These idiosyncratic
disturbances can be viewed as the measurement error and series-specific features. The
latent factors is usually written as a VAR form. Thus, the dynamic factor model is
represented as

\[
\begin{align*}
X_t &= \lambda(L)f_t + e_t \\
f_t &= \Psi(L)f_{t-1} + \eta_t
\end{align*}
\]

where \( X_t \) and \( e_t \) are \( n \times 1 \), the number of dynamic factors is \( q \) so \( f_t \) and \( \eta_t \) are \( q \times 1 \),
\( L \) is the lag operator. All the processes in equation (3.20) and (3.21) are assumed to be
stationary. We also assume that \( Ee_t\eta_{t-k} = 0 \) for all \( k \). In the DFM, we assume that the
idiosyncratic disturbances are mutually uncorrelated at all leads and lags; that is,
\( Ee_{it}e_{js} = 0 \) for all \( s \) if \( i \neq j \).
Following Stock and Watson (2010), we rewrite equations (3.23) and (3.24) as:

(3.22) \[ X_t = \Lambda F_t \]

(3.23) \[ \Phi(L) F_t = G \eta_t \]

where \( F_t = (f_t, f_{t-1}, \ldots, f_{t-p})' \) denotes an \( r \times 1 \) vector, where \( r < (p + 1)q \), \( \Lambda = (\lambda_0, \lambda_1, \ldots, \lambda_p) \) and \( \lambda_i \) are the \( n \times q \) matrix of coefficients on the \( i^{th} \) lag in \( \lambda(L) \). Thus the \( i^{th} \) row of \( \Lambda \) in equation (3.23) is \( (\lambda_{i0}, \ldots, \lambda_{iq}) \). Similarly, \( \Phi(L) \) denote the matrix consisting of 1s, 0s, and the elements of \( \Psi(L) \) such that the VAR in equation (3.22) is rewritten in terms of \( F_t \). \( G \) is a matrix of 1s and 0s so that equation (3.24) and (3.22) are equivalent. As stated by Stock and Watson (2002a), given the static representation of the DFM the factor can be estimated using principal components.\(^{33}\)

Our target is to predict some variables at time \( t+h \), with all the variables \((x_{1t}, \ldots, x_{nt})'\) as predictors. The forecasting model can be represented as the following linear projection:

(3.24) \[ y_{t,t+h|t} = \text{proj}\{y_{t,t+h} | \Omega_t\} \]

where \( \Omega_t = \text{span}\{X_{t-p}, p = 0,1, \ldots\} \) is potentially a large data set at time \( t \), and \( y_{t+h} = x_{1t+h} = \beta_h(L) x_{i,t+h} \) is a filtered version of \( x_{it} \) for \( i = 1, \ldots, n \).

Traditional VAR approximates the linear projection using only a limited lags of order, \( p \), of \( X_t \). Particularly, some studies consider the linear regression model as following:

(3.25) \[ y_{t+h} = X_t' \beta_0 + \cdots + X_{t-p} \beta_p + u_{t+h} = Z_t' \beta + u_{t+h} \]

\(^{33}\) See Stock and Watson (2002a, 2002b) for details.
where $\beta = (\beta_0', \ldots, \beta_p')'$ and $Z_t = (X_{t}', ..., X_{t-p}')'$. The implied forecast is given by $y_{t+h|t} = X_t'\hat{\beta}$, and the implied forecast error is $u_{t+h} = y_{t+h} - y_{t+h|t}$. The forecast error is assumed to be orthogonal to $x_{i,t-s}$ for $s = 0, 1, \ldots, p$ and $i = 1, \ldots, n$. We will denote $Z = (Z_{p+1}', ..., Z_{t-h}')'$ as the $(T - h - p) \times n(p + 1)$ matrix of observations on the independent variables and denote $y = (y_{p+1+h}', ..., y_T)'$ as the $(T - h - p) \times 1$ matrix of the observations on the dependent variable. In this way, the model can be estimated using OLS, and thus $\hat{\beta}_{OLS} = (Z'Z)^{-1}Z'y$, and the forecast is given by $\hat{y}_{T+h|T} = Z'_T\hat{\beta}_{OLS}$. Given a large information set, the number of parameters which need to be estimated is very large, which may result in the problem of over-parameterization and a loss of degrees of freedom. Besides, if the number of regressors is too large to exceeds the sample size, $n(p + 1) > T$, OLS estimation is not feasible.

In order to solve this problem, DFM has been proposed in some studies claiming that the forecasts can be computed as a projection on the first few principal components using (Stock and Watson, 2002a, 2002b; Forni et al., 2005). The main advantage of DFM is that, if the factors $f_t$ can be consistently estimated and if $(e_t, \eta_t)$ are Gaussian, an individual variable then can be forecasted by regressing that variable on the lagged factors. Thus, the researcher gets the benefit of incorporating information from a large number of variables with only a small number of factors.

The sample covariance matrix of the regressors can be spectral decomposed as following:

(3.26) $S_Z V = V D$

where the diagonal matrix $D = diag(d_1, \ldots, d_{n(p+1)})$ has the eigenvalues of $S_Z = \frac{1}{T-h-p}Z'Z$ on the diagonal in decreasing order of magnitude, and $V = (v_1, \ldots, v_{n(p+1)})$
is the \( n(p + 1) \times n(p + 1) \) matrix whose columns are the corresponding normalized eigenvectors. We define the normalized principal components as:

\[
(3.27) \quad \hat{f}_{it} = \frac{1}{\sqrt{a_i}} v_i' Z_t
\]

for \( i = 1, \ldots, N \) where \( N \) represents the number of non-zero eigenvalues.

If most dynamic relationships among the variables in the large panel are driven by a few underlying factors, the information contained in the large data set can be represented by a few common factors, Therefore, principal components can be viewed as a good representation of the underlying factors. And the corresponding forecast is defined as:

\[
(3.28) \quad y_{t+h|t} = \text{proj}\{y_{t+h} | \Omega_t^f\} = \text{proj}\{y_{t+h} | \Omega_t\}
\]

where \( \Omega_t^f = \text{span}\{\hat{f}_{1t}, \ldots, \hat{f}_{rt}\} \), with \( r < n(p + 1) \), represents the information contained in the data set. Thus, equation (3.32) shows that common factors could be estimated using principal components, thus the forecasting projection could be estimated using OLS with the estimated common factors as observables.

3.3.4 Factor Augmented VAR

DFM has been widely used as an effective tool in macroeconomic forecasting given a large data set. In our study, we want to conduct an exercise of forecasting comparison between factor models and the standard VAR, in which the model is simultaneously estimated as a system rather than as a set of single equations. Therefore, we augment a small VAR with common factors estimated by principal components method from a large data set. This is the FAVAR, which has been well-developed in the literature such as Bernanke et al. (2005) and Stock and Watson (2005b).
Let $Y_t$ be an $m \times 1$ observable macroeconomic variable and a subset of $X_t$. It is assumed that the large information set can be summarized by the unobserved factors $F_t$ and observable macroeconomic variable $Y_t$. The FAVAR extends the state equations (3.20) and (3.21) about the factors by allowing $Y_t$ to have a VAR form as:

\[
(3.29) \begin{pmatrix} F_t \\ Y_t \end{pmatrix} = B(L) \begin{pmatrix} F_{t-1} \\ Y_{t-1} \end{pmatrix} + \varepsilon_t^f
\]

where $B(L)$ represents the lag polynomial of finite order $p$, and $\varepsilon_t^f$ is i.i.d. $N(0, \Sigma^{f})$. Since $F_t$ is a vector of unobservable factors, equation (3.29) can only be estimated after $F_t$ is derived. We apply the two-step estimation procedure as Banbura et al. (2010).

