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Forecasting Inflation in China

by

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Abstract

Throughout Chinese history, inflation has been the cause of many revolutions or dynastic changes. More recently, since the economic reform began in 1978, Chinese economy has always become more vulnerable when inflation picks up. As a consequence, Chinese economic policies, both monetary and fiscal ones, were conditional on how inflation evolved in many periods. Hence closely monitoring living costs has been one of the most important tasks for Chinese policy makers.

In this thesis I explore various ways to forecast Chinese inflation and evaluate the performance of these techniques. Chapter 1 documents the stylized facts of Chinese inflation in the past three decades and assesses the performance of bottom-up approach, the most commonly used method in forecasting inflation. In Chapter 2 I evaluate the inflation forecast performance of various time series models with other macroeconomic variables. Chapter 3 estimates several DSGE models and conducts the inflation forecasts using recent Chinese data. In the last chapter, I attempt to explore possible ways to forecast inflation during crisis periods.

My dissertation has three major contributions. First of all, I evaluate whether various up-to-date techniques, including both econometric approaches and model based estimations, can be applied to forecast Chinese inflation in a coherent fashion. Some techniques have never been used for this purpose. Secondly, I confirm the important role of monetary policy in forecasting inflation in China. Price rules, using short-term

interest rates as the policy instruments, are more informative in forecasting Chinese inflation than quantity rules which use the money aggregates. And lastly, I provide a benchmark model, which can be easily modified and extended, to forecast inflation in crisis periods.

To my parents,

thanks them for believing in me and encouraging me to further my studies.

And to my beautiful wife, *Vivi*,

for her continuous support and patience through this long journey.

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Chapter 1

Inflation in China– A Brief Introduction

Abstract

This chapter documents the stylized facts of Chinese inflation in the past three decades and assesses the performance of so-called bottom-up approach, the most commonly used method in forecasting inflation. China has experienced brief deflation, moderate inflation, and high inflation periods since 1978, which can be largely explained by business cycles and policy responses. I document such high volatilities, as well as prevalent explanations in literature. The bottom-up approach to forecasting Chinese inflation—tracking prices changes of some CPI component with frequent data availability—is the most commonly used one. One problem is that the government does not release full details of inflation data. For instance, weights of these CPI components, as well as methods used for determining these weights, remain unpublished. Even if I estimate these weights and use them to forecast inflation in China, this bottom-up approach produces only relatively good short-term forecasts but very inaccurate medium- to long-run predictions. This finding provides strong incentives to explore other methods for forecasting Chinese inflation.

Keywords: Inflation Forecasting, Stylized Facts, China, Bottom-Up Approach.

1.1 Introduction

Closely monitoring living costs has been one of the most important tasks for Chinese policy makers for centuries. Throughout Chinese history, inflation has been the cause of many revolutions or dynastic changes. More recently, since the economic reform began in 1978, Chinese economy has always become more vulnerable when inflation picks up. As a consequence, Chinese economic policies, both monetary and fiscal ones, were conditional on how inflation evolved in many periods. In this chapter, I attempt to provide a brief introduction of Chinese inflation in recent three decades, present existing obstacles to forecasting inflation, and check whether the widely used bottom-up approach is good enough for policy makers.

Before jumping to stylized facts, distinguishing the commonly used indicators for overall price levels is helpful. The three well-cited price indicators in China are the consumer price index (CPI), producer price index (PPI), and retail price index (RPI).

In early 1980s, RPI was regarded as the best indicator to gauge living costs. As services were trivial, and the government put strict controls on consumption goods, prices changes of RPI provided reliable sources of inflationary pressure. PPI, capturing costs of raw materials in agriculture and industrial sectors, also caught lots of attention, since the pass-though from agriculture goods prices to consumption goods prices was important. However, CPI became more popular since the 1990s. There were two reasons. Firstly, the share of service sector in GDP roses sharply as households accumulated wealth and many official restrictions on this sector were removed gradually. Secondly, the statistics bureau had more experience in collecting and process raw data from thousands of collection spots all over China. Reliable CPI data were released regularly. Over the long horizon, the dynamics of these three price indicators shared similar patterns (Table 1.1).

Table 1.1: Year-over-Year Price Changes: China (1951–2011)

	CPI	RPI	PPI
Mean	3.66	3.06	4.73
Median	2.00	1.50	3.05
Maximum	24.10	21.70	24.00
Minimum	−5.90	−5.90	−5.40
Std. Dev.	5.80	5.61	6.79
Skewness	1.65	1.61	1.17
Kurtosis	5.49	5.25	3.98

Source: National Statistics Bureau of China.

According to the National Bureau of Statistics, Chinese CPI has the following eight components, namely food; tobacco, liquor and articles; clothing; household facilities, articles and services; health care and personal articles; transportation and communication; recreation, education and culture articles; and residence. The National Bureau of Statistics of China also releases price changes of five subcategories under *food*: grain; meat, poultry and their products; eggs; aquatic products; fresh vegetables and fresh fruits. The above 8 components can be categorized further into 262 subcategories. For an international comparison, US current surveys 8 categories and 211 subcategories; Canada, 8 categories and 169 subcategories; Japan, 10 categories and 585 subcategories; and Australia, 11 categories and 87 subcategories. As we can see, price changes of some components are much more volatile than others (*see* Table 1.2). Food is the most volatile component with standard deviation reaching 5.98, while transportation and communication is the least volatile one, with standard deviation of less than one. The residence price index, which rises sharply since 2008, grows on average at 4% year-over-year. It is also the second most volatile component in all CPI categories.

I use the following acronyms for CPI components in this chapter:

FOOD	=	food
BEV	=	tobacco, liquor and articles
APP	=	clothing
HOME	=	household facilities, articles and services
HEALTH	=	health care and personal articles
TRANS	=	transportation and communication
RECR	=	recreation, education and culture articles
HOUS	=	residence

Chinese CPI data are collected by the Statistics Bureau of China (SBC) and local government statistics agencies. A survey of more than 120,000 households is conducted to determine which consumer goods should be included. Local government statistics agencies can propose changes for such consumer goods, but changes are subject to final approval by SBC. The number of consumer goods varies across locations. For instance, 1429 consumer goods are surveyed in Beijing and only 647 in Guiyang, the capital of Guizhou Province. Around 4,000 people are currently employed to collect price data all over China.

The composition of the basket of goods is updated every year, but the weights are updated every five years per current laws. Those items whose prices are relatively more volatile are surveyed more frequently. Prices of grain, meat, fresh vegetables are updated every 5 days except holidays. Price changes of most industrial products, such as clothing, durable goods, transportation, and communication articles, are released two to three times a month. Government-controlled services, including prices of water and electricity, are surveyed on monthly basis.

The headline CPI is computed by averaging price data collected from 476 urban and 883 rural counties and cities, by their population and consumption levels. SBC

Table 1.2: Descriptive Statistics: China CPI Growth YoY by Components

	FOOD	BEV	APP	HOME
Mean	5.92	1.23	−0.96	0.08
Median	4.90	1.30	−1.41	0.21
Maximum	23.25	3.87	3.81	3.38
Minimum	−3.30	−0.60	−2.90	−2.90
Std. Dev.	5.98	1.22	1.65	1.98
Skewness	0.82	0.37	1.65	−0.02
Kurtosis	2.93	2.25	4.99	1.56
	HEALTH	TRANS	RECR	HOUS
Mean	1.26	−1.02	0.91	3.06
Median	1.35	−1.10	0.50	4.00
Maximum	4.13	1.00	9.60	7.73
Minimum	−1.50	−2.97	−2.27	−5.80
Std. Dev.	1.58	0.99	2.32	3.02
Skewness	−0.07	−0.01	2.51	−0.97
Kurtosis	1.88	2.08	9.62	3.60

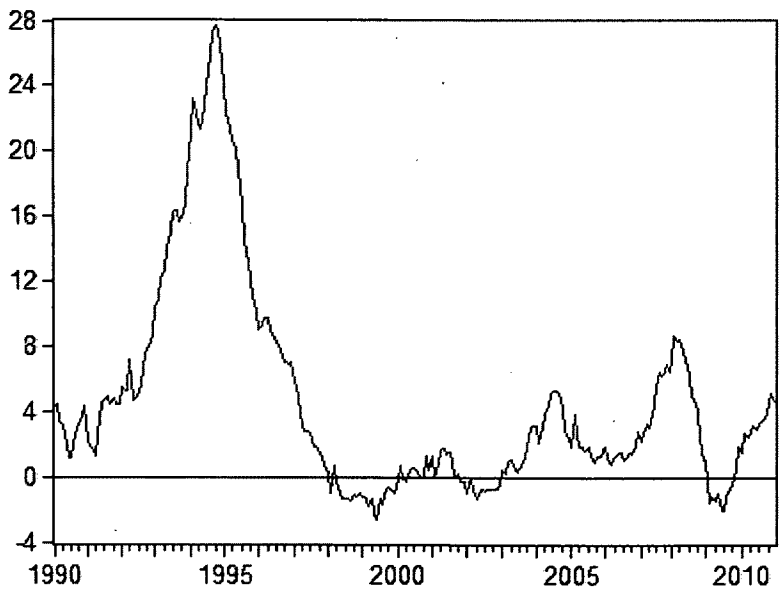
Source: National Statistics Bureau of China.

provides unified instruction on data collection. Unlike most countries, China also publishes regional CPI at provincial level, and in a number of cities and even counties.

1.2 High Volatility of Chinese CPI Inflation

Consumer prices in China historically have been very volatile. The volatility became even higher after China's economic reform in late 1970s. Figure 1.1 shows the monthly consumer price index (CPI) inflation[1] from 1990 to 2010.

Figure 1.1: China CPI Inflation (%)



Source: National Statistics Bureau of China.

Inflation rates are very high within most years in the 1990s. The monthly CPI inflation rose from around 4 percent in early 1990s to some 27 percent at the end of 1994, before it gradually retreated to around zero in 1998. The deflationary periods,

[1] Inflation here is defined as the price change relative to the same month of previous year, following the Statistics Bureau of China.

or very low inflation periods, lasted from 1998 to the summer of 2003, following by a rather moderate inflation period until January 2009, while a short deflationary period began. The inflation started to pick up again in 2010 until the present. Between 1990 and 2010, as stated in Table 1.3, deflation occurred in 19% of the months studied, moderate inflation (under 5%) occurred in 50% of the months, and high inflation (above 10%) occurred in around 15% of the months. These periods of high volatility in inflation can adversely affect decision making of private sector and policy makers. And such high volatility also makes it more difficult to accurately forecast inflation behavior.

Table 1.3: China CPI Inflation–Distribution

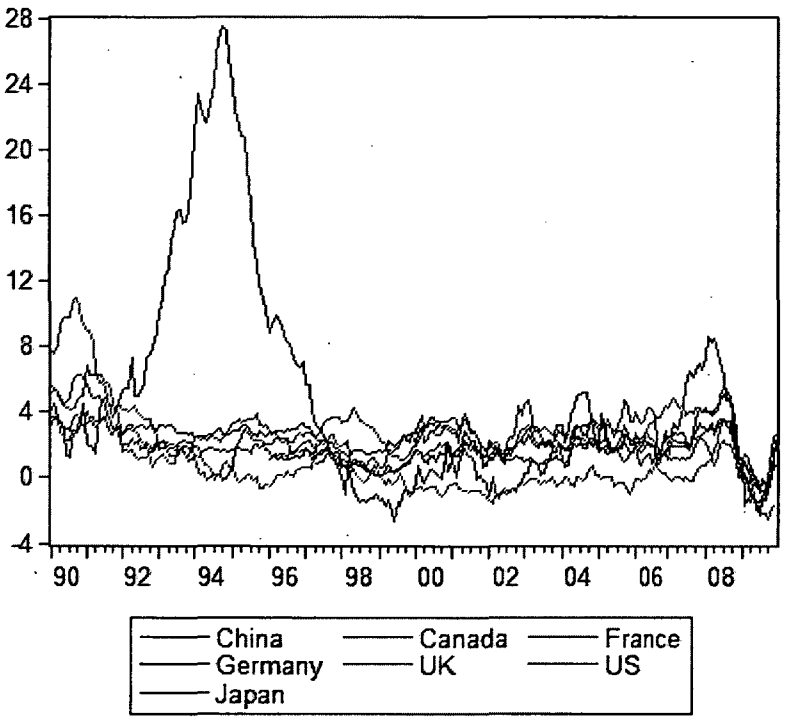
Value (CPI YoY Inflation, %)	Counts (months)	Percent
Less than 0	48	19.05
0–5	126	50.00
5–10	42	16.67
10–15	10	3.97
15–20	9	3.57
20–25	12	4.76
Above 25	5	1.98
Total	252	100

Source: National Statistics Bureau of China.