First, principal components are estimated from a large data set. Variables are transformed to be stationary first. Following Stock and Watson (2002b), we first standardize the variables and then the factors are recursively estimated at each $T$ from the standardized variables. Second, the FAVAR in equation (3.29) which consists of $\hat{F}_t$ and $Y_t$, is estimated. Because Bayesian method is feasible for the estimation of equation (3.29), we also consider estimate the FAVAR using Bayesian method, choosing the shrinkage hyperparameter $\lambda$ that generates the same in-sample fit and using the Bayesian information criteria (BIC) criterion to set $p$. 

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3.4 Data and estimation

This section documents the sample data used in the different forecasting models and the experiment design of our out-of-sample forecasting analysis. We take Hong Kong as the representative of a small open economy. Hong Kong is known to depend massively on one sector, namely the export of financial services abroad. And the manufacturing production has been relocating to the Mainland China (Li et al. 2009). In fact, its financial system accounts for a large proportion of employment and GDP (Garcia-Herrero, 2011). Given the importance of the financial system in Hong Kong, it is reasonable to believe that the information contained in the financial variables is significant for predicting the key macroeconomic variables in Hong Kong. Thus, we incorporate more financial variables and less production variables in our large data set.

3.4.1 Data transformation

The DSGE model includes data on only the six variables as in Chapter 2, namely real output, real consumption, employment, gross CPI-based inflation, gross housing price inflation, and nominal interest rate. The large BVAR and DFM include 86 quarterly data series of Hong Kong, covering the real, nominal, and financial sectors. Since Hong Kong adopts the currency board system in which the Hong Kong dollar is effectively pegged to the U.S. dollar at a fixed rate and the Hong Kong economy is highly influenced by Mainland China, the data set also includes some series of U.S. and China. Our data set is not identical to that of Pang (2010), but it is similar in the sense that the selection and treatment of the data closely follow the data description in Pang (2010) and the same series are used where applicable. All data are obtained from the websites of the Census and Statistics Department of Hong Kong, the Rating and Valuation Department of Hong Kong, Hong Kong Monetary Authority, Federal
Reserve Bank of St. Louis, and Bloomberg. As in Stock and Watson (2002b) all series are seasonally adjusted and transformed to stationary (by differencing or log differencing) as described in the Appendix D. For factor models, all time series are further standardized with a zero mean and a unit variance. Besides, the transformed data are automatically screened for outliers (due to measurement errors or exceptional events such as political changes), and observations exceeding 10 times the interquartile range from the median are replaced by missing values. After the data treatment, the underlying common factors are estimated by the principal component method, as discussed in section 3.3. We use BIC to select the appropriate lag length so that stochastic error term doesn’t contain serial correlation. For the factor models, there are various statistical approaches in determining the number of factors. We use the information criteria developed by Bai and Ng (2002) to select the appropriate number of factors that can represent the principal components. The idea of this information criteria is that the benefit of including one more additional factor should be traded off against the cost of increased sampling variability resulting from estimating another parameter. The information criteria is satisfied by minimizing a penalized likelihood or log sum of squares, where the penalty factor linearly increases in the number of factors (or parameters). As proposed by Bai and Ng (2002), the penalized sum of squares is minimized according to the following,

\[ IC(r) = ln V_r(\hat{\Lambda}, \hat{F}) + rg(N,T) \]

where \( r \) represents the number of static factors, \( V_r(\hat{\Lambda}, \hat{F}) \) is the least square objective function:

\[ V_r(\hat{\Lambda}, \hat{F}) = \frac{1}{NT} \sum_{t=1}^{T}(X_t - \Lambda F_t)'(X_t - \Lambda F_t). \]
Given the estimated principal components estimators \((\hat{\Lambda}, \hat{F})\), and where \(g(N, T)\) is a penalty factor such that \(g(N, T) \to 0\) and \(\min(N, T) g(N, T) \to \infty\) as \(N, T \to \infty\). Bai and Ng (2002) show that, in the approximate DFM, the value of \(r, \hat{r}\), which minimizes an information criteria with \(g(N, T)\) is consistent for the true value of \(r\). The approach by Bai and Ng (2002) suggests four static factors in our data set.

### 3.4.2 Forecasting experimental design

We analyze forecasting models of different sizes. We consider totally seven forecasting models as follows:

1. **DSGE model.** As in Chapter 2, the six observables are seasonally adjusted, made to stationary, and demeaned, in order to match the log-linearized model variables.

2. **DFM contains total 86 variables.**

3. **Large-scale BVAR (LBVAR) contains total 86 variables.**

4. **The small-scale BVAR (SBVAR) contains 10 variables, namely output, consumption, employment, gross CPI-based inflation, gross housing price inflation, real wages, domestic fixed capital formation, U.S. interest rate, Hang Seng Index, and terms of trade.**

5. **FAVAR includes total 86 variables to extract the principal component and then combines the four common static factors with the five variables which we want to forecast, namely output, consumption, employment, housing price inflation, and CPI-based inflation, into a VAR to model the joint dynamics.**

6. **BFAVAR uses the same variables and factors as FAVAR but is estimated using Bayesian methods rather than OLS.**
(7) Classical VAR includes the five variables which we want to forecast and is estimated by the standard OLS.

When applying the Bayesian methods, we need to assign different priors to different series. For nonstationary variables, we set the prior of random walk; i.e., \( \delta_i = 1 \). For stationary variables, we use the prior of white noise; i.e., \( \delta_i = 0 \).

The data spans from 1993Q3 to 2014Q1. We carry out an out-of-sample forecasting exercise. We denote the forecasting horizon as long as \( H \), and denote \( T_0 \) and \( T_1 \) as the beginning and the end period in the evaluation sample, respectively. For \( h \)–period ahead forecasting, in each period \( T = T_0 + H - h, ..., T_1 - h \), we compute the \( h \)-step-ahead forecasts, \( Y_{T+h|T} \) using the information only up to period \( T \). For the out-of-sample forecasting experiments, we use recursive regressions with the forecasting evaluation period from 2006Q1 to 2014Q1. Forecasting horizons up to 8 quarters are considered. All models are fully re-estimated for each recursive estimation sample over the out-of-sample forecasting horizon until all sample observations are exhausted.

As the measurements of the forecasting performance of the models, we report the two most common criteria:

Mean Absolute Error (MAE): 

\[ MAE^h = \frac{\sum_{T=T_0}^{T_1} |Y_{T+h|T} - Y_{T+h}|}{T_1 - T_0 - h + 1} \]

Root Mean Squared Error (RMSE): 

\[ RMSE^h = \sqrt{\frac{\sum_{T=T_0}^{T_1} (Y_{T+h|T} - Y_{T+h})^2}{T_1 - T_0 - h + 1}} \]

The model that generates the lowest average value of the MAE and RMSE is chosen as the best forecasting model for a specific variable to be forecasted.
3.5 Evaluation of Forecasting Accuracy

To evaluate the predictive ability among difference models, we compare the forecasting performance using the same statistics, namely MAE and RMSE. This section reports our forecasting results of all the models. Then we exploit alternative models to conduct out-of-sample forecasting for five key macroeconomic variables across one to eight period-ahead.

Tables 3.1a through 3.5b report the results for all our forecasting exercises using the recursive method as mentioned above. Our empirical results suggest that there is no single model that predominates the other models. In fact, we find that some models do well in some cases, but not necessarily in others. Nonetheless, a few interesting stories arise.

3.5.1 Output forecasting

From Tables 3.1a and 3.1b, we observe that, for the forecasting horizon within 4 periods, there are not much differences between structural and non-structural models. To be more specific, in the short run, SBVAR improves over the other forecasting models beyond the first quarter. For the one-quarter-ahead forecasts, classical VAR estimated by OLS performs better than the other forecasting models, although SBVAR shows very similar results. However, we find that DFM results in the best forecast accuracy at longer horizons, and the advantage of DFM becomes larger as the forecasting horizon grows, especially for the 6- to 8-quarters-ahead forecasts.
### Table 3.1a Output forecasting (MAE)

<table>
<thead>
<tr>
<th></th>
<th>DSGE</th>
<th>DFM</th>
<th>FAVAR</th>
<th>BFAVAR</th>
<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 H</td>
<td>1.0187</td>
<td>1.3146</td>
<td>1.1769</td>
<td>0.9317</td>
<td>0.9422</td>
<td>1.1651</td>
<td>0.8760</td>
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<td>2 H</td>
<td>1.1097</td>
<td>1.2684</td>
<td>1.5212</td>
<td>1.0785</td>
<td>0.9340</td>
<td>1.3918</td>
<td>0.9821</td>
</tr>
<tr>
<td>3 H</td>
<td>1.1646</td>
<td>1.1323</td>
<td>1.6566</td>
<td>1.0837</td>
<td>0.9789</td>
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<td>0.9862</td>
</tr>
<tr>
<td>4 H</td>
<td>1.1872</td>
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<td>1.5699</td>
<td>1.0955</td>
<td>0.9722</td>
<td>1.6347</td>
<td>1.0150</td>
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<td>0.9890</td>
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<td>0.8869</td>
<td>1.6059</td>
<td>0.9555</td>
</tr>
<tr>
<td>7 H</td>
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<td>1.1631</td>
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<td>0.9302</td>
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<td>1.1881</td>
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<td>0.9115</td>
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<td>0.9151</td>
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### Table 3.1b Output forecasting (RMSE)

<table>
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<th>DFM</th>
<th>FAVAR</th>
<th>BFAVAR</th>
<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 H</td>
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<td>1.4201</td>
<td>2.0926</td>
<td>1.4558</td>
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<tr>
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<td>0.8067</td>
<td>1.8927</td>
<td>1.4902</td>
<td>1.4417</td>
<td>2.2984</td>
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</tr>
</tbody>
</table>

### 3.5.2 Consumption forecasting

Tables 3.2a and 3.2b show that, at short horizons, SBVAR performs best in terms of consumption forecasting. It also indicates that incorporating a large data set does not help at all. But as the forecasting horizon grows, the advantage of SBVAR becomes lesser and is shown to be comparable with classical VAR. On the other hand, the predictive ability of DFM tends to improve quickly relative to other models at longer forecasting horizons. When the forecasting horizon grows more than 1 year, DFM predominates all of the other models in the long run.
Table 3.2a  Consumption forecasting (MAE)

<table>
<thead>
<tr>
<th></th>
<th>DSGE</th>
<th>DFM</th>
<th>FAVAR</th>
<th>BFAVAR</th>
<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 H</td>
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<td>1.2058</td>
</tr>
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<td>4 H</td>
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<td>1.0703</td>
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<td>1.0497</td>
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<td>0.8385</td>
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Table 3.2b  Consumption forecasting (RMSE)

<table>
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<th>DFM</th>
<th>FAVAR</th>
<th>BFAVAR</th>
<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
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<td>1 H</td>
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<td>1.5556</td>
<td>2.1823</td>
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<tr>
<td>2 H</td>
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<td>2.7484</td>
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<td>2.5841</td>
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<tr>
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<tr>
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<tr>
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<td>1.5580</td>
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<tr>
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<tr>
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<td>1.4672</td>
<td>3.9557</td>
<td>1.4257</td>
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</table>

3.5.3 Employment forecasting

Tables 3.3a and 3.3b show that non-structural models are able to forecast significantly better than the structural DSGE model. For non-structural models, although no significant differences are found among alternative VAR models, SBVAR outperforms other models in the short run, but loses its advantage as the forecasting horizon grows. Moreover, DFM, overall, has the best forecasting performance beyond the 1-year-ahead horizon, and its advantage becomes greater as the forecasting horizon grows.
### Table 3.3a Employment forecasting (MAE)

<table>
<thead>
<tr>
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<th>DSGE</th>
<th>DFM</th>
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<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 H</td>
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<td>0.2394</td>
<td>0.2675</td>
<td>0.1661</td>
<td>0.1382</td>
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</tr>
<tr>
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<td>0.3845</td>
<td>0.2073</td>
<td>0.3259</td>
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<tr>
<td>3 H</td>
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<td>0.1536</td>
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<tr>
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<td>0.1265</td>
</tr>
<tr>
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</table>

### Table 3.3b Employment forecasting (RMSE)

<table>
<thead>
<tr>
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<th>DSGE</th>
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<th>FAVAR</th>
<th>BFAVAR</th>
<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
<tr>
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### 3.5.4 Housing price inflation forecasting

Unlike the previous discussion, Tables 3.4a and 3.4b tell a different story about forecasting housing price inflation. Classical VAR outperforms other models only at the first-quarter horizon. As the forecasting horizon grows over two periods ahead, DFM dominates the other models and its advantage becomes more obvious even in the long run. It is also worth noting that the structural small open-economy DSGE including the housing sector is not able to generate significant forecasts for housing price inflation at all. This result is consistent with Gupta et al. (2011), which shows that the DSGE model with the housing sector is outperformed by non-structural models in terms of foresting the U.S. real housing price.
Table 3.4a  Housing price inflation forecasting (MAE)

<table>
<thead>
<tr>
<th></th>
<th>DSGE</th>
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<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
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<td>6 H</td>
<td>3.6359</td>
<td>1.0550</td>
<td>3.2723</td>
<td>2.6403</td>
<td>2.6800</td>
<td>5.7471</td>
<td>2.6477</td>
</tr>
<tr>
<td>7 H</td>
<td>3.7455</td>
<td>0.8516</td>
<td>3.3495</td>
<td>2.7840</td>
<td>2.6812</td>
<td>4.8830</td>
<td>2.6542</td>
</tr>
<tr>
<td>8 H</td>
<td>3.7767</td>
<td>0.7965</td>
<td>3.7674</td>
<td>2.6987</td>
<td>2.7031</td>
<td>4.6589</td>
<td>2.6510</td>
</tr>
</tbody>
</table>

Table 3.4b  Housing price inflation forecasting (RMSE)

<table>
<thead>
<tr>
<th></th>
<th>DSGE</th>
<th>DFM</th>
<th>FAVAR</th>
<th>BFAVAR</th>
<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 H</td>
<td>4.9213</td>
<td>4.4726</td>
<td>6.1723</td>
<td>4.8376</td>
<td>3.9230</td>
<td>5.4478</td>
<td>3.9368</td>
</tr>
<tr>
<td>3 H</td>
<td>4.3538</td>
<td>2.5716</td>
<td>6.8892</td>
<td>4.3768</td>
<td>3.9542</td>
<td>8.8514</td>
<td>3.8097</td>
</tr>
<tr>
<td>5 H</td>
<td>4.4977</td>
<td>1.8366</td>
<td>5.2310</td>
<td>4.1251</td>
<td>3.9311</td>
<td>10.083</td>
<td>3.9430</td>
</tr>
<tr>
<td>6 H</td>
<td>4.5178</td>
<td>1.3481</td>
<td>4.9183</td>
<td>3.9413</td>
<td>3.9335</td>
<td>8.5317</td>
<td>3.9498</td>
</tr>
<tr>
<td>7 H</td>
<td>4.5905</td>
<td>1.0789</td>
<td>4.9647</td>
<td>4.0158</td>
<td>3.9807</td>
<td>7.8386</td>
<td>3.9636</td>
</tr>
<tr>
<td>8 H</td>
<td>4.6357</td>
<td>1.0175</td>
<td>5.4092</td>
<td>3.9607</td>
<td>3.9944</td>
<td>7.2658</td>
<td>3.9668</td>
</tr>
</tbody>
</table>