Compared to other major developed economies, the inflation pattern in China is very different (Figure 1.2). Chinese CPI inflation was very high before 1997, and then it became quite stable afterwards. However, inflation rates in the US, Canada, UK, France, and Germany were relative higher at around six percent in the early 1990s before they dropped to a much lower band centering at around 2–3 percent since then. Japan has had both inflationary and deflationary periods like China, but

in general the magnitudes have been quite small. There are some possible reasons why inflation during the study period is more contained in developed economies. First of all, the share of food, one of the most volatile components, in total CPI is higher in China comparing to developed economies. Second of all, policy credibility seems to be weaker in China as no official price or inflation targeting framework has been adopted. And this leads to the third reason: inflation is better anchored in developed economies.

Figure 1.2: CPI Inflation in Major Developed Economies (Unit: YoY %)

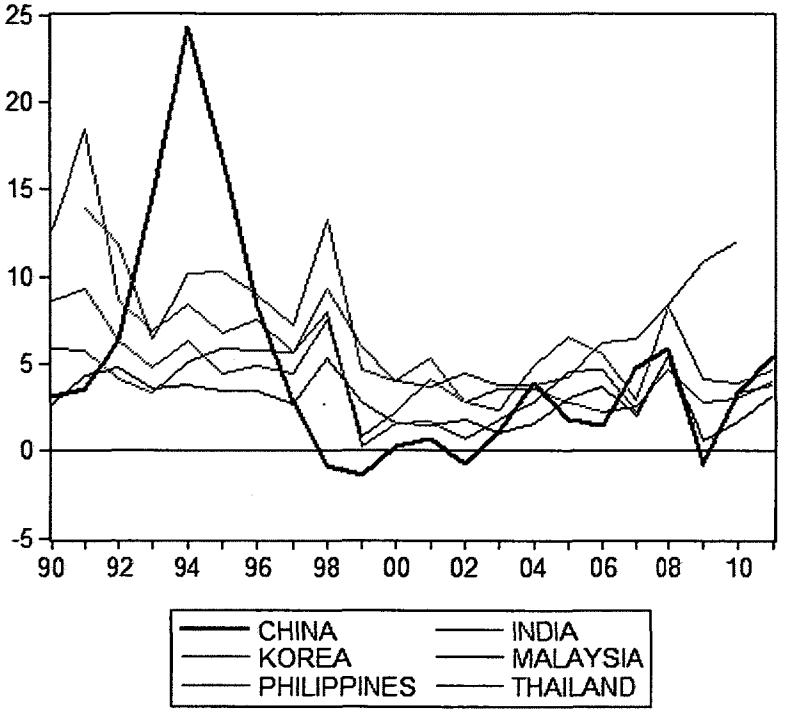


Source:IMF.

But even compared with some major developing economies, Chinese inflation seems to still be much more volatile(Figure 1.3). For instance, India had a similar pattern in the 1990s when its inflation rate shot up to some 10 percent before

entering a more stable period in the first half of the 2000s. One notable difference is that inflation rates in India picked up quickly again since 2005 while Chinese inflation became more subdued. However, reviewing the price changes over the entire study period, Chinese inflation outscores many other developing economies in terms of magnitudes and paces. Admittedly, when comparing to historical hyperinflation periods of some Latin American countries such as Argentina and Brazil, inflation in China is better controlled. But these hyperinflation periods were due to many other factors and should be treated as exceptions. Compare price changes in 'normal' periods makes more sense when conducting cross-country comparisons.

Figure 1.3: CPI Inflation in Major Developing Economies (Unit: YoY %)



Source:IMF.

Such high inflation volatility in China, to some extent, was due to shocks of large

magnitudes on both supply and demand sides. For example, the price surges in 2004 and 2008 were largely due to property bubbles. And hiking food and energy prices led to the latest peak in 2011.

The change of policy regimes is another important source of inflation volatility. It corresponds with three inflation cycles observed in post-reform data. When China began its economic reform in late 1970s, the price control of commodities in China loosened, starting in some industrial and agriculture goods. The direct effects included the price surges in commodities in early 1980s, and the pass-through to general consumer price levels. However, the central bank has not implemented measures to curb inflationary pressure in a timely fashion. When they realize the pressure, they tend to push it down sharply rather than smoothly (e.g. very tight credit control in 1986). That is why CPI increased, as well as decreased, very sharply within the first inflation cycle. In early 1992, as Xiaoping Deng decided to promote economic reforms, the credit control was loosened, echoed by the fact that M2 increased by more than 50% in 1993. When inflation reached 24.1% in 1994, monetary policy became tight again and persisted until the Asian Financial Crisis. That largely explains the price movement within the second inflation cycle. When the real economy is hit by the crisis with deflationary risk materializing, policy makers try to boost demand by using fiscal stimulus and more accommodative monetary measures.

Foreign exchange pass-through (FEPT) also has led to inflationary pressure, especially since 2001. Maintaining RMB exchange rate *vis-a-vis* US dollars within a certain range has always been one important policy goal for PBoC. When China had no or little trade surplus, as in the early years after the economic reform, the source of inflation was almost purely from domestic factors. However, when China's trade surplus rose, particulary since its entry to WTO in 2001, such sterilization policy increased Chinese money supply substantially, and in turn the aggregate consumer

price inflation.

Inflation seemed to moderate in the third cycle compared with the previous two, despite the newly introduced FEPT. One intuitive explanation for lower inflation volatility is the 'good luck.' Alternatively this reflects possible policy regime shifts. As reported in Zhang (2010), improved monetary policy accounts for only a small fraction of the reduction in inflation uncertainty from the pre-1997 period to the post-1997 period in China. The bulk of the significant moderation in inflation uncertainty arises from smaller shocks. This result is consistent with intellectual reasoning. PBoC does not have an inflation target, nor a medium term path of inflation. Hence when the magnitude of shocks rises sharply, Chinese inflation seems to change fairly quickly. One example is that when food and energy prices soared in the first half 2011, inflation quickly picked up. And when domestic demand slowed down afterwards, growth rates of CPI (year-over-year) declined from 6.5% in July 2011 to 1.8% in July 2012. One implication is that, as long as inflation is seconded by growth targets on PBoC's list, Chinese inflation is likely to remain volatile.

1.3 The Bottom-Up Approach: Retrieving Weights of CPI Components

A natural way to predict CPI inflation is to track price changes of each CPI component. These components provide better understanding of inflationary pressure, and how it evolves over time. For example, as in many other emerging economies, a hike in food price usually leads to an increase in overall price level. The effect sometimes could last for months. As a matter of fact, this bottom-up approach is one of the most commonly used methods in practice.

However, China does not release official weights of CPI components. Instead, the

official data include only year-over-year price changes of these components. Thus as the preliminary step, one needs to retrieve the weights of these CPI components. The OLS is an appropriate technique to do so. The aggregate inflation series is a weighted average of these CPI components. And all are stationary series.

To retrieve the weights, I ran the following OLS estimation:

$$Headline\ CPI_t = \sum_{i=1}^{8} \beta_i CPI\ Component_{it} + \epsilon_t \tag{1.1}$$

where i represents each of the 8 CPI components and β_i is the weight of component i in headline CPI. Both headline CPI and its components are in year-over-year growth rates. To explore the possible changes in weights over different time periods, I broke the entire sample period into two sub-sample periods: 2001–2005 and 2005–2012. The results are shown in Table 1.4.

From the above results we can see that food price accounts for almost one-third of CPI changes. Housing and recreation, education, and culture rank the second and the third largest drivers. Comparing two sub-sample periods with each other, after 2005 the weight of tobacco, liquor, and articles rises from 5.6% to 9.2%, and the weight of health care and personal articles reduces from over 10% to less than 3%. Residence price also becomes of more importance in calculating aggregate CPI. The fitted CPI is very close to the true data (*see* Figure 1.4), suggest this approach is meaningful.

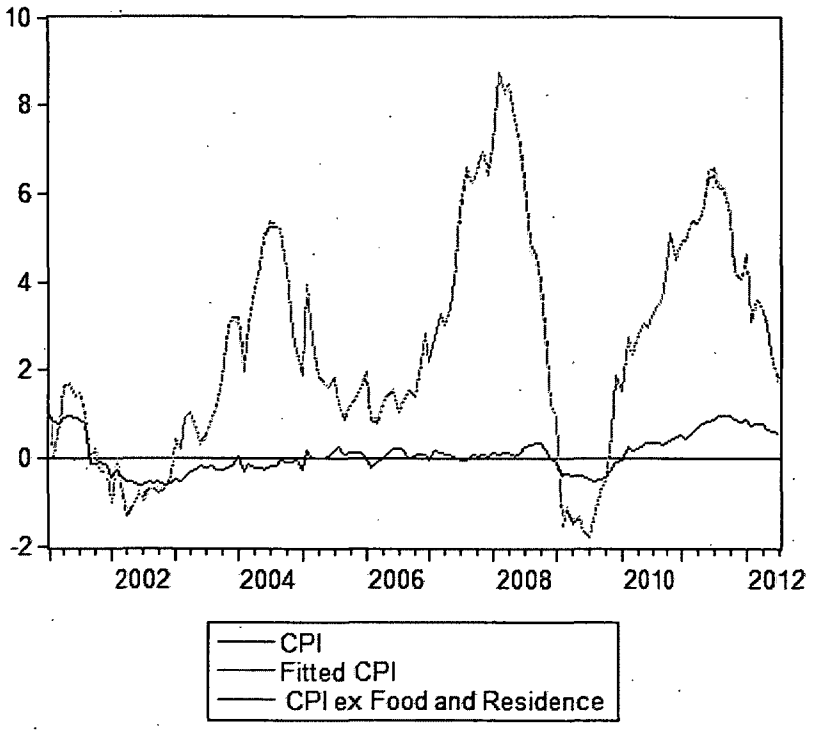
One benefit of retrieving the weights of CPI components, in terms of monetary policy transmission mechanism, is that the core CPI inflation, excluding the most volatile components, can be constructed. By excluding the two most components of CPI, food and residence, I construct the a less volatile consumer price inflation series. As shown in Figure 1.4, the 'core' CPI inflation seems to be significantly less volatile than original data.

Table 1.4: Retrieving Weights of CPI Components

Jan 2001–July 2012	Coefficient	Std. Error	t-Statistic	Prob.
FOOD	0.33	0.00	216.02	0.00
BEV	0.04	0.01	5.30	0.00
APP	0.08	0.01	14.48	0.00
HOME	0.05	0.01	8.50	0.00
HEALTH	0.08	0.00	16.10	0.00
TRANS	0.11	0.01	13.57	0.00
RECR	0.14	0.00	51.49	0.00
HOUS	0.15	0.00	62.68	0.00
Jan 2001–December 2005				
FOOD	0.33	0.00	125.98	0.00
BEV	0.06	0.02	2.79	0.00
APP	0.09	0.02	4.92	0.00
HOME	0.05	0.02	3.18	0.00
HEALTH	0.10	0.01	13.77	0.00
TRANS	0.09	0.01	7.06	0.00
RECR	0.14	0.00	50.29	0.00
HOUS	0.14	0.01	18.55	0.00
Jan 2006–July 2012				
FOOD	0.33	0.00	161.75	0.00
BEV	0.09	0.02	6.08	0.00
APP	0.06	0.01	9.43	0.00
HOME	0.04	0.01	3.64	0.00
HEALTH	0.03	0.01	1.77	0.08
TRANS	0.13	0.01	9.64	0.00
RECR	0.15	0.01	13.00	0.00
HOUS	0.16	0.00	34.64	0.00

Source: author's calculation.

Figure 1.4: True CPI, Fitted CPI and 'Core' CPI (unit: YoY %)



Source: National Statistics Bureau of China, author's calculation.

This has important implication to policy makers. Chinese monetary policy has been long criticized as being 'pig-led.' China is the largest pork consumer in the world, and pork is not easily substituted by other types of meat. When pork prices increases, the general food price is usually pushed up quickly and then the aggregate CPI (easily over 6%). PBoC, in this scenario, tends to react by tightening monetary policy. At the time raising pigs became so profitable that a vast investment was pouring into this business. And this was the potential of pork over-supply after six months or so when the monetary authority faces pressure to loosen monetary stance to offset the deflationary risk. The overall economy, in many cases, does not change during the course of such a 'pork cycle.' One important reason that PBoC wastes its

efforts in dealing with such price fluctuations is due to the lack of indicators of less volatile price measurement. Thus the index constructed by this chapter can serve as one of many candidates to measure fundamental consumer price levels which the central bank should respond to.