3.5.5  CPI-based inflation forecasting

From Tables 3.5a and 3.5b we find that SBVAR performs better than other models in terms of forecasting CPI-based inflation in the short run. It is just slightly better than classical VAR and can only keep its advantage at no more than the two-period horizon. As the forecasting horizon grows over three periods ahead, DFM outperforms other models, and its advantage becomes more significant at longer horizons.
Table 3.5a  CPI-based inflation forecasting (MAE)

<table>
<thead>
<tr>
<th></th>
<th>DSGE</th>
<th>DFM</th>
<th>FAVAR</th>
<th>BFAVAR</th>
<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 H</td>
<td>0.7087</td>
<td>0.2527</td>
<td>0.2110</td>
<td>0.1860</td>
<td>0.1745</td>
<td>0.3182</td>
<td>0.1918</td>
</tr>
<tr>
<td>2 H</td>
<td>0.5694</td>
<td>0.1914</td>
<td>0.2625</td>
<td>0.2002</td>
<td>0.1888</td>
<td>0.3567</td>
<td>0.2065</td>
</tr>
<tr>
<td>3 H</td>
<td>0.5928</td>
<td>0.1668</td>
<td>0.2808</td>
<td>0.2404</td>
<td>0.2105</td>
<td>0.3525</td>
<td>0.2173</td>
</tr>
<tr>
<td>4 H</td>
<td>0.5824</td>
<td>0.1082</td>
<td>0.2735</td>
<td>0.2363</td>
<td>0.2229</td>
<td>0.3606</td>
<td>0.2210</td>
</tr>
<tr>
<td>5 H</td>
<td>0.5702</td>
<td>0.0795</td>
<td>0.2330</td>
<td>0.2052</td>
<td>0.2104</td>
<td>0.3455</td>
<td>0.2114</td>
</tr>
<tr>
<td>6 H</td>
<td>0.5529</td>
<td>0.0635</td>
<td>0.2498</td>
<td>0.2146</td>
<td>0.2155</td>
<td>0.3594</td>
<td>0.2118</td>
</tr>
<tr>
<td>7 H</td>
<td>0.5516</td>
<td>0.0441</td>
<td>0.2260</td>
<td>0.1997</td>
<td>0.2128</td>
<td>0.3172</td>
<td>0.2130</td>
</tr>
<tr>
<td>8 H</td>
<td>0.5687</td>
<td>0.0385</td>
<td>0.2602</td>
<td>0.2049</td>
<td>0.2004</td>
<td>0.3379</td>
<td>0.2009</td>
</tr>
</tbody>
</table>

Table 3.5b  CPI-based inflation forecasting (RMSE)

<table>
<thead>
<tr>
<th></th>
<th>DSGE</th>
<th>DFM</th>
<th>FAVAR</th>
<th>BFAVAR</th>
<th>SBVAR</th>
<th>LBVAR</th>
<th>classical VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 H</td>
<td>0.8357</td>
<td>0.3623</td>
<td>0.3172</td>
<td>0.3048</td>
<td>0.2890</td>
<td>0.4990</td>
<td>0.2860</td>
</tr>
<tr>
<td>2 H</td>
<td>0.6969</td>
<td>0.2386</td>
<td>0.3863</td>
<td>0.3073</td>
<td>0.2925</td>
<td>0.5230</td>
<td>0.3144</td>
</tr>
<tr>
<td>3 H</td>
<td>0.7128</td>
<td>0.2221</td>
<td>0.4139</td>
<td>0.3530</td>
<td>0.3188</td>
<td>0.5187</td>
<td>0.3236</td>
</tr>
<tr>
<td>4 H</td>
<td>0.7064</td>
<td>0.1382</td>
<td>0.3945</td>
<td>0.3420</td>
<td>0.3255</td>
<td>0.5777</td>
<td>0.3220</td>
</tr>
<tr>
<td>5 H</td>
<td>0.7023</td>
<td>0.0979</td>
<td>0.3400</td>
<td>0.3077</td>
<td>0.3136</td>
<td>0.5428</td>
<td>0.3162</td>
</tr>
<tr>
<td>6 H</td>
<td>0.6890</td>
<td>0.0745</td>
<td>0.3822</td>
<td>0.3183</td>
<td>0.3177</td>
<td>0.5624</td>
<td>0.3159</td>
</tr>
<tr>
<td>7 H</td>
<td>0.6949</td>
<td>0.0548</td>
<td>0.3561</td>
<td>0.3087</td>
<td>0.3145</td>
<td>0.4502</td>
<td>0.3164</td>
</tr>
<tr>
<td>8 H</td>
<td>0.7062</td>
<td>0.0500</td>
<td>0.4131</td>
<td>0.3271</td>
<td>0.3035</td>
<td>0.4986</td>
<td>0.3070</td>
</tr>
</tbody>
</table>

Among all variables at various forecasting horizons, we find that structural small open-economy DSGE model with the housing sector fails to generate the best forecasting performance. In all of the cases above, the structural model does not show any significant predictive advantages compared to the non-structural models. Moreover, the small open-economy DSGE model does not show any predictive power in housing price inflation forecasting, despite the fact that this structural model includes a housing sector and allows for news shocks. But it is also worth noting that, although the DSGE model is shown to be ineffective at forecasting relative to other models, it can produce similar forecasting performance for real variables. For example, we observe that the DSGE model shows comparable forecasting results with the non-structural models for output and consumption. But for nominal variables such as housing price inflation and
CPI-based inflation, the predictive ability of the DSGE model tends to underperform compared to the other models, and the advantages of non-structural models become greater.

In addition, our forecasting experiment shows that, at short horizons, no single model dominates the others, regardless of the choice of variables to be forecasted. Among the alternative non-structural models, SBVAR outperforms other competing models in most cases. This finding is consistent with Gupta et al. (2011), which shows that a small-scale VAR including 10 variables posts better forecasting performance at most horizons than other LBVAR, FAVAR, and BVAR. Banbura et al. (2010) also produces similar results, which shows that a rich sectoral and conjunctural information set does improve the forecasting accuracy significantly compared to other models within the category of BVAR. Although DFM does not always show the best predictive ability at short horizons, it does not lose much advantage, and its forecasting performance is comparable to other models. Moreover, factor analysis using a large data set is helpful to improve forecasting performance at longer horizons. Hence, DFM stands out as the best-suited model for forecasting all of the five key macroeconomic variables at 4- to 8-quarters-horizon forecasts. From Tables 3.1a to 3.5b, we find that, as the forecasting horizon grows more than one year, DFM can provide substantially informative forecasts in the long run. Thus, the current study points to the fact that DFM with a large data set could improve the forecasting accuracy of key macroeconomic variables in a small open economy and that DFM is a valid alternative to BVAR in a data-rich environment, especially at longer forecasting horizons.
3.6 Predicting the turning points of business cycles

In this sector, we investigate the ability of various models to forecast the recent turning point in the housing price inflation and output over 2007Q4-2009Q3. The vertical axis represents the growth rate of housing price and output in percentage (after data transformation), and the horizontal axis represents the time point.

Figure 3.1 Predicting the turning point in housing price inflation
Figure 3.1 illustrates that the Hong Kong housing market experienced a marked fluctuation of the housing price inflation after the peak in 2007Q4. We can find that the increasing trend of the housing price inflation reversed itself in 2007Q4 and then proceeded to fall, and it bottomed out in 2008Q4. After the trough in 2008Q4, the Hong Kong housing price inflation experienced a recovery, peaked again at 2009Q3, and fell afterward. After examining the actual data, we choose 2006Q1 as the starting date to forecast the turning point. That is, all of the models are estimated until 2005Q4, and then we forecast over the period of 2006Q1 until the end of the sample period in 2014Q1.

As can be observed from Figure 3.1, most of the forecasting models do not predict the peak of housing price inflation in 2007Q4 and rather forecast the following trough due to the financial crisis. However, only DFM accurately predicts the second peak in 2009Q4 coincident with the actual turning point. Other models accurately predict neither the peak nor the trough during the sample period. For example, SBVAR and OLS even predict the opposite trend to the actual data of housing price inflation over 2007Q4-2009Q3.

Figure 3.2 Predicting the turning point in output
Figure 3.2 illustrates that the output of Hong Kong shares a similar pattern to housing price inflation. The Hong Kong macroeconomy experienced a recession during the financial crisis of 2008–2009. The output sank to its bottom in 2009Q1 and has been recovering since then. The recovery proceeded until reaching the peak in 2009Q2. As for the predicting ability of the turning point in output, DFM does not perform well relative to the other models. SBVAR accurately predicts the recovering peak in 2009Q2 instead. Classical OLS also predicts the peak in 2009Q2, but tends to over-predict the recovery period over 2009Q1 to 2009Q2.
3.7 Conclusion

This paper carries out out-of-sample forecasting horse races for five key macroeconomic variables between structural and non-structural models. The structural model refers to the small open-economy DSGE model with a housing sector allowing for both contemporaneous and news shocks. The non-structural models include six types of data-driven prevailing models, some of which incorporate a large data set and are estimated as using principal component analysis or Bayesian methods. The predictive ability among alternative models is compared based on MAE and RMSE. Our results indicate that non-structural models outperform the structural DSGE model with a solid micro-foundation for all variables and across all horizons. One surprising result is that the DSGE model shows a weak predictive ability about housing price inflation, even though it explicitly models a housing sector of the small open economy. However, the DSGE model is able to produce comparable forecasts for real variables such as output and consumption. Furthermore, in most cases, SBVAR is superior to other competing models at short horizons and shows some advantages in predicting the turning point of output. But as the forecasting horizon grows, DFM dominates the other models, especially at longer horizons. Moreover, DFM also shows the best ability in predicting the turning point of housing price inflation. This indicates that incorporating a rich set of data in factor analysis does help in the macroeconomic forecasting in the long run.

We also find that incorporating a large data set in a BVAR does not always lead to an improvement in macroeconomic forecasting. Our experiment shows that better performance is obtained with the small-scale VAR estimated using Bayesian technique and that incorporating a large data set in LBVAR gets even worse. This point is also
confirmed by Banbura et al. (2010) and Koop (2010). The advantages of a data-rich environment turn out to be obvious only for DFM, especially at longer forecasting horizons. Nonetheless, the importance of large-scale models and especially that of data-rich DFM cannot be ignored when one could access to a large panel of macroeconomic data, and in practice, economic agents do make use of a large amount of economic variables to conduct the forecasting and policy analysis.

Although the non-structural models result in better forecasting performance in our experiment, they are not immune to the “Lucas Critique.” 34 Furthermore, the estimation methods used in the data-driven models in nature assumes a linear relationship among time series, and thus, the nonlinear relationship in the data is not taken into account. However, DSGE models which is firmly grounded in the macroeconomic theories, are capable of handling issues of nonlinearity and probably be the best response to “Lucas Critique”. Given the fact the various specifications about the DSGE models have been developed in the literature, this study should not be viewed as an exhaustive investigation into the forecasting power of DSGE models. Future research along this line should try to further investigate the impact of different structural restrictions on the DSGE models in order to gain some deep understanding about the predictive ability of the structural model.

34 See Lucas (1976) for details.
Chapter 4

Conclusion

In this thesis, we explore the business cycle implications of both contemporaneous and news shocks to domestic and external fundamentals in a small open economy. We also examine the forecasting ability of structural and non-structural models. The theoretical model and empirical analysis could provide significant understanding about the past dynamics and future movement of macroeconomy for both academic researchers and policy makers.

First, we construct a small open-economy DSGE model with a housing sector to address the role of both contemporaneous and news shocks to domestic and external fundamentals in explaining housing market dynamics and the macroeconomy. Using Hong Kong data, we find that external shocks and news shocks play a significant role in driving housing market dynamics for a small open economy. Cyclical fluctuations in housing prices are mainly driven by contemporaneous shock to foreign housing preference, contemporaneous shock to terms of trade, and news shocks to technology in the consumption goods sector. Each of the three shocks accounts for about one third of the variance of the housing prices. Cyclical movements in housing investment are also largely influenced by contemporaneous shock to terms of trade and news shocks to technology in the consumption goods sector. The former accounts for 36% of the variance in housing investment, while the latter accounts for 59%. The first essay contributes to the development of quantitative theory approaches, mainly in the context of business cycle models, to investigate the driving forces behind housing market dynamics and the business cycles. The findings could also provide insight to policy
makers who would like to identify the key driving forces behind the housing market dynamics and the interaction between housing price fluctuation and the macroeconomy in Hong Kong. Moreover, the results would be helpful for policy makers to evaluate the relative importance of various factors that drive the housing market dynamics.

Second, we examine the forecasting ability of both structural and non-structural models in a small open economy. We apply seven models with some of them using information from a large data set to forecast five key macroeconomic variables: output, consumption, employment, housing price inflation, and CPI-based inflation in Hong Kong. The structural DSGE model uses six observables as described in Chapter 2 to estimate the parameters. The non-structural data-driven models contain a large data set covering different sectors of the Hong Kong economy, except that SBVAR and classical VAR only include a few key variables which are used as predictor variables. Based on two measures of point forecasts, MAE and RMSE, we find that the non-structural models outperform the structural micro-foundation DSGE model for all variables and across all horizons. The most surprising result is that the DSGE model shows the weak predictive ability about housing price inflation, even though it explicitly models a housing sector of the small open economy. Furthermore, in most cases, SBVAR is superior to the other competing models at short horizons. But as the forecasting horizon grows, DFM improves over other models, especially at longer horizons. This indicates that forecasts can be improved by using factor model with the information from a large data set, especially when the forecasting horizon increases. The poor forecasting performance of DSGE model might be due to the lack of some real frictions in the model, such as business capital in the production function, the capital adjustment cost, and the price setting rule only considering the forward-looking
behavior. The advantage of DFM comes from the full information contained in the large data set and doesn’t allow for the subjective pre-sample information in the forecasting model. Because the missing economic features in the structural DSGE model contained in the data, the data-driven models which extract all the useful information perform better than the structural model in our forecasting exercise.

Recently, factor models have gained great success and are widely used by macroeconomists. In practice, central banks and policy makers monitor a great number of variables during the decision-making process (Bernake and Boivin 2003), which results in the increasing importance of accurate forecasts of economic fundamentals. Thus, the findings of the thesis are potentially helpful for forecasting purpose in both academic and professional research.