1.4 The Bottom-Up Approach: Forecasting Performance

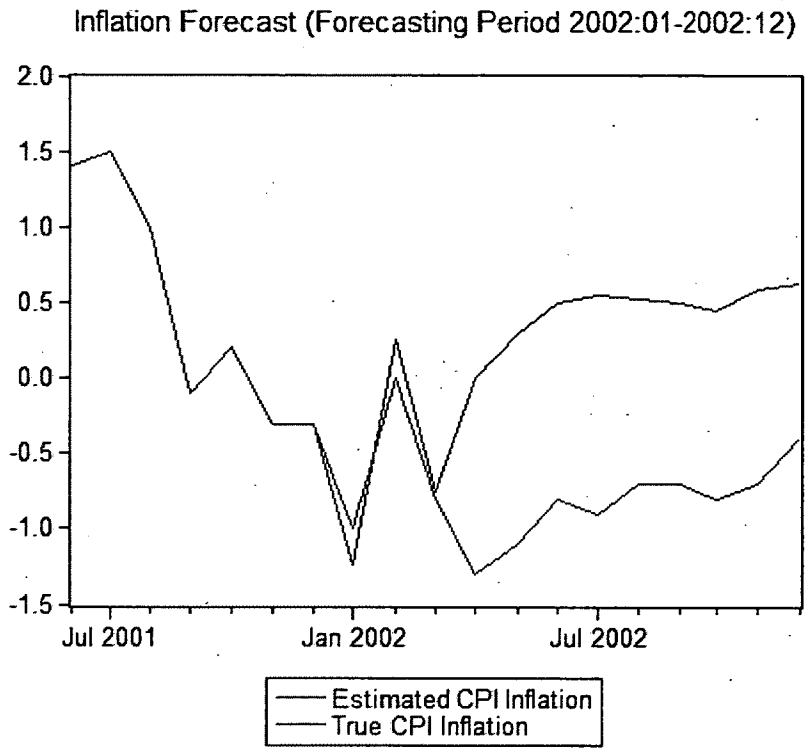
In terms of forecasting inflation, one natural way is to use high-frequency data (as mentioned, prices of grain, meat, fresh vegetables are updated every 5 days). By estimating the relative importance of these commodities to determine the path of future food prices, one can infer the monthly CPI inflation in light of the relative fixed fraction (one-third) of food in aggregate CPI.

Figures 1.5 and 1.6 show the estimated and the true CPI inflation rates in 2002 and 2009[2]. This bottom-up approach seems to predict the short-term CPI accurately (1 to 3 months ahead). However, it fails to predict inflation longer than 4 months. The longer the forecasting horizon the lower the accuracy. There are at least three possible reasons for the lack of power to forecast longer term inflation.

The first one is directly related to the weight of food in total CPI. In aforementioned tests, the proportion of food prices is relatively stable across both sub-sample periods. However, small variations of the weight can lead to relatively larger differences in estimated CPI inflation. The second reason comes from the high volatility of prices of some items in food. Pork prices, for instance, are notoriously difficult to

[2]Ideally it is worthwhile to comparing forecasts from the bottom-up approach to professional surveys. However such data for China are not publicly available.

Figure 1.5: Inflation Forecasts Using the Bottom-Up Approach: Year 2002 (unit: YoY %)



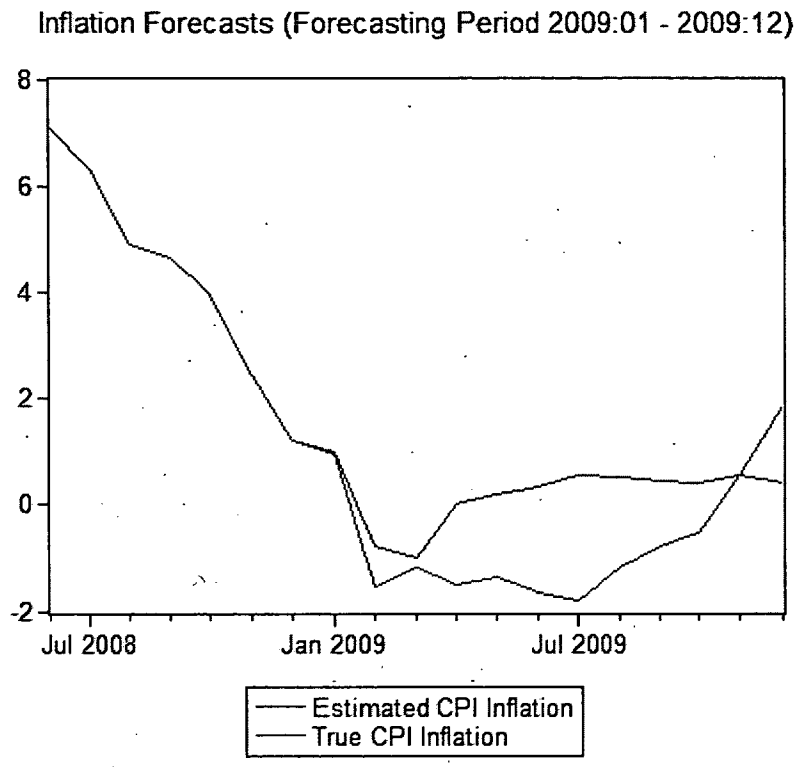
Source: National Statistics Bureau of China, author's calculation.

predict.[3]

The last but also the most important reason is that this method does not factor in policy interventions. As mentioned in previous sections, policies played important roles in driving Chinese inflation in the past. The effects of policies are more obvious in the medium run as it takes a few months before policies become effective. If this is correct, even in the short run the bottom-up approach works without policy indicators; in the medium to long run such approach should not perform well as it

[3]Much recent research, such as Gale, Marti and Hu (2012), confirms the cyclical behavior of the entire pork industry. Even if such cycles are identified and controlled, no empirical studies have been able to provide robust and accurate forecasts of pork prices in the medium run.

Figure 1.6: Inflation Forecasts Using the Bottom-Up Approach: Year 2009 (unit: YoY %)



Source: National Statistics Bureau of China, author's calculation.

misses probably the most important driving factor.

The bottom line here is that the bottom-up approach should be used only for predicting short-term inflation developments, but as to longer term forecasting, which is more relevant to policy makers, alternative ways are worth exploring. Two natural candidates are the time series approach and model approach. These two are the most commonly used ones in many other central banks. Besides the choices of forecasting techniques, another interesting question is whether there are better ways to forecast inflation in economic crises, as the normal robust links between prices and other macroeconomic variables, used in both time series and model approaches, may cease

to exist. I document the details in the next three chapters of this dissertation.

This result echoes similar studies for some other economies. Bernanke summarizes the benefit of using the bottom-up approach to forecast inflation in near term. But in longer time, he believes other approaches seem to be more appropriate (Bernanke 2007). Duarte and Rua (2005) find that inflation forecasts using bottom-up approach outperform aggregate forecasting only up to a five-months-ahead horizon. Jakaitiene and Dees (2009) also report better out-of-sample price forecasts in a short forecasting horizon.

Chapter 2

Forecasting Inflation in China: A Comparison of Time Series Models

Abstract

As shown in the previous chapter, the commonly used bottom-up approach cannot produce accurate medium- to long-run inflation forecasts in China. One natural extension is to turn to time series models. However, the conventional unemployment rate Phillips Curve model is not applicable due to the lack of accurate unemployment data. Thus in this chapter I evaluate the inflation forecast performance of various time series models with other macroeconomic variables. My contributions are threefold. Firstly, some time series methods have been used to analyze responses to policy shocks in China but not for inflation forecast purposes. Also some relatively new techniques have not been applied to China, yet I find that at least a few nonparametric techniques such as the artificial neural network model have great potential in forecasting Chinese inflation in the longer horizon. Secondly, multivariate models seem to provide better inflation forecasts than univariate ones. And last but not least, monetary aggregates are less informative than short-term interest rates. Results of this chapter can be treated as the benchmark to explore the forecast performances of theory-based techniques (e.g. inflation forecasts of DSGE models).

Keywords: Inflation Forecasting, VAR, VECM, Bayesian methods, Nonparametric methods, Neural Network, China.

2.1 Introduction

As shown in the previous chapter, the commonly used bottom-up approach cannot produce good inflation forecasts in the medium to long run. Time series models, which have been applied extensively, are natural alternative methods on this issue.

The conventional unemployment rate Phillips Curve seems to produce more accurate inflation forecasts in the US. Detailed discussions have been documented in Stock and Watson (1999). However, this approach is not appropriate when applied to China. China does not have robust unemployment data so far. The official unemployment rates of urban areas are based on self-reports of unemployed people. Without linking to unemployment benefits as in many developed countries, the quality of official unemployment rate is highly doubtful. The official unemployment rate was around 4% even when the economy slowed down in the 3rd quarter of 2012, which contradicted many other measures of Chinese labor market conditions.

Lots of existing studies use time series techniques with other macroeconomic variables for forecasting inflation in major economies. Mitra and Rashid (1996) compare the inflation forecasts of several time series models in Canada. They found that in the short run the univariate technique performs better and so does the multivariate models in the long run. Moser, Rumler and Scharler (2007) forecast Australian HCPI inflation using Bayesian VAR, VAR, and ARIMA models, as well as the factor models proposed in Stock and Watson (1999). The authors suggest the best way is to aggregate sub-indices than forecasting inflation itself. Similar results are found in France. (Bruneau, De Bandt, Flageollet and Michaux 2007). Canova (2007) analyzes data in G7 countries and concludes that bivariate and trivariate models suggested by economic theory or statistical analysis are not much better than univariate ones in forecasting inflation. A VECM framework is used in Duasa, Ahmad, Ibrahim and Zainal (2010) to forecast inflation in Malaysia. The authors also find that an

aggregation of indices improves the accuracy of inflation forecasts. Nonparametric models, such as the neural network regime switching model, are used in McNelis and Yoshino (2005) to analyze the deflation in Japan. The authors claim the nonparametric technique is superior to linear parametric ones.

Many of the aforementioned time series techniques have been applied to study Chinese inflation. For instance, Lütkepohl and Krätzig, eds (2005) comprehensively study the inflation dynamics in China. The authors show the clear causality between money and inflation. This study implies that money supply should be informative in forecasting Chinese inflation. Some studies (Mehrotra, Peltonen and Santos-Rivera 2010) use provincial data and find that the New Keynesian Phillips Curve model provides reasonable inflation processes only in the coastal provinces.

However, few studies applied these techniques to inflation forecasts *per se*. One exception is Mehrotra and Sánchez-Fung (2008), where multivariate time series models, the Phillips Curve ones, and principal component models outperform single-variable approaches. However, there are a few caveats of this model. Models in this chapter using the unemployment rate Phillips Curve and principal component extraction produce only marginally better inflation forecasts than univariate ones. The possible problem is the poor quality of unemployment data and the limited number of variables available for principal component analysis. Many similar studies for developed countries usually have around 100 series. In general it is troublesome to apply factor analysis to China due to the data issues at this stage. For instance, more than two-thirds of monthly Chinese macroeconomic indicators going back to early 2000s are price related. The factors extracted from this type of analysis are very much price biased and fail to generate better forecast accuracy. More importantly, many new time series techniques are not explored in Mehrotra and Sánchez-Fung (2008).

In this chapter I apply the commonly used econometric techniques, including the

Bayesian techniques and nonparametric models, to forecasting CPI inflation in China and assess the forecasting performance, in various forecasting horizons, of these techniques. The main findings are that monetary aggregates are more informative than short-term interest rates; that multivariate time series models produce the same forecasting accuracy as the univariate ones; and that some nonparametric techniques have good potential in forecasting inflation rates in the longer horizon. Results are informative and can be easily compared with other model-based forecasting techniques, for instance, inflation forecasts from dynamic stochastic general equilibrium (DSGE) models.

The rest of the chapter is organized as follows: Section 2.2 describes the methodology of the econometric techniques used for forecasting, including univariate, multivariate, Bayesian, and nonparametric approaches. The accuracy of these inflation forecasts is assessed in Section 2.3. And Section 2.4 concludes.

2.2 Methodology

Relevant monthly Chinese data series until the end of 2009 have been analyzed by using a few econometric techniques. Then I derive the inflation forecasts for Year 2010 from each technique. These forecasts are treated as out-of-sample forecasts and are compared with the true Chinese inflation rates in 2010.

Using the simple 'eyeball' approach, a structural break seems to exist around 1997, when Chinese inflation rates have been trimmed from the pervious very high levels. Many other studies have confirmed the existence of the structural breaks. For instance, Kojima, Nakamura and Ohyama (2005) mention the policy changes such as market mechanism introduced by Chinese government which affects inflation dynamics since then. One structural break is identified in Zhang and Pang (2008).

The authors claim that the inflation dynamics differ substantially before and after 1997. Dickenson and Liu (2007) argue that 1997 was the time when there was a concerted change in the behavior of the banking sector, with the central bank adopting more indirect monetary control methods. To avoid the bias introduced by possible structural breaks, I choose the data after 1997 for estimation.

Monthly data of CPI inflation, M1, M2, and foreign reserves from January 1997 to December 2010 were obtained from IMF's *International Financial Statistics*. Industrial output, M0, and the seven-day repo rate (end-of-month value) of the same periods are from the *Wind Information*, which collects data from the China Monthly Statistics.[1] Computer packages used include Eviews, JMULTI, and Matlab.