There are several avenues in which the current study could be expanded. The financial crisis in 2007-08 has renewed interests in the role that financial factors play in driving the business cycle. In particular, the rapid propagation of disruptions in the U.S. housing market to the financial markets in the onset of the financial crisis brings our attention to the sectoral transmission of shocks through financial linkages. One important theme is an understanding of the role of the financial sector in the transmission of business cycles. It is worthwhile to extend the current small open-economy model with the inclusion of a financial sector and study the spillovers of the housing market to the financial sector and the aggregate economy. It is also interesting to apply the current model to other small open economies with different exchange rate arrangements, such as a floating exchange rate regime rather than the currency board system in Hong Kong. Further research along this line should be considered. Besides, a recent paper by Sims (2015) points out that the traditional variance deposition has a
conceptual difficulty in assessing the quantitative importance of unrealized news shocks. The unconditional variance decomposition will ascribe the dynamics in the endogenous variables to both unrealized news about future exogenous fundamentals that has yet to materialize and realized news about fundamental that were anticipated in the past. In future research we should apply the method proposed by Sims (2015) to differentiate the quantitative importance of unrealized news shocks from that of realized news shocks. Although non-structural models show some advantages in our forecasting experiment, the lack of micro-foundation still make them less attractive in modelling the dynamic transmission between different sectors of the macroeconomy. Thus, the extension of DSGE model should be highly appreciated for macroeconomic forecasting, given the fact that the advantages of structural model could deliver a consistent theoretical interpretation about the future state of the macroeconomy.
Bibliography


Khan, H. and Tsoukalas, J. (2012). The quantitative importance of news shocks in estimated DSGE models. Journal of Money, Credit and Banking, 44(8), 1535-1561.


Appendix

A: First order conditions for impatient households (Chapter 2)

Given the budget and borrowing constraint that impatient households face, we can derive the first-order conditions for the optimization problem as:

\[ W^{b}_{j,t} = \frac{(X^b_{j,t})^\gamma (N^b_{j,t})^\sigma (\tilde{C}^b_{j,t})^{\gamma e^D}}{(1 - \gamma e^D)(D^b_{j,t})^{\gamma e^D}}, \quad j = C, D \]

\[ P_{D/C,j} = \left(1 - \gamma e^D\right) \frac{\tilde{C}^b_{j,t}}{D^b_{j,t}} + (1 - \chi)(1 - \delta) \Psi_t P_{Dj[\hat{C},t+1]} E_t [\Pi_{Dj,t+1}] \epsilon_t^{LTV} \]

\[ + \beta_b (1 - \delta) E_t \left[ \left(1 - \gamma e^D\right) \left(\frac{X^b_{t+1}}{X^b_t}\right)^{-\sigma} \left(\frac{D^b_{t+1}}{\tilde{C}^b_{t+1}}\right)^{\gamma e^D} P_{Dj[t+1]} \right] \]

\[ \Psi_t = 1 - \beta_b E_t \left[ \left(1 - \gamma e^D\right) \left(\frac{X^b_{t+1}}{X^b_t}\right)^{-\sigma} \left(\frac{D^b_{t+1}}{\tilde{C}^b_{t+1}}\right)^{\gamma e^D} \frac{R_t}{\Pi_{C,t+1}} \right] \]

where \( \lambda_t \) and \( \lambda_t \Psi_t \) represent the Lagrangian multiplier on the budget constraint and borrowing constraint respectively, and \( \Psi_t \) represents the marginal value of borrowing.

If \( \Psi_t = 0 \), equation (A3) coincides with the New Keynesian Euler equation. Thus, a rise in \( \Psi_t \) means a tightening of the collateral constraint. Equation (A1) represents the trade-off between labor and leisure, which means that the marginal disutility of an additional unit of labor is equal to the marginal utility of an additional unit of consumption. Equation (A2) represents that the marginal utility of consumption is equal to the shadow value of housing, and equation (A3) represents an Euler equation of consumption which is adjusted to capture the borrowing constraint.
B: The Log-linearized model (Chapter 2)

After log-linearizing the first order conditions around the steady state, we can get the following equations:

\[(B1)\]
\[
\hat{p}_{D/C,t} = \Omega^b \left( \hat{c}_t^b - \hat{d}_t^b \right) + \beta_b (1 - \delta) [(1 - \delta) \gamma E_t (\Delta \hat{d}_{t+1}^b) - \Gamma E_t (\Delta \hat{c}_{t+1}^b)] + \beta_b (1 - \delta) E_t (\hat{p}_{D/C,t+1})
\]
\[+ \psi(1 - \chi) (\hat{\psi}_t + \hat{p}_{D/C,t} + \hat{\pi}_{d,t+1} + \epsilon_i^{TV}) + \Lambda^b \epsilon_i^D
\]

\[(B2)\]
\[
\hat{p}_{D/C,t} = \Omega^t \left( \hat{c}_t^t - \hat{d}_t^t \right) + \beta_t (1 - \delta) [(1 - \delta) \gamma E_t (\Delta \hat{d}_{t+1}^t) - \Gamma E_t (\Delta \hat{c}_{t+1}^t)] + \beta_t (1 - \delta) E_t (\hat{p}_{D/C,t+1}) + \Lambda^t \epsilon_i^D
\]

\[(B3)\]
\[
\hat{\psi}_t = \frac{\beta_b}{\beta_t - \beta_b} \left( \Gamma E_t (\Delta \hat{c}_{t+1}^b) - (1 - \sigma) \gamma E_t (\Delta \hat{d}_{t+1}^b) - \hat{\pi}_{t, \hat{c},t+1} - \alpha_c E_t (\Delta \hat{s}_{c,t+1}) \right)
\]
\[+ (1 - \sigma) \gamma [\ln b - \ln \tilde{c}^b] (1 - \rho_D) \epsilon_i^D - \hat{r}_t
\]

\[(B4)\]
\[
\Gamma \hat{c}_t^t = \Gamma \hat{c}_{t+1}^t + (1 - \sigma) \gamma E_t (\Delta \hat{d}_{t+1}^t) - (\hat{r}_t - \hat{\pi}_{t, \hat{c},t+1}) + \alpha_c \Delta \hat{s}_{c,t+1} + (1 - \sigma) \gamma (\ln \tilde{c}^t - \ln (\tilde{c}^t))(1 - \rho_D) \epsilon_i^D
\]

\[(B5)\]
\[
\hat{c}_t^b = \frac{B_{h}^b}{C^b} [\hat{h}_t^b - \beta_s^{-1} (\hat{h}_{t-1}^b + \hat{b}_{t-1}^b - \hat{\pi}_{c,t+1} - \alpha_c \Delta \hat{s}_{c,t})] + M_c (\tilde{\omega}_{c,t} + \hat{n}_{c,t}^b) + P_{D/C} M_D (\tilde{\omega}_{d,t} + \hat{n}_{d,t}^b)
\]
\[+ P_{D/C} D_{b}^b (\hat{p}_{D/C,t} + \hat{\pi}_{d,t} - (1 - \delta) \hat{d}_{t+1}^b)
\]

\[(B6)\]
\[
\tilde{c}_{c,t} = (1 - \alpha_c) \hat{c}_t + \alpha_c \hat{c}_t + \alpha_c \gamma \hat{s}_{c,t}
\]

\[(B7)\]
\[
\tilde{c}_{d,t} = \hat{c}_{d,t}
\]

\[(B8)\]
\[
\hat{c}_t = \omega \frac{C^b}{C} \hat{c}_t^b + (1 - \omega) \frac{C^t}{C} \hat{c}_t^t
\]

\[(B9)\]
\[
\hat{d}_t = \omega \frac{D^b}{D} \hat{d}_t^b + (1 - \omega) \frac{D^t}{D} \hat{d}_t^t
\]

\[(B10)\]
\[
\hat{\pi}_{c,h,t+1} = \beta_s E_{c,t} \hat{\pi}_{c,h,t+1} + m c_{c,t} + \hat{\pi}_{c,t}^D
\]

\[(B11)\]
\[
2 \ast m c_{d,t} = - \hat{\mu}_{d}^D
\]

\[(B12)\]
\[
\hat{\mu}_{c,t} = \Gamma \hat{c}_t - (1 - \sigma) \gamma \hat{d}_t + \alpha \hat{\pi}_{c,t} + \alpha_c \hat{s}_{c,t} - \alpha_c - \epsilon_i^D
\]

\[(B13)\]
\[
\hat{\mu}_{d,t} = \Gamma \hat{d}_t - (1 - \sigma) \gamma \hat{d}_t + \alpha \hat{\pi}_{d,t} - \gamma \hat{p}_{D/C,t} - \alpha - \epsilon_i^D
\]

\[(B14)\]
\[
(1 - \alpha_c) \hat{s}_{c,t} = \Gamma (\hat{c}_t^c - \hat{c}_t^c) - (1 - \sigma) \gamma (\hat{d}_t^c - \hat{d}_t^c) - (1 - \sigma) \gamma (\ln D^c - \ln \hat{C}^c) - (1 - \gamma) (\epsilon_i^D - \epsilon_i^c)
\]
\( \hat{y}_{j,t} = \hat{a}_{j,t} + \hat{n}_{j,t} \)

\( \hat{w}_{j,t} = \Gamma \hat{c}_i - (1 - \sigma) \gamma d_i + \Phi \hat{n}_{j,t} - [(1 - \sigma) \gamma (\ln D - \ln \tilde{C}) - \frac{\gamma}{1 - \gamma}] \varepsilon_i^D \)

\( \hat{w}_{j,t} = \Gamma \hat{c}_i - (1 - \sigma) \gamma d_i + \Phi \hat{n}_{j,t} - [(1 - \sigma) \gamma (\ln D^i - \ln \tilde{C}^i) - \frac{\gamma}{1 - \gamma}] \varepsilon_i^D \)

\( \hat{p}_{D/c,t} = \hat{p}_{D/c,t-1} + \hat{\pi}_{d,t} - \hat{\pi}_{ch,t} - \alpha_c \Delta \hat{c}_{ct} \)

\( \hat{\pi}_{c,t} = \hat{\pi}_{ch,t} + \alpha_c \Delta \hat{c}_{ct} \)

\( \hat{r} = \rho_{r_{t-1}} + (1 - \rho_r)(\rho_x \pi_{c,t-1} + \rho_y y_i^f) + \varepsilon_i^f \)

\( \hat{y}_i^f = \rho_y \hat{y}_{i-1}^f + \varepsilon_i^f \)

\( \hat{y}_t = \frac{P_{D/c} \hat{c}}{Y} \hat{c}_{ct} + \frac{\delta P_{D/c} \hat{c}}{Y} \hat{d}_{ct} + \xi \hat{y}_{D/c,H,t} - \xi \ln P_{D/c}(\varepsilon_i^D + \varepsilon_i^*) \)

\( \hat{p}_{D/c,H,t} = \hat{p}_{D/c,t} + \alpha_c \hat{\pi}_{c,t} \)

\( \hat{n}_i = \frac{N_c}{N} \hat{c}_{ct} + \frac{N_D}{N} \hat{n}_{d,t} \)

where \( \hat{w} = \hat{w}_{j,t} - \hat{p}_{c,t} \), \( \kappa_c = \frac{(1 - \theta_c)(1 - \beta_d \theta_c)}{\theta_c} \), \( \Gamma = \frac{\sigma + (1 - \sigma) \gamma}{1 - h_c} \),

\[ \Lambda^j = \frac{\Omega^j}{1 - \gamma} - (1 - \rho_d) \beta_j (1 - \delta) [(1 - \sigma) \gamma (\ln D^j - \ln \tilde{C}^j) - \frac{\gamma}{1 - \gamma}] \]

\[ \Omega^j = \frac{\gamma}{1 - \gamma} \frac{\tilde{C}^j}{D^j P_{D/c}} \]

\[ M_j = \frac{1}{1 + \mu_j} \frac{N_j}{\tilde{C}^j} \]

\[ \Sigma = (1 - \sigma) \gamma (\ln D - \ln \tilde{C}) - \frac{\gamma}{1 - \gamma} \]
In the deterministic steady state, the net inflation rate is assumed to be zero. Hence, the nominal interest rate $R$ is pinned down by the savers’ discount rate through the consumption Euler equation. Due to the assumed heterogeneous discount rate of households and thus the borrowing limit, we can ensure a well-defined steady state. In fact, if the discount rate of both types of households were equal, the steady state of the debt would be indeterminate.\footnote{See Becker (1980), and Becker and Foias (1987) for details.} In this case, $\beta_b / \beta_s = \beta_b R = 1$. Thus, the steady state of the economy depends on the initial conditions, because the economy would always replicate the initial conditions of the wealth forever. With heterogeneous discount rate and complete financial market, the consumption of impatient households would reduce, and the ratio of consumption to income would converge to zero asymptotically.\footnote{With different discount rate $\beta_b < \beta_s$, we can derive that $\beta_b R < 1$.} Hence, a binding borrowing constraint makes a constant consumption path compatible with heterogeneity at a discount rate. Under the assumption of zero net inflation rates in the steady state, PPP holding, with the same preferences and working skills of both types of households, we obtain $N^*_j = N^b_j = N_j$ and the following equations describing the steady state:

\begin{align}
(C1) & \quad R = \beta_s^{-1} \\
(C2) & \quad \psi = \beta_s - \beta_b \\
(C3) & \quad MC_j = \frac{1}{1 + \mu_j} \\
(C4) & \quad P_{Dj/C} = \frac{1 + \mu_D}{1 + \mu_C}
\end{align}
(C5) \[\frac{C^b}{D^b} = \frac{1 - \gamma}{\gamma} \frac{1 - \beta_s (1 - \delta)(1 - \chi)(1 - \delta)(\beta_s - \beta_b)}{1 - h_c} P_{D/C}\]

(C6) \[\frac{C^s}{D^s} = \frac{1 - \gamma}{\gamma} \frac{1 - \beta_s (1 - \delta)}{1 - h_c} P_{D/C}\]

(C7) \[\frac{B_{\mu}^b}{D^b} = \beta_s (1 - \chi)(1 - \delta) P_{D/C}\]

(C8) \[D^b = \frac{C^b}{D^b} \frac{1}{(1 + \mu_c)} N \frac{C^b}{D^b} + \delta - (1 - \chi)(1 - \delta)(\beta_s - 1) \right] P_{D/C}\]

(C9) \[C^b = \frac{C^b}{D^b} D^b\]

(C10) \[N = N_c + N_d\]

(C11) \[N_d = \frac{\frac{1}{(1 - \omega) \delta} C^s + \frac{1}{(1 - \omega)} \frac{C^s}{D_s} (N \frac{1}{1 + \mu_c} - \omega C^b)}{(1 - \omega) \frac{C^s}{D_s} 1 + \mu_c + \frac{1}{(1 - \omega) \delta} 1 + \mu_d}\]

(C12) \[D^s = \frac{1}{(1 - \omega) \delta} (N_d - \omega \delta D^b)\]

(C13) \[C^s = \frac{1}{1 - \omega} (N_c - \omega C^b)\]

(C14) \[C = N_c = Y_c\]

(C15) \[\delta D = N_d = Y_d\]
D: Data description (Chapter 3)

All series are downloaded from the websites of the Census and Statistics Department of Hong Kong, the Rating and Valuation Department of Hong Kong, Hong Kong Monetary Authority, Federal Reserve Bank of St. Louis and Bloomberg. We set the transformation codes as: 1=no transformation, 2=first transformation, 4=logarithm, 5=first difference of logarithms, 6=second difference of logarithms. The following abbreviations appear in the data definitions: SA=seasonally adjusted, NSA=not seasonally adjusted. All the transformation follows Stock and Watson (2002b) and Pang (2010).