2.2.1 Univariate Approaches

ARIMA (autoregressive integrated moving average) models may be the most commonly applied univariate methods to forecast time series. Three tools are used to model the serial correlation in the disturbance of the series.

The autoregressive, or AR, terms are the first tool. Each AR term corresponds to a lagged values of the residual in the forecasting equation for the unconditional residual. AR(p) stands for an autoregressive model of order p, which takes the form of

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \cdots + \rho_p u_{t-p} + \epsilon_t \tag{2.1}$$

The second tool is the integration term. Each integration order corresponds to differencing the series being forecast. Let d be the order of the integration.

[1] Industrial output, repo, and inflation are seasonally adjusted by using the census X12 method.

The third tool is the moving average, or MA term. A moving average forecasting model uses lagged values of the forecast error to improve the current forecast. An MA(q) takes the form

$$u_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \tag{2.2}$$

In general ARIMA(p, d, q) means a model with autoregressive of order p, integration of order d, and moving average of order q. Although the ARIMA theory is about the residuals from regression models, the specification also is applied directly to a series by econometricians as an univariate model, specifying the conditional mean of the series as a constant, and measuring the residuals as differences of the series from its mean. More details have been discussed in Carnot, Koen and Tissot, eds (2004).

Optimal lags are selected following the Hanna–Rissanen model (Hanna and Rissanen 1982). I use the inflation data from 1997M1 to 2009M12 to identify the optimal values of p, d, and q. The unit root test suggests that inflation is I(0) so that $d = 0$. Both the Hannan–Quinn and Schwarz criteria suggest that $p = 2$ and $q = 0$. Alternatively the Akaike Info Criterion suggests that $p = 2$ and $q = 2$. Thus inflation between 1997 and 2009 should be either AR(2) or ARIMA(2, 0, 2). I compute the inflation forecasts using both specifications, shown in Table 2.1. The true Chinese CPI inflation data in 2010 are shown in the same table for comparison purpose.

The AR(2) model under-forecasts the inflation for all the forecasting periods except the one-month-ahead forecast, while ARIMA$(2, 0, 2)$ over-forecasts inflation rates for the first eight forecasting periods. In general ARIMA$(2, 0, 2)$ seems to outperform the inflation forecasts from AR(2).

Table 2.1: Inflation Forecasts—ARIMA

Horizon	True Data	AR(2)	ARIMA(2, 0, 2)
1	1.790	2.190	2.329
2	2.471	2.180	2.718
3	2.376	2.143	3.030
4	2.765	2.105	3.265
5	3.034	2.069	3.430
6	2.981	2.035	3.529
7	3.287	2.002	3.569
8	3.500	1.971	3.556
9	3.616	1.944	3.497
10	4.388	1.917	3.400
11	4.963	1.892	3.272
12	4.738	1.868	3.120

Source: National Statistics Bureau of China, author's calculation.

2.2.2 Vector Autoregressive Models

Vector autoregressive, or VAR models, have been widely applied to study the relationship of several variables simultaneously. Sims (1980) specifies a VAR model to analyze US monetary policy by looking a few closely related macroeconomic variables. After that, VAR models have been used as the benchmark multivariate technique to explore issues in many fields including the forecasts of macroeconomic variables.

The following equation has been estimated:

$$Z_t = C + \sum_{i=1}^{j} A_i Z_{t-j} + V_t \tag{2.3}$$

where Z_t is a vector of endogenous variables, C is a vector of constants and V_t is assumed to be identically independently distributed (i.i.d.), such that the system's primitive shocks are uncorrelated with each shock. Z_t includes the following four variables: industrial output, CPI, foreign reserves, and monetary policy instrument. The variables are placed in this order, because monetary policy actions are assumed to react to information about output and price at the current month, and should have impact on these variables for the next month. Price is placed after output, because inflation is assumed to be influenced mainly through the output gap. Foreign reserves is an important variable in that it also captures part of the monetary policy in China. If not sterilized, foreign exchange inflows result in an increase in the money supply of a country with a fixed exchange rate. Given the sheer size of the recent influx of foreign capital, it would be most interesting to see whether such increase in foreign reserves would have an impact on money supply, i.e. whether sterilization was successful, and the subsequent impact on real economic activities.

I experimented with two types of monetary policy instruments: monetary aggregates and short-term interest rates. Monetary aggregates are traditionally the monetary instrument used by the People's Bank of China (PBoC). In the 1980s and most of the 1990s, China's monetary policy was targeted at the money supply. According to Yu (2001), it was only in the last quarter of 1999 that the central bank stopped targeting the growth rate of M2, due to infertile efforts to boost inflation at the end of the 1990s. M1 and M2 are also common policy instruments in earlier literature (Christiano, Eichenbaum and Evans 1999). However, short-term interest rates are widely used as the monetary policy instrument for developed economies. Although the importance of such variables is not clear in China, nominal interest rates such as China Interbank Offer Rate (CHIBOR) and the repo rate have been increasingly adopted by PBoC as the monetary policy instruments in recent years. Furthermore, the market interest rate in China still does not reflect the overall cost of borrowing in the economy. Many rates faced by depositors and lenders are still determined directly by the PBoC. The four VARs, denoting as VAR1 to VAR4, are associated with M0, M1, M2, and 7-day repo rate, respectively, as the monetary policy instrument.

The unit root test shows that all above mentioned variables, except CPI inflation and repo rate, are integrated of order one. Here I apply the Phillips–Perron (1988) and the Augmented Dicky Fuller (1979) unit root tests. Since VAR requires stationary series, the first differences of all I(1) series are used in VAR models. CPI inflation and repo rate are in levels. Alternatively, Vector Error Correction Models (VECMs) are used with the level of each series studied. The details of VECMs are reported in the VECM section.

The optimal number of lags, p, is chosen with the help of model selection criteria. Here I look at the following commonly used criteria: Akaike Information Criterion

(AIC), Hanna–Quinn Criterion (HQ), Final Prediction Error (FPE), Schwarz Information Criterion (SC), and sequential modeled LR test statistics (LR). In this case the optimal lag equals four.[2]

The forecasts are based on conditional expectations and the assumption of white noise V_t. An h step of forecast at period T is

$$Z_{T+h|T} = \sum_{i=1}^{p} A_i Z_{T+h-i} + V_{T+h} \tag{2.4}$$

The forecasts start recursively from $h = 1, 2, \ldots$. The inflation forecasts of the four VAR models are reported in Table 2.2, with the actual data for comparison purposes.

Table 2.2: Inflation Forecasts—VARs

Horizon	True Data	VAR1	VAR2	VAR3	VAR4
1	1.790	1.897	2.462	2.344	2.461
2	2.471	1.815	2.510	2.457	2.612
3	2.376	1.780	2.300	2.465	2.778
4	2.765	1.745	2.132	2.456	3.228
5	3.034	1.712	1.999	2.496	3.280
6	2.981	1.686	1.923	2.403	3.274
7	3.287	1.660	1.868	2.337	3.235
8	3.500	1.636	1.814	2.221	3.146
9	3.616	1.614	1.771	2.099	3.070
10	4.388	1.592	1.737	2.008	2.995
11	4.963	1.571	1.706	1.921	2.843
12	4.738	1.552	1.675	1.848	2.742

Source: National Statistics Bureau of China, author's calculation.

[2]Results of lag selection are different using various selection criteria. Here three out the five criteria suggest the optimal number of lags should be four.

VARs with M0 and M1 turn out to under-forecast inflation except for the first quarter. The VAR with M2 produces over-forecasts for the first half of the forecast horizon and under-forecasts for the rest half. The four-quarters-ahead forecasts are less accurate comparing to ARIMA$(2, 0, 2)$.

2.2.3 Vector Error Correction Models

As suggested in Enders, ed (2004), a VECM may lead to a better understanding of the nature of nonstationary series and can also improve long-term irresistibility over an unconstrained model such a VAR. Following Engle and Granger (1987),[**AU: Add to ref. list.**] the cointegration is defined as if the linear combination of nonstationary variables is stationary.

The VECM(p) takes form of

$$\Delta Z_t = A + BZ_{t-1} + \sum_{i=1}^{p-1} \Delta Z_{t-i} + V_t \tag{2.5}$$

where Δ is the differencing operator and V_t is the assumed to be i.i.d.

I conducted the Johansen–Juselius (1990) system cointegration tests to the four VARs with different policy instrument variables. The test results suggest that there are two cointegrating vectors and thus I specify the VECMs with two cointegrating vectors as follows. The lag selection and the computation of inflation forecasts are similar to the VAR models. The results are shown in Table 2.3.

The forecasts from the four VECMs are much closer to the actual data, compared to the corresponding VARs. Again, models with monetary aggregates as the policy instrument seem to provide more accurate inflation forecasts comparing to the one with short-term interest rates.

Table 2.3: Inflation Forecasts—VECMs

Horizon	True Data	VECM1	VECM2	VECM3	VECM4
1	1.790	2.299	2.335	2.325	2.350
2	2.471	2.372	2.403	2.513	2.510
3	2.376	2.387	2.429	2.835	2.787
4	2.765	2.399	2.460	3.100	3.173
5	3.034	2.414	2.487	3.296	3.200
6	2.981	2.427	2.513	3.410	3.311
7	3.287	2.439	2.539	3.452	3.401
8	3.500	2.450	2.563	3.546	3.353
9	3.616	2.460	2.587	3.604	3.440
10	4.388	2.469	2.610	3.648	3.499
11	4.963	2.478	2.632	3.709	3.467
12	4.738	2.485	2.653	3.730	3.513

Source: National Statistics Bureau of China, author's calculation.

2.2.4 Bayesian VARs

A Bayesian approach to vector autoregressions has in particular been put forward by Doan, Litterman and Sims (1984).Unconstrained VARs have been long criticized for not factoring in any theory in the choice of variables included. BVARs estimated unconstrained VARs using Bayesian techniques that contain any prior information for the modeler. The forecast performance can be improved from this aspect. Many studies show that BVARs produce better forecasts in some macroeconomic variables such as output and employment, particularly in the long run. However, BVAR models are less impressive in forecasting inflation. There are a few exceptions. Artist and Zhang (1990) use BVAR to forecast inflation for the G7 countries. For most countries the inflation forecasts are as accurate as output and employment forecasts. Alvarez, Ballabriga and Jareno (1998) forecast Spanish inflation using the BVAR framework. The authors find that the multivariate BVAR model is superior to unconstrained VAR and the univariate BVAR in terms of forecasting inflation. Kenny, Meyler and Quinn (1998) also find that the Bayesian technique has improved the accuracy of Irish inflation forecasts. In light of these studies I construct the BVAR models from the perspective of forecasting Chinese inflation.

Koop and Korobilis (2009) provide some details about using Matlab to estimate BVARs and how to compute the forecasts and impulse response functions. In short, first let me rewrite Equation 2.3 in vector form:

$$Z_t = X_t A + V_t; \; V_t \sim N(0, \Sigma). \tag{2.6}$$

This is equivalent to

$$z_t = (I_M \bigotimes X_t)\alpha + V_t \tag{2.7}$$

or

$$z_t = Y_t\alpha + V_t \tag{2.8}$$

In literature there are many types of priors have been used in BVARs. Here I focus on the two most widely used priors: the Diffusion or the Jeffrey's Prior and the Minnesota Prior. The former relaxes some restrictions of the latter.

The Diffusion Prior for α and Σ takes the form of

$$p(\alpha, \Sigma) \propto |\Sigma|^{-(M+1)/2} \tag{2.9}$$

The associated conditional posterior are

$$\alpha|\Sigma, z \sim N(\hat{\alpha}, \Sigma) \tag{2.10}$$

And,

$$\Sigma|z \sim IW(\hat{S}, T-K) \tag{2.11}$$

where S is the sum squared error of the VAR, T is the number of observations, and K is the number of lags.

The Minnesota Prior, first introduced in Litterman (1986),is a commonly used way to account for the near non-stationarity of some macroeconomic time series. In other words, these variables are assumed to follow patterns similar to random walk processes. At the same time, it helps to weakly reduce the dimensionality of a VAR model. The prior mean of the VAR coefficients on the first own lag is set equal to one and the mean of remaining coefficients is equal to zero. Also the covariance matrix is assumed to be diagonal. The variance-covariance matrix of the coefficient is assumed

to be fixed and known. To be specific, α in above equations is still assumed to be normal and Σ is assumed to be known. The restriction is mainly on hyperparameter of α. Comparing these two types of priors, two restrictions in the Minnesota Prior are relaxed in the Diffusion Prior, namely the posterior independence between equations and the fixed residual variance-covariance matrix.