<table>
<thead>
<tr>
<th>Description</th>
<th>Transformation</th>
</tr>
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<tbody>
<tr>
<td><strong>Real Income and Activities</strong></td>
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</tr>
<tr>
<td>Hong Kong Qtrly GDP per capita Chain Volume SA</td>
<td>5</td>
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<tr>
<td>Hong Kong Qtrly GDP Private Consumption Expenditure per capita Chain Volume SA</td>
<td>5</td>
</tr>
<tr>
<td>Hong Kong Qtrly CPI based Inflation SA</td>
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<tr>
<td>Hong Kong Gross value of construction works performed by main contractors analysed by broad trade group (at constant (2000) market prices) yoy</td>
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<tr>
<td>Hong Kong Qtrly GDP Domestic Fixed Capital Formation Chain Volume yoy</td>
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</tr>
<tr>
<td>Hong Kong Qtrly GDP Government Consumption Expenditure Chain Volume yoy</td>
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</tr>
<tr>
<td>HK terms of trade yoy</td>
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</tr>
<tr>
<td>Hong Kong Real Wages All Industry Sectors yoy</td>
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</tr>
<tr>
<td>HK Imports yoy</td>
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<tr>
<td>HK Domestic Exports yoy</td>
<td>1</td>
</tr>
<tr>
<td>HK Re-exports yoy</td>
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<tr>
<td>HK Total exports yoy</td>
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<tr>
<td><strong>Housing Market</strong></td>
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<tr>
<td>HK real residential property price index</td>
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<tr>
<td>HK housing price inflation SA</td>
<td>5</td>
</tr>
<tr>
<td>HK retail sales value yoy</td>
<td>1</td>
</tr>
<tr>
<td>Hong Kong Sale &amp; Purchase Agreements Consideration All Building Units</td>
<td>5</td>
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<tr>
<td><strong>Labor Market</strong></td>
<td></td>
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<tr>
<td>Economic Indicator</td>
<td>Frequency</td>
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<tr>
<td>labor force yoy</td>
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<tr>
<td>unemployment rate % SA</td>
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<tr>
<td>labor force participation rate %</td>
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<td>HK employed person SA</td>
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<tr>
<td>HK unemployed export &amp; import trade %</td>
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<tr>
<td>Hong Kong Unemployed Construction %</td>
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<tr>
<td>Hong Kong Unemployed finance &amp; insurance &amp; Real Estate &amp; business service %</td>
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<tr>
<td>Hong Kong Unemployed community &amp; social &amp; personal service %</td>
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<tr>
<td>Hong Kong Unemployed Manufacturing %</td>
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</table>

**Money and Exchange Rate**

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<thead>
<tr>
<th>Economic Indicator</th>
<th>Frequency</th>
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<tbody>
<tr>
<td>HK M1 yoy</td>
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<tr>
<td>HK prime rate HSBC</td>
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<tr>
<td>HK effective exchange rate</td>
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<tr>
<td>Switzerland / U.S. Foreign Exchange Rate</td>
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<tr>
<td>Hong Kong / U.S. Foreign Exchange Rate</td>
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<tr>
<td>Japan / U.S. Foreign Exchange Rate</td>
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**Price level**

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<th>Economic Indicator</th>
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<tbody>
<tr>
<td>HK CPI A yoy</td>
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<tr>
<td>HK CPI B yoy</td>
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<tr>
<td>HK CPI C yoy</td>
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<tr>
<td>IMF China Hong Kong PPI/WPI</td>
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</table>

**Loans, Deposits and Interest Rate**

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<th>Frequency</th>
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<tbody>
<tr>
<td>HIBOR 1M</td>
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<td>HIBOR 3M</td>
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<tr>
<td>HIBOR 6M</td>
<td>2</td>
</tr>
<tr>
<td>HIBOR 12M</td>
<td>2</td>
</tr>
<tr>
<td>HK deposite rate 1M</td>
<td>2</td>
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<tr>
<td>HK deposite rate 3M</td>
<td>2</td>
</tr>
<tr>
<td>HK deposite rate 6M</td>
<td>2</td>
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<tr>
<td>HK deposite rate 12M</td>
<td>2</td>
</tr>
<tr>
<td>HK loans &amp; advances yoy</td>
<td>1</td>
</tr>
<tr>
<td>HK total deposits-restricted banks (mln HKD)</td>
<td>6</td>
</tr>
<tr>
<td>HK Savings deposit rate</td>
<td>2</td>
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<tr>
<td>HK Best lending rate(% per annum)</td>
<td>2</td>
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<tr>
<td>HKMA Hong Kong Official Foreign Currency Reserve Assets (bln USD)</td>
<td>6</td>
</tr>
<tr>
<td>Total Credit to Private Non-Financial Sector, Adjusted For Breaks, for HK yoy</td>
<td>1</td>
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**Stock Market**

<table>
<thead>
<tr>
<th>Economic Indicator</th>
<th>Frequency</th>
</tr>
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<tbody>
<tr>
<td>Hang Seng Index</td>
<td>5</td>
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<tr>
<td>Hang Seng Property index</td>
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</tr>
<tr>
<td>Hang Seng Property index volume</td>
<td>6</td>
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<tr>
<td>Hang Seng index volume</td>
<td>6</td>
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<tr>
<td>H-share index</td>
<td>5</td>
</tr>
<tr>
<td>HK stock exchange turnover</td>
<td>5</td>
</tr>
</tbody>
</table>

**China Data**

| China real GDP YoY                      | 1 |
| China CPI yoy                           | 1 |
| China export yoy                        | 1 |
| China import yoy                        | 1 |
| China M1 yoy SA                         | 1 |
| Total Credit to Private Non-Financial Sector, Adjusted For Breaks, for China yoy | 1 |
| RMB per US. Dollar                      | 5 |
| China discount rate                     | 2 |
| Reserve asset for China                 | 6 |

**U.S. Data**

| US. 3-Month Treasury Bill: Secondary Market Rate % | 2 |
| GDP US Chained 2009 Dollars yoy SA                 | 1 |
| NASDAQ composite index                            | 5 |
| US. Effective Federal Funds Rate                   | 2 |
| US dollar per British pound                        | 5 |
| US. All-Transactions House Price Index              | 5 |
| US. Net export yoy SA                              | 1 |
| US. PPI yoy                                         | 1 |
| US. Trade Balance (mln USD)                         | 2 |
| US. Industrial production index yoy SA              | 1 |
| US. Housing Starts: Total: New Privately Owned Housing Units yoy SA | 1 |
| US. CPI yoy                                         | 1 |
| US. Real Residential Property Prices index         | 5 |
| US. Nominal Residential Property Prices index      | 5 |
| US. Household Debt Service Payments as a Percent of Disposable Personal Income % SA | 2 |
| Total Credit to Private Non-Financial Sector, Adjusted For Breaks, for US. yoy | 1 |
| US. Monetary base total yoy                        | 1 |
| US. M1 yoy SA                                      | 1 |
| US. M2 yoy SA                                      | 1 |
| US. Unemployment rate % SA                         | 1 |
| SPX index                                           | 5 |
| SPX index volume                                    | 6 |
CURRICULUM VITAE

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- Received the degree of Bachelor of Economics from Ocean University of China, June 2008.
- Received the degree of Master of Economics from Ocean University of China, June 2011.

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