The inflation forecasts of BVARs are presented in Table 2.4. BVAR1 to BVAR4 are the ones with the Diffusion Prior, using repo, M0, M1, and M2 as policy instruments, respectively. And the remaining four are with the Minnesota Prior. In general BVARs do not improve the forecastability over standard VARs. The forecasts seem to get closer to the actual data in the 12-months-ahead forecast, comparing to short forecasting horizons. Interestingly enough, many counterfactual deflationary periods are predicted by BVARs.

2.2.5 Nonparametric Techniques

Since the inflation rates seem to have nonlinearity properties, as seen in Figure 1.1, some nonparametric techniques have been applied to forecast Chinese CPI inflation, namely the Heteroskedastic Nonlinear Autoregressive (NAR) model, the Seasonally Nonlinear Autoregressive (SNAR) model, and the Artificial Neural Network (ANN) model.

Heteroskedastic Nonlinear Autoregressive Model

A stochastic process of Z_t is generated by the following equation:

$$Z_t = \mu(X_t) + \sigma(X_t)\xi_t \tag{2.12}$$

where $X_t = (Z_{t-i_1}, Z_{t-i_2}, \ldots, Z_{t-i_m})'$, and ξ_t is random with zero mean and unit variance. The functions $\mu(X_t)$ and $\sigma(X_t)$ denote the conditional mean and volatility

Table 2.4: Inflation Forecasts—Bayesian VARs

Horizon	True Data	BVAR1	BVAR2	BVAR3	BVAR4
1	1.790	0.838	0.817	0.838	0.801
2	2.471	0.169	0.109	0.154	0.090
3	2.376	0.214	0.161	0.087	0.034
4	2.765	−0.344	−0.286	−0.488	−0.476
5	3.034	−1.001	−0.962	−1.343	−1.306
6	2.981	−0.469	−0.403	−0.574	−0.607
7	3.287	0.740	0.753	0.517	0.514
8	3.500	−0.570	−0.365	−0.983	−0.808
9	3.616	−0.382	−0.172	−1.149	−0.915
10	4.388	1.142	1.258	0.541	0.676
11	4.963	1.488	1.670	0.640	0.905
12	4.739	3.043	3.094	2.053	2.239
Horizon	True Data	BVAR5	BVAR6	BVAR7	BVAR8
1	1.790	1.052	0.978	0.742	0.734
2	2.471	0.266	0.158	0.215	0.145
3	2.376	0.185	0.078	0.163	0.104
4	2.765	−0.253	−0.294	−0.578	−0.544
5	3.034	−1.002	−1.056	−1.260	−1.240
6	2.981	−0.229	−0.291	−0.463	−0.544
7	3.287	0.741	0.614	1.037	0.834
8	3.500	−0.548	−0.518	−0.423	−0.401
9	3.615	0.688	0.473	−0.554	−0.482
10	4.387	1.125	1.248	0.589	0.763
11	4.963	0.706	0.947	0.496	0.807
12	4.738	1.938	2.203	1.998	2.219

Source: National Statistics Bureau of China, author's calculation.

function, respectively. The asymptotic properties of nonparametric estimation and lag selection methods for the conditional mean function have been derived only for the case that the lag vector of $\sigma(X_t)$ is a subvector of the lag vector of the conditional mean function. The inflation forecasts using NAR model are shown in Table 2.5.

Seasonally Nonlinear Autoregressive Model

To address the possible issue of seasonality, the time index t can be replaced by $t = s + S\tau$, where $s = 1, 2, \ldots, S$ denotes the season and $\tau = 0, 1, \ldots$. Then the estimation equation becomes

$$Z_{s+S\tau} = \mu_s(X_{s+S\tau}) + \sigma_s(X_{s+S\tau})\xi_{s+S\tau} \tag{2.13}$$

The inflation forecasts using SNAR model are shown in Table 2.5.

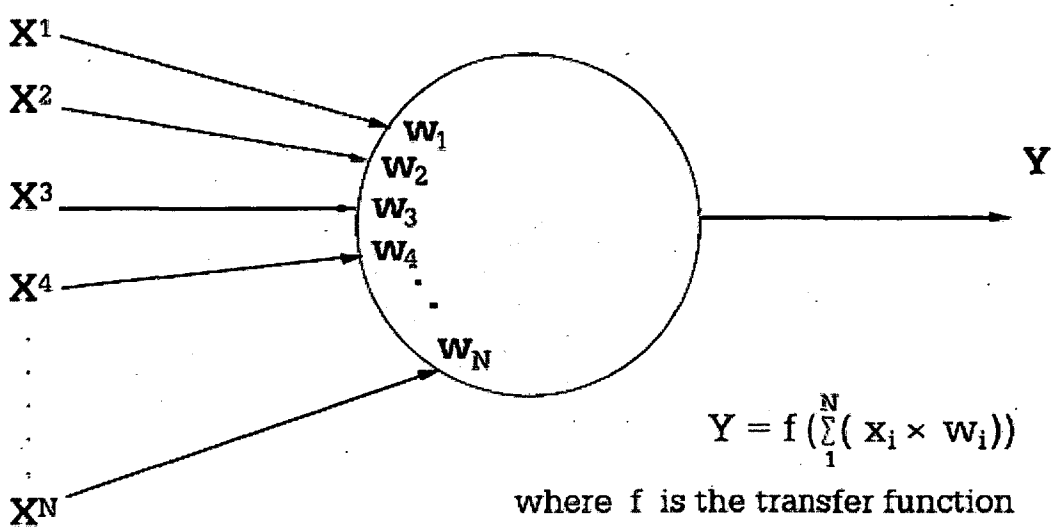
Artificial Neural Network Model

The neural network has been used in medicine and robots for years. Recently this technique has been introduced to forecast economic and financial indicators. It is useful for nonlinear process that have an unknown function (Enders, ed 2004).

ANN has several nodes or neurons, the basic unit that sums inputs from various resources and then processes the information. Figure 2.1 shows how a typical node works. One node takes information from a database or other nodes, modified with weights associated to each input source. These inputs are aggregated by the inputs and the weights and then transferred to determine the final output.

Nodes are usually arranged in several layers as in Figure 2.2. The layers include at least the input, output, and hidden ones. The input nodes can be the independent variables and the output node is treated as the dependent variable. The hidden nodes

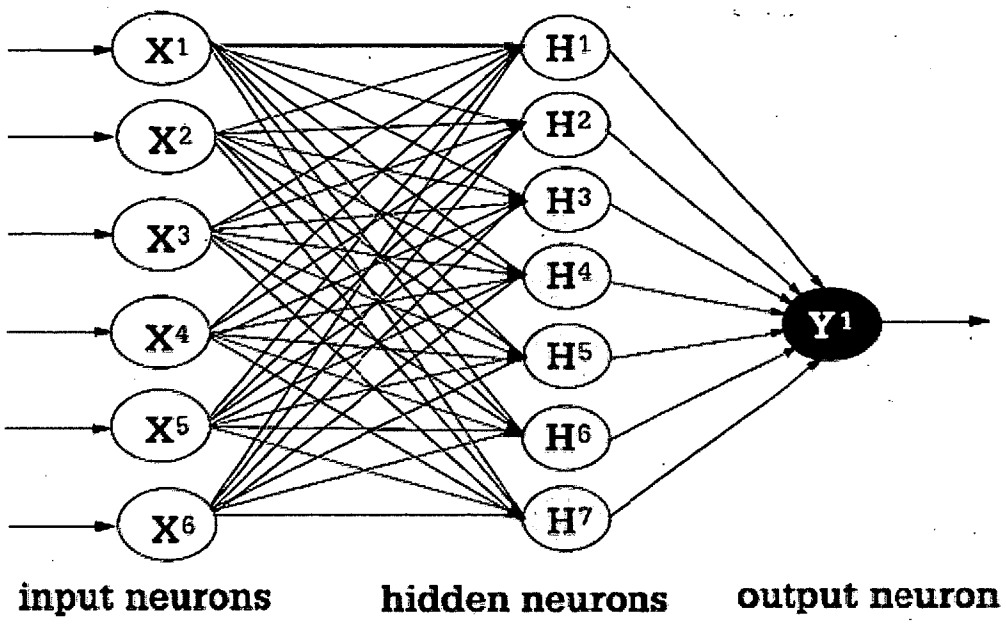
Figure 2.1: A Typical Node



capture the relationship between independent and dependent variables. Each hidden node receives signals or information from X1 to X6, each node in the input layer. After the receipt of the signals, all the information is processed in each hidden nodes, usually in a nonlinear way, determined by the input value and the associated weights. The final output is the aggregation of output passed through from each hidden node.

Training rules are important for ANN models. The ANN needs to learn from some examples, say the first few periods of the data. During this training process, the model is able to find a series of connective weighting among the layers that minimize the errors between the model's output and the true number at each point of the time. If the error is small enough, no changes are made about the weights. If the error is big enough then the weights are adjusted through the training algorithm.

Figure 2.2: Layers



Mathematically, the simple form of an ANN model can be

$$Z_t = A_0 + A_1 Z_{t-1} + \sum_{i=1}^{N} A_i f_i(Z_{t-i}) + \epsilon_t \tag{2.14}$$

In this chapter I choose the two hidden layers, 80% of the observation as the training set with 10% learning rate. The forecasts using ANN model are shown in Table 2.5.

The SNAR and the ANN are the only techniques tested that correctly predict inflation above 4 percent, as seen in the last quarter of 2010. Forecasts in the first few periods of all three nonparametric methods are far from the actual data.

Table 2.5: Inflation Forecasts—Nonparametric Models

	True Data	NAR	SNAR	ANN
1	1.790	0.539	0.647	0.206
2	2.471	0.183	-0.078	0.332
3	2.376	0.220	0.108	0.831
4	2.765	0.568	0.387	1.167
5	3.033	0.860	0.756	1.850
6	2.981	1.531	1.663	3.158
7	3.287	4.564	1.316	3.238
8	3.499	2.344	4.749	3.175
9	3.615	3.048	0.453	2.136
10	4.387	1.313	3.762	3.015
11	4.963	2.960	2.105	3.801
12	4.738	3.343	4.067	4.373

Source: National Statistics Bureau of China, author's calculation.

2.3 Forecasting Performance

The accuracy of the inflation forecasts stemmed from the above mentioned approaches is measured by the associated Root Mean Squared Errors (RMSEs). The other two commonly used summary statistics, the mean error (ME) and the mean absolute error (MAE), are less informative in assessing the forecast accuracy, as stated in Lütkepohl and Krätzig, eds (2005).

Let E_t be the forecast error in period t.[3] ME stands for the average of the forecast errors of all forecasting periods. $ME = \sum_1^T E_t/T$. ME equals zero if forecasts are one hundred percent accurate. The problem is that it says little about the forecast variance. A small ME can indicate more accurate forecasts, but it can also stand for large forecast errors where the over- and underestimates offset each other. MAE and RMSE or MSE (Mean Squared Error) clear this ambiguity. MAE is the average of the absolute values of forecast errors of each forecasting period. $MAE = \sum_1^T |E_T|/T$. RMSE is the square root of the average of squared errors. $RMSE = 1/T \sum_1^T E_t^2$. RMSE is preferred to MAE in that it is more sensitive to outliers, which is very important to forecasts (Lütkepohl and Krätzig, eds 2005).

Here I compute the RMSEs for forecast horizons from one to twelve periods.[4] RMSEs are summarized in Tables 2.6 to 2.10.

Table 2.6 suggests that AR(2) is outperformed by ARIMA$(2, 0, 2)$ in forecasting inflation except in the one quarter. The latter provides more accurate forecasts in the longer forecasting horizon. To be specific, the three-quarters-ahead inflation forecasts are the closest to the actual inflation data, comparing with other forecasting horizons.

RMSEs from the four VAR models are listed in Table 2.7. In general monetary

[3] $E_t = \hat{X}_t - X_t$, where X_t and $\hat{X}_t$ are the true value and the forecast value in period t.

[4] The MEs and MAEs are also computed but they are not used for assessing the forecast accuracy in this chapter.

Table 2.6: RMSE—ARIMA

Horizon	AR(2)	ARIMA(2, 0, 2)
1	0.399	0.538
2	0.349	0.418
3	0.315	0.509
4	0.428	0.506
5	0.577	0.486
6	0.653	0.497
7	0.775	0.472
8	0.904	0.442
9	1.018	0.419
10	1.242	0.505
11	1.504	0.701
12	1.661	0.818

Note: RMSE statistics for different forecast horizons. Lower value means more accurate forecast.

Table 2.7: RMSE—VARs

Horizon	VAR1	VAR2	VAR3	VAR4
1	0.106	0.671	0.553	0.670
2	0.470	0.475	0.391	0.484
3	0.515	0.390	0.323	0.458
4	0.677	0.463	0.320	0.459
5	0.846	0.621	0.373	0.425
6	0.936	0.713	0.414	0.406
7	1.063	0.850	0.526	0.376
8	1.192	0.994	0.668	0.374
9	1.307	1.121	0.807	0.396
10	1.523	1.354	1.073	0.579
11	1.776	1.622	1.374	0.844
12	1.933	1.787	1.558	0.993

Note: RMSE statistics for different forecast horizons. Lower value means more accurate forecast.

aggregates seem to be less informative than short-term interest rates in forecasting twelve-months-ahead inflation rates. In the short term, from one to six months, the VAR model with M2 produces better inflation forecasts. In the longer term, from three to four quarters, most accurate inflation forecasts are computed from the VAR model with repo rate. SM0 does not seem to be very informative. The VAR model with 7-day repo rate performs as well as ARIMA$(2, 0, 2)$ in most of the forecast periods.

Table 2.8: RMSE—VECMs

Horizon	VECM1	VECM2	VECM3	VECM4
1	0.508	0.545	0.534	0.559
2	0.366	0.388	0.379	0.396
3	0.299	0.318	0.407	0.401
4	0.317	0.315	0.390	0.403
5	0.396	0.373	0.368	0.368
6	0.427	0.390	0.379	0.361
7	0.509	0.459	0.356	0.337
8	0.603	0.542	0.333	0.320
9	0.687	0.615	0.314	0.307
10	0.890	0.810	0.379	0.405
11	1.132	1.044	0.523	0.594
12	1.264	1.167	0.579	0.669

Note: RMSE statistics for different forecast horizons. Lower value means more accurate forecast.

Similar to the results of the VARs, VECMs with M1 and M2 underperform the one with repo rate when the forecasting horizons are more than six months. M0 becomes more informative than in the VAR framework in the short run. In general VECMs produce better forecasts than other multivariate techniques. The magnitude

of RMSEs, especially in terms of the longer horizon inflation forecasts, seems to be superior to univariate time series models.

BVARs do not provide reasonable inflation forecasts. The RMSEs are much higher than the ones in VARs and VECMs. The choice of various priors seem to have little effect on forecasting performances.

Nonparametric techniques do not provide better inflation forecasts over the whole forecasting horizon either. This can be driven by the poor forecasts in the first few forecasting periods. The ANN model makes much better predicted inflation in the last quarter, superior to the ones with M1 and M2. The RMSEs are also comparable. It seems that the longer the forecasting horizons, the more comparable inflation forecasting performance that the ANN model can generate.

2.4 Conclusion

Chinese inflation has been very volatile in the last two decades, unlike most other major economies in the world. Since forecasting is one of the most important aspect of empirical analysis, such high volatility makes the inflation forecasting a challenging work in China. Using monthly data since 1997, when the inflation rates became more stable, I applied a number of time series techniques to find the best model in forecasting Chinese inflation. These techniques include univariate models, multivariate models, the Bayesian techniques, and some nonparametric methods. Some of these techniques have not been previously used for the purpose of inflation forecasts.

There are three main findings. Firstly, some nonparametric techniques with certain training rules, such as the artificial neural network model, seem to have good potential in longer term inflation forecasting. The forecasts from the ANN model are quite off the true data in the first few forecasting periods. Forecasting errors drop

Table 2.9: RMSE—BVARs

Horizon	BVAR1	BVAR2	BVAR3	BVAR4
1	0.952	0.972	0.952	0.989
2	1.761	1.806	1.771	1.823
3	1.904	1.952	1.959	2.011
4	2.266	2.277	2.350	2.379
5	2.714	2.709	2.872	2.880
6	2.850	2.833	2.996	3.009
7	2.808	2.792	2.965	2.977
8	2.995	2.948	3.194	3.174
9	3.122	3.052	3.405	3.352
10	3.135	3.060	3.451	3.389
11	3.167	3.082	3.540	3.456
12	3.072	2.989	3.476	3.386
Horizon	BVAR5	BVAR6	BVAR7	BVAR8
1	0.738	0.812	1.047	1.056
2	1.644	1.733	1.759	1.806
3	1.844	1.939	1.922	1.973
4	2.197	2.271	2.359	2.378
5	2.668	2.734	2.853	2.860
6	2.766	2.831	2.960	2.981
7	2.735	2.809	2.869	2.911
8	2.932	2.987	3.021	3.053
9	2.931	3.004	3.169	3.186
10	2.966	3.018	3.237	3.232
11	3.106	3.122	3.368	3.327
12	3.081	3.077	3.320	3.267

Note: RMSE statistics for different forecast horizons. Lower value means more accurate forecast.

Table 2.10: RMSE—Nonparametric Models

Horizon	NAR	SNAR	ANN
1	1.251	1.143	1.583
2	1.843	1.975	1.881
3	1.953	2.077	1.776
4	2.016	2.156	1.733
5	2.048	2.181	1.638
6	1.961	2.062	1.497
7	1.879	2.049	1.386
8	1.804	1.967	1.301
9	1.712	2.133	1.322
10	1.892	2.033	1.327
11	1.903	2.121	1.313
12	1.866	2.040	1.262

Note: RMSE statistics for different forecast horizons. Lower value means more accurate forecast.

substantially, so that the predicted inflation rates of the last three months are very close to the true data. Secondly, the forecasting errors of some multivariate methods are smaller to univariate techniques. Comparing to ARIMA$(2, 0, 2)$, the VAR model with the repo rate produces more accurate forecasts in forecasting periods of two to three quarters. The VECM models seem to outperform other techniques in the whole forecasting periods (12 months).

Last but not least, monetary aggregates are less informative in forecasting Chinese inflation. Results from both VARs and VECMs confirm this result. This is counterintuitive, because monetary aggregates are traditionally used as the policy instruments. In fact the PBoC still targets the growth rate of M2 as of today. Short-term interest rates such as the repo rate do not reflect the actual borrowing cost of the overall economy. Many interest rates, such as bank deposit and lending rates, are still controlled by the central bank. One possible explanation could be that interest rates become more and more dominant in monetary policy transmission mechanisms.

Another interesting finding is that many existing papers suggest that only those time series models considering many macroeconomic variables have better forecasting performance than the univariate benchmark. This is problematic when forecasting Chinese inflation as the data-rich environment existing in many developed countries does not apply to China. In this chapter I show that multivariate models with only four variables are superior to the ARIMA models, which can be set as the benchmark compare with other forecasting techniques. For instance, dynamic general stochastic general equilibrium (DSGE) models are more and more popular in forecasting macroeconomic variables. Sound time series forecasting models are helpful in evaluating the forecastability of DSGE models for China.

Chapter 3

How Useful Are DSGE Models for Forecasting Inflation in China?– The Role of Monetary Policy Rules

Abstract

Dynamic Stochastic General Equilibrium (DSGE) models are widely used for forecasting macroeconomic variables since Smets and Wouters (2007). However, very few studies have applied DSGE models to forecast Chinese inflation. This chapter estimates several DSGE models and conducts the inflation forecasts using recent Chinese data. The forecast performance is found to be superior to commonly used time series techniques such as VAR and BVAR in the longer forecasting horizons. On a separate note, forecast errors are affected by the choice of monetary policy rules. Price rules, using short-term interest rates as the policy instruments, are more informative in forecasting Chinese inflation than quantity rules that use the money supply as the policy instrument. Results support the conclusion that DSGE models should be included in the inflation forecasting toolbox of Chinese monetary policy makers.

Keywords: Inflation Forecasting, BVAR, VAR, DSGE, China.

3.1 Introduction

Dynamic Stochastic General Equilibrium (DSGE) models have become quite popular for central banks in the past few years for evaluating policy experiments. DSGE models in general lacked forecasting powers until Smets and Wouters (2007). Many recent studies show that DSGE models are useful on the forecasting dimension. Adolfson, Jesper and Villani (2005) confirm that the open economy DSGE model compares well with more empirical models in forecasting macroeconomic variables. The empirical evidence from a recent study for Europe indicates that log-linearized DSGE models using Bayesian methods compare quite well with the reduced-form models (Christoffel, Coenen and Warne 2010). Edge, Kiley and Laforte (2008) examine forecasting performance of one DSGE model at a relatively detailed level by separately considering the forecasts for various components of consumer expenditures and private investment. Lees, Matheson and Smith (2007) forecasts from a DSGE-VAR and a 'vanilla' DSGE model are competitive with, and in some dimensions superior to, the Reserve Bank of New Zealand's official forecasts. Liu, Gupta and Schaling (2009) have developed a New Keynesian DSGE model for South Africa. They find this model outperforms classical VAR and BVAR models in forecasting inflation. Rubaszek and Skrzypczyński (2008) compared the forecasts from small-scale DSGE models, professional forecasts, and time series models. They conclude that the DSGE model can produce better output forecasts than other two techniques, but not the inflation forecasts. Inflation forecasts for Austria based on the present value of the hybrid New Keynesian Phillips Curve, commonly used in DSGE models, are found to be superior to time series models (Rumler and Valderrama 2010). Hodge, Robinson and Stuart (2008) find that the forecast performance of the BVAR–DSGE model is competitive with a BVAR and an independently estimated DSGE model.

Only a few papers in the existing literature include micro-founded DSGE models

for China. Zhang (2009) specified a small-scale New Keynesian DSGE model and explored the role of the price and quantity monetary policy rules in China. The author found that the price rule is likely to be more effective in managing the macroeconomy than the quantity rule, and the economy would have experienced less fluctuation had interest rates responded more aggressively to inflation. A DSE model of China with financial frictions is simulated to show the contribution of China in global imbalance (Bénassy-Quéré, Carton and Gauvin 2011). In a recent study, Mehrotra, Nuutilainen and Pääkkönen (2011) conducted a small-scale DSGE model and calibrated the model with Chinese data. The authors focussed on the impacts of technological and monetary shocks on the real economy. Liu (2008) built up an open-economy DSGE model with financial-accelerator for monetary policy analysis and applied the Bayesian technique to estimate the model based on the actual data of China. However, none of these studies provide information from the perspective of forecasting Chinese inflation.

The People's Bank of China (PBoC) does not have official monetary policy rules, although the objective of Chinese monetary policy is stated in law as to maintain price stability so as to promote economic growth. Traditionally PBC uses money supply as the main instrument. Even as of today M2 is still targeted. The rationale is Fisher's quantity theory of money, which assumes the velocity of money is stable in the short run. But China's velocity of money seems to have been unstable since 1990, given that the country has experienced structural changes in economic development. Another assumption for using money supply as the policy instrument is that the quantity of money and inflation are closely related. This is not true in China. Wolters, Teräsvirta and Lütkepohl (1998) show that the link between money and inflation in China became looser due to financial deepening. Targeting money supply also has problems in practice. As stated in Laurens and Maino (2007), between 1994 and

2004 the difference between actual and target money growth in China is relatively large. Money supply seems to be a less appropriate instrument. Short-term interest rates are widely used as the monetary policy instrument for developed economies. Although the importance of such variables is not clear in China, and as in many developing countries that it is more difficult to be controlled by the central bank, nominal interest rates such as the China Interbank Offer Rate (CHIBOR) and the repo rate have been increasingly adopted by PBoC as the monetary policy instruments in recent years. The market interest rate in China still does not reflect the overall costs of borrowing in the economy. Many rates faced by depositors and lenders are still determined directly by the PBoC. However, some studies find interest rates become more effective in affecting the real economy. For instance, investment is more sensitive to short-term interest rates in more recent years (Ha and Fan 2003). Kong (2007) estimates four monetary policy rules in China and finds that Taylor rules are better than McCallum rules in evaluating Chinese monetary policy performance.

This chapter attempts to address the following two questions: Firstly, comparing to prevalent time series techniques such as VAR or BVAR, do DSGE models have forecasting power in forecasting inflation in China? And secondly, if they do, is the forecasting performance affected by various monetary policy rules in China?

To answer the first question, a benchmark DSGE model is estimated. The prior parameters are chosen from recent studies about China. The inflation forecasts from this model, as well as the ones from other relevant DSGE models, are compared with the forecasts from time series models. Four monetary policy rules are tested in proposed DSGE models to address the second issue. Inflation forecasts, associated with these monetary policy rules, are evaluated and compared with time series forecasts.

There are two main findings. Firstly, DSGE models with appropriate monetary policy rules can produce the same degree of inflation forecast accuracy as time series

models like VAR and BVAR. Secondly, the inflation forecasting performances are affected by the choice of monetary policy rules. The price rules seem to be more informative than quantity rules in forecasting Chinese inflation.

The rest of the paper is organized as follows: Section 3.2 describes the methodology to forecast with DSGE models. The benchmark proposed DSGE model is introduced in Section 3.3. The inflation forecasts are also computed in this section. Section 3.4 lists several alternative DSGE models to check the robustness of the result. Inflation forecasts from time series models are conducted in Section 3.5. Section 3.6 evaluates the forecast performance of inflation forecasts from DSGE and time series models. And Section 3.7 concludes.

3.2 Forecasting Methodology for DSGE Models

I estimated proposed models using Bayesian inference methods. The essence is to obtain posterior distribution of the DSGE model's parameters given its log–linear state-space representation using the Kalman filter. The inflation forecasts are computed based on the estimation result.

3.2.1 Bayesian Inference

The advantage of Bayesian inference is that it can deal with the situation where the data span is short, as in China. This method allows the prior information from previous studies to be formalized in the estimation of DSGE models. It also helps to reduce the numerical difficulty in solving highly nonlinear estimation problems. The posterior distribution of the vector of parameters of the model is computed following

the Bayes' theorem:

$$P(\theta_m|Y_T, m) \propto P(Y_T|\theta_m, m)P(\theta_m|m) \tag{3.1}$$

where $P(\theta_m|m)$ is the prior distribution of a vector $\theta_m \in \Theta_m$ with parameters from the DSGE model $m \in M$. $P(Y_T|\theta_m, m)$ is the likelihood function of the observed data, $Y_t = \{y_1, y_2, \ldots, y_T\}$, conditional on the model m and parameters θ_m. $\propto$ denotes proportionality. The joint posterior distribution of θ_m is determined by the combination of the observed data Y_t and the prior distribution of θ_m.

3.2.2 Forecasting

The solution of a log-linearized DSGE model can be written as

$$\xi_t = F\xi_{t-1} + B\eta_t; \; t = 1, 2, \ldots, T \tag{3.2}$$

where ξ_t is the r-dimensional vector of model variables, η_t is the q-dimensional vector of i.i.d. structural shocks. F and B are uniquely determined by θ_m. The n-dimensional observed variable is linked to ξ_t and a k-dimensional deterministic vector x_t. And this equation is also the state equation. The observation equation takes form of

$$y_t = A'x_t + H'\xi_t + w_t; \; t = 1, 2, \ldots, T. \tag{3.3}$$

where w_t is i.i.d. noise with zero mean and covariance matrix R. w_t and η_t are independent with each other, and A, H, and R are uniquely determined by θ_m.

The population mean of of y_{T+h} given Y_T and θ_m is

$$E[y_{T+h}|Y_T, \theta_m] = A'x_{T+h} + H'F^h\xi_{T+h|T};\ h = 1, 2, \ldots, H. \tag{3.4}$$

The first term in Equation 3.4 can be estimated by the sample average of the $E[y_{T+h}|Y_T, \theta_m^{(i)}$ for M draws from $P(\theta|Y_t)$. $\theta_m^{(i)} \sim P(\theta|Y_t)$, $i = 1, 2, \ldots, M$. When M is large enough the error of the estimator of $E[y_{T+h}|Y_T, \theta_m]$ is very small.

The covariance matrix of y_{T+h} given Y_T and θ_m is

$$C[y_{T+h}|Y_T, \theta_m] = H'F^hP_{T|T}(F^h)'H + H'\left(\sum_{j=1}^{h} F^{j-1}BB'(F^{j-1})'\right)H + R \tag{3.5}$$

Following Adolfsona, Laséena, Lindé and Villani (2008), the prediction covariance matrix of y_{T+h} is

$$E[y_{T+h}|Y_T] = E_T[C[y_{T+h}|Y_T, \theta_m]] + C_t[E[y_{T+h}|Y_T, \theta_m]] \tag{3.6}$$

were E_T and C_t are the expectation and covariance with respect of θ_m in period T. The first term on the right-hand side of Equation 3.6 represents the uncertainties caused by unobserved state variables, measurement errors, and structural shocks. This term can be estimated by the sample average of $C[y_{T+h}|Y_T, \theta_m^{(i)}]$ using M draws from $P(\theta|Y_t)$. The second term shows that the parameter uncertainty has impact on the h-step ahead forecasts based on the population mean. It can be estimated from the sample covariance matrix of $E[y_{T+h}|Y_T, \theta_m]$ using Mdraws. Again when M is large enough, the errors of the estimators are negligible.

3.3 The Benchmark Model

I chose the model proposed in Smets and Wouters (2007), a widely cited paper as the benchmark. There are three major advantages for using this model as the start. First of all, it is the first DSGE model reporting better forecasts than time series models. One caveat of earlier DSGE models is the incapability of forecasting key variables. As Smets and Wouters (2007) provide relatively good out-of-sample forecasts, it is natural to explore whether this model can also be applied to forecast inflation in China. Second of all, it is easy to extend this model to explore the role of different monetary policy rules, in that the monetary policy is imposed in this model. The previous chapters show that monetary policy instruments matter when forecasting inflation in China. The original model in Smets and Wouters (2007) has a simple monetary policy rule similar to the Taylor rule. As this is an extra equation in the final system for estimation, changing it to a quantity rule that uses money supply as the policy instrument is relatively easy to handle in techniques. And finally, this model contains sufficient flexibility for further extensions. For instance, the labor elasticity coefficient is not time invariant in China as structural breaks exist. And when longer series become available, this coefficient is likely to change. There are many such time-variant coefficients when modeling Chinese economy. When more robust studies on these issues become available in the future, they can be substituted into the benchmark model settings without the effort to construct entirely new models.

Admittedly not all characteristics of the Smets–Wouters model are applicable in the Chinese context. The first best approach should be constructing models for Chinese economies from scratch. However, it has practical obstacles such as the difficulty in modeling some non-market behaviors, the lack of some key data availabilities, etc. Even if this type of models are developed, their forecast performance still needs to be compared with some benchmark models. In this sense, this chapter provides the

first step which can potentially benefit many further studies.

The Smets–Wouters model is an extended New Keynesian model, similar to Christiano, Eichenbaum and Evans (2005). In this world there exist a continuum of households, who supply labor in monopolistic competition. They set wages, which are Calvo-sticky. A continuum of intermediate goods firms supply intermediate goods in the form of monopolistic competition. They set prices of intermediate goods and the prices are Calvo-sticky. Final goods firms use intermediate goods to produce final goods in perfect competition. The monetary authority in this model follows a Taylor rule to set the short-term interest rate.

3.3.1 The Household

The representative household derives utility from consumption C_t and disutility from labor l_t. It maximizes the sum of expected utilities from all periods:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t U_t \tag{3.7}$$

where U_t is the single-period utility function at period t:

$$U_t = \epsilon_t^b \left(\frac{(C_t - H_t)^{1-\sigma_c}}{1-\sigma_c} - \epsilon_t^L \frac{(l_t)^{1+\sigma_l}}{1+\sigma_l} + \frac{(M_t/P_t)^{1-\sigma_M}}{1-\sigma_M} \right) \tag{3.8}$$

Here H_t is the external habit (the 'Catching up with the Joneses' type), $\frac{M_t}{P_t}$ is the real money holding by households in period t. ϵ_t^b and ϵ_t^L are infratemporal substitution shocks and labor supply shocks, respectively. Both shocks are assumed to follow AR(1) process. Each household is assumed to supply a complete set of differentiated labour types, so that household's consumption and labour income are not sensitive to the firm-specific labour and wage conditions. H_t is assumed to be a fraction of

the consumption of the previous period. The original Smets–Wouters model does not have the money-in-utility specification. Money is unmodeled but implicitly assumed to be there. Since the purpose of this chapter is to assess the role of different monetary policy rules, including the ones using money supply as the policy instrument, I modify the original model by assuming households have money in the utility function:

$$H_t = hC_{t-1} \tag{3.9}$$

Here h is a constant.

The infratemporal budget constraint takes the form

$$\frac{M_t}{P_t} + b_t\frac{B_t}{P_t} = \frac{M_{t-1}}{P_t} + \frac{B_{t-1}}{P_t} + Y_t - C_t - I_t \tag{3.10}$$

B_t is the nominal discounted bonds in period t with market price of b_t. Bonds are assumed to be one-period securities. Y_t is the real income, I_t is the real investment, and P_t is the aggregate price level in period t. Current income and financial wealth can be used for consumption and investment in physical capital. Again money is added to the original model.

Real income Y_t is the sum of labor income, earnings from financial assets (security), net capital income, dividends, and net of lump-sum tax:

$$Y_t = W_t l_t + A_t + (r_t^K z_t K_{t-1} - \Psi(z_t)K_{t-1}) + Div_t - tax_t \tag{3.11}$$

where $W_t l_t$ is the labor income, A_t is the security payoffs, Div_t is the dividends from imperfectly competitive firms, tax_t is the lump-sum tax. $r_t^K Z_t K_{t-1}$ represents the return on real capital stock, and $\Psi(Z_t)K_{t-1}$ is the costs from capital utilization z_t.

In this model, households act as price-setters in the labor market. Individual households supply different types of labor, which is not perfectly substitutable. The total labor supply is aggregated as follows:

$$L_t = \left(\int_0^1 (l_t)^{1/(1+\lambda_{w,t})} \, d\tau \right)^{1+\lambda_{w,t}} \tag{3.12}$$

τ represents the index of the individual. The degrees of substitution is randomly specified as

$$\lambda_{w,t} = \lambda_w + \eta_t^w \tag{3.13}$$

where η_t^w is the wage markup shock. If the wage is perfectly flexible, $1 + \lambda_{w,t}$ stands for the markup of real wage over the ratio of marginal disutility of labor to marginal utility of consumption.

Wages are set by households in a monopolistic competitive way. Individual τ offers the labor in the quantity determined by the current wage W_t^τ. Wages are Calvo-sticky. Every period household τ having probability $1 - \xi_t$ can freely choose a new nominal wage $\tilde{W}_t^\tau$. Or wages are set following the index rule:

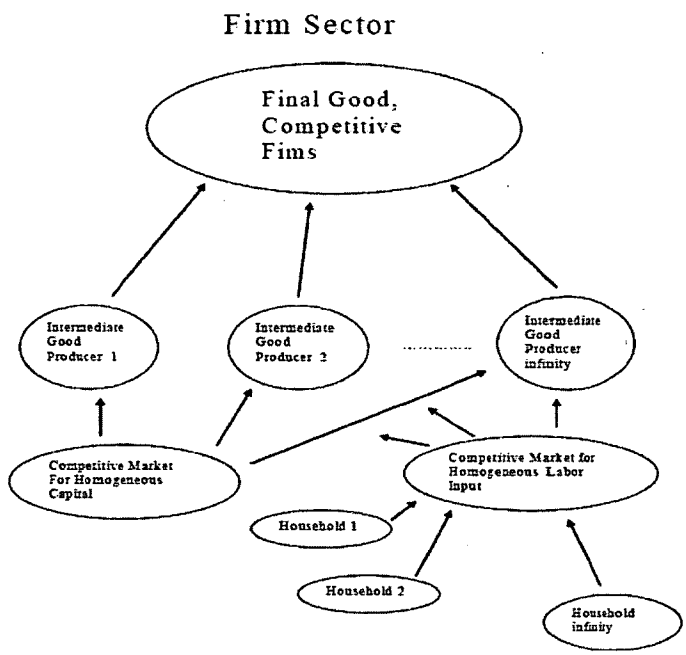
$$W_t^\tau = \frac{P_{t-1}}{P_{t-2}}^{\gamma_W} W_{t-1}^\tau \tag{3.14}$$

$\gamma_W = 1$ indicates the perfect indexation, and $\gamma_W = 0$ means no indexation at all. The assumption of perfect insurance market guarantees that the consumption of one individual equals the aggregate consumption and marginal utility of consumption is equal across individuals. Consequently the capital stock, bond holdings, and dividends are identical across different types of individuals.

3.3.2 Final Goods Firms

Homogeneous final goods are produced by a continuum of intermediate goods, which are imperfectly substitutable. The relationship of the final and intermediate firms is shown in Figure 3.1.

Figure 3.1: Final and Intermediate Firms



And the aggregate process of the final firm follows:

$$Y_t = \left(\int_0^1 (y_{j,t})^{1/(1+\lambda_{p,t})} \, dj \right)^{1+\lambda_{p,t}} \tag{3.15}$$

$\lambda_{p,t}$ is the degree of substitutability, which is assumed to be random.

$$\lambda_{p,t} = \lambda_p + \eta_t^p \tag{3.16}$$

Here η_t^p is the typical cost-push shock or the goods markup shock.

3.3.3 Intermediate Goods Firms

Intermediate goods firms produce intermediate goods using capital and labor. Labor is a combination of labor supplied by each individual. New capital is produced by old capital stock, investment, and depreciation, subject to an investment adjustment cost. Here the deprecation is assumed to be time varying and determined by capital utilization of each period. The profits of intermediate goods firms are paid in the form of dividends Div_t.

The production function for the intermediate goods firms is

$$y_{j,t} = \epsilon_t^{\alpha} \tilde{K}_{j,t}^{\alpha} L_{j,t}^{1-\alpha} - \Phi \tag{3.17}$$

where $\tilde{K}_{j,t}$ is the effective utilization of capital stock, Φ is the fixed cost, and ϵ_t^{α} is the aggregate productivity shock following an AR(1) process.

$$\tilde{K}_{j,t} = z_t K_{j,t-1} \tag{3.18}$$

$$\epsilon_t^{\alpha} = \rho_t^{\alpha} \epsilon_{t-1}^{\alpha} + \eta_t^{\alpha} \tag{3.19}$$

Intermediate goods firms are assumed to be monopolistically competitive, thus they offer the goods in the amount of determined by the Calvo-sticky price $P_{j,t}$. Each period the firm has probability $1 - \xi_p$ to freely choose the new price $\tilde{P}_{j,t}$. Similar to the wage setting, the price has the probability ξ_p to follow the indexation rule. More discussions of alternative price settings are documented in Khan (2005).

$$P_{j,t} = \left(\frac{P_{t-1}}{P_{t-2}}\right)^{\gamma_P} P_{j,t-1} \tag{3.20}$$

Again $\gamma_P = 0$ means no indexation and $\gamma_P = 1$ represents full indexation.

Households choose real capital stock, investment and the utilisation rate to maximise their intertemporal objective function subject to the intertemporal budget constraint and the capital accumulation equation. To be specific, capital is assumed to evolved in the following way:

$$K_t = (1-\tau)K_{t-1} + \left(1 - S\left(\epsilon_t^I \frac{I_t}{I_{t-1}}\right)\right) I_t \tag{3.21}$$

where I_t is the gross investment, τ is the depreciation rate, and $S(\cdot)$ is the investment adjustment cost function. $S(1) = 0$, $S'(1) = 0$, and $S''(1) > 0$. ϵ_t^I is the AR(1) shock to investment cost.

$$\epsilon_t^I = \rho_t^I \epsilon_{t-1}^I + \eta_t^I \tag{3.22}$$

3.3.4 Government

The government spending is assumed to be financed by a lump-sum tax imposed on households.

$$G_t = tax_t \tag{3.23}$$

3.3.5 Monetary Authority

The monetary authority uses either money or nominal interest rates as the policy instruments. The monetary policy rules are described in the section on *Monetary Policy Rules.*

3.3.6 Market Clearing Conditions

Three markets, namely the labor market, the final goods market, and the capital rental market, clear in equilibrium. The labor market is in equilibrium if firms demand for labor equals labor supply at the wage level optimally set by households.The capital rental market is in equilibrium when the demand for capital by the intermediate goods producers equals the supply by the households.

$$\int_0^1 L_{j,t} dj = \left(\int_0^1 (l_t)^{1/(1+\lambda_{w,t})} \, d\tau \right)^{1+\lambda_{w,t}} \tag{3.24}$$

$$Y_t = C_t + I_t + G_t + \psi(z_t) K_{t-1} \tag{3.25}$$

$$\int_0^1 K_{j,t-1} \, dj = K_{t-1} \tag{3.26}$$

3.3.7 The Log-Linearized Model

The linearized model used for estimation and forecasting consists of the following equations:

The capital accumulation equation:

$$\hat{K}_t = (1-\tau)\hat{K}_{t-1} + \tau \hat{I}_t \tag{3.27}$$

The labor demand equation:

$$\hat{L}_t = -\hat{W}_t + (1+\psi_t)\hat{r}_t^K + \hat{K}_{t-1} \tag{3.28}$$

The goods market equilibrium condition:

$$\hat{Y}_t = (1 - \tau k_y - g_y)\hat{C}_t + \tau k_y \hat{I}_t + \epsilon_t^G \tag{3.29}$$

The production function becomes

$$\hat{Y}_t = \phi\epsilon_t^\alpha + \phi\alpha\hat{K}_{t-1} + \phi\alpha\psi\hat{r}_t^K + \phi(1-\alpha)\hat{L}_t \tag{3.30}$$

The monetary policy—the Taylor rule used in the original model—is

$$\begin{aligned} \hat{R}_t &= \rho\hat{R}_{t-1} + (1-\rho)\left(\bar{\pi}_t + r_\pi(\pi_{t-1} - \bar{\pi}_t) + r_Y(\hat{Y}_t - \hat{Y}_t^P)\right) \\ &\quad + r_{\Delta\pi}(\hat{\pi}_t - \hat{\pi}_{t-1}) + r_{\Delta Y}(\hat{Y}_t - \hat{Y}_t^P - \hat{Y}_{t-1} + \hat{Y}_{t-1}^P) + \eta_t^P \end{aligned} \tag{3.31}$$

Many studies have shown that other monetary policy rules are more appropriate in China (Kong 2007). Thus Equation 3.31 is replaced by the monetary policy rule equations presented in the section on *Monetary Policy Rules.*

The consumption equation is

$$\begin{aligned} \hat{C}_t &= \frac{h}{1+h}\hat{C}_{t-1} + \frac{1}{1+h}E_t\hat{C}_{t+1} \\ &\quad - \frac{1-h}{(1+h)\sigma_C}(\hat{R}_t - E_t\hat{\pi}_{t+1}) + \frac{1-h}{(1+h)\sigma_C}\epsilon_t^b \end{aligned} \tag{3.32}$$

The investment equation is

$$\hat{I}_t = \frac{1}{1+\beta}\hat{I}_{t-1} + \frac{\beta}{1+\beta}E_t\hat{I}_{t+1} + \frac{\varphi}{1+\beta}\hat{Q}_t + \epsilon_t^I \tag{3.33}$$

The Q equation is

$$\begin{aligned}\hat{Q}_t &= -(\hat{R}_t - E_t\hat{\pi}_{t+1}) + \frac{1-\tau}{1-\tau+\bar{r}_t^K}E_t\hat{Q}_{t+1} \\ &+ \frac{\bar{r}_t^K}{1-\tau+\bar{r}_t^K}E_t r_{t+1}^K + \eta_t^Q \end{aligned} \tag{3.34}$$

The inflation equation is

$$\begin{aligned}\hat{\pi}_t &= \frac{\beta}{1+\beta\gamma_P}E_t\pi_{t+1} + \frac{\gamma_P}{1+\beta\gamma_P}\pi_{t-1} \\ &+ \frac{1}{1+\beta\gamma_P}\frac{(1-\beta\xi_P)(1-\xi_P)}{\xi_P}[\alpha\hat{r}_t^K + (1-\alpha)\hat{W}_t - \epsilon_t^\alpha] + \eta_t^P \end{aligned} \tag{3.35}$$

The real wage equation is

$$\begin{aligned}\hat{W}_t &= \frac{\beta}{1+\beta}E_t\hat{W}_{t+1} + \frac{1}{1+\beta}\hat{W}_{t-1} + \frac{\beta}{1+\beta}E_t\hat{\pi}_{t+1} \\ &- \frac{1+\beta\gamma_W}{1+\beta}\hat{\pi}_t + \frac{\gamma_W}{1+\beta}\hat{\pi}_{t-1} \\ &- \frac{\lambda_W(1-\beta\xi_W)(1-\xi_W)}{(1+\beta)(\lambda_W+(1+\lambda_W)\sigma_L)\xi_W}[\hat{W}_t - \sigma_L\hat{L}_t - \frac{\sigma_C}{1-h}(\hat{C}_t - h\hat{C}_{t-1}) + \hat{\epsilon}_t^L] + \eta_t^W \end{aligned} \tag{3.36}$$

3.3.8 Monetary Policy Rule

Two types of monetary policy rules are explored: namely the price rule, treating short-term interest rates as the monetary policy instrument; and the quantity rule, using money supply as the policy instrument. This is consistent with previous studies such as Zhang (2009) and Kong (2007). For each type of rule, both the original and the modified rules are analyzed. Equation 3.31 is the original Taylor rule. Liu and

Zhang (2007) suggest that both the original Taylor rule and McCallum rule cannot capture Chinese monetary policy well during 1991–2006, especially after 1997. For sensitivity analysis, I estimate the specifications with both original monetary policy rules.

The modified Taylor rule, as proposed in Zhang (2009), is

$$\hat{R}_t = \lambda_1 \hat{R}_{t-1} + (1 - \lambda_1)[\lambda_2(E_t\hat{\pi}_{t+1} - \hat{\pi}_t) + \lambda_3\hat{\pi}_t + \lambda_4\hat{Y}_t] + \eta_t^P \tag{3.37}$$

Here η_t^P is assumed to follow an AR(1) process.

$$\eta_t^P = \rho_P \eta_{t-1}^P + \epsilon_t^P \tag{3.38}$$

The modified McCallum rule, used in Zhang (2009), is

$$\hat{m}_t = \lambda_5 \hat{m}_{t-1} - \lambda_6 E_t\hat{\pi}_{t+1} - \lambda_7\hat{Y}_t + \eta_t^m \tag{3.39}$$

The original McCallum rule, developed from Kong (2007), is

$$\hat{m}_t = \lambda_8 \hat{m}_{t-1} - \lambda_9\hat{Y}_t + \eta_t^m \tag{3.40}$$

Similarly η_t^m is assumed to follow an AR(1) process.

$$\eta_t^m = \rho_m \eta_{t-1}^m + \epsilon_t^m \tag{3.41}$$

3.3.9 Parameterization and Estimation

The model is first calibrated with prior parameter distributions. It is difficult to parameterize a DSGE model for China because of the data availability issue and the

short time horizon, and also in that the growth path of China in the past three decades suggests possible structural changes in data. Taken these issues into consideration, I borrow parameter values from other studies for China, either estimating single equations or simultaneous systems. The parameter values for alternative monetary policy rules are listed in Table 3.1. The sources are Liu and Zhang (2007) and Kong (2007).

Table 3.1: Parameter Values for Alternative Monetary Policy Rules

λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9
0.75	2.6	0.4	0.6	0.8	1	0.5	0.6	0.65

Source: Zhang (2009) and Kong (2007).

The remaining parameter values, including the estimated, calibrated, and shock processes, as well as estimation results, are summarized in Tables 3.2 and 3.3.

Table 3.2: Parameter Values—Calibrated Parameters

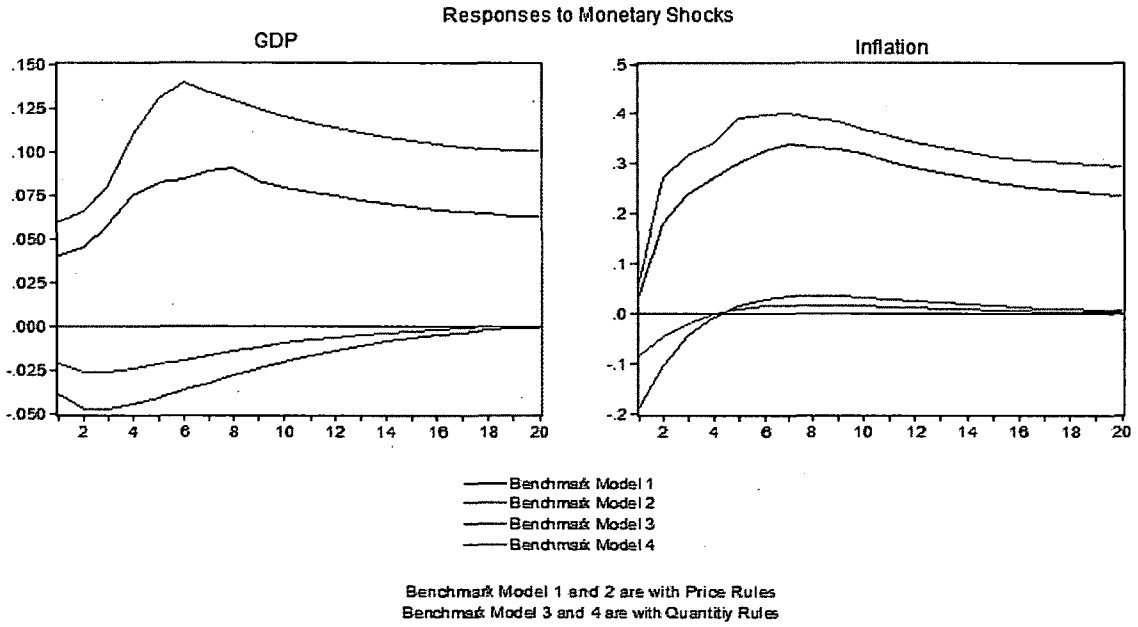
Parameter		Value
depreciation rate of capital	τ	0.06
markup in wage setting	λ_W	0.5
wage markup	ϵw	10
price markup	ϵP	10
government spending share	g_y	0.25

Note: These parameters were from Smets and Wouters (2007). Ideally a set of China-specific parameters should be better, but unfortunately relevant studies were scarce.

The impulse responses of GDP and inflation to monetary shocks are presented in Figure 3.2. As we can see here, output turns out to negatively respond to interest rate

shocks, but positively to money supply shocks. Inflation seems to have the opposite relationship. Also, money seems not neutral in the benchmark model framework. Impacts of short-term interest rates, on the other hand, are transitory.

Figure 3.2: Impulse Response Functions to Monetary Shocks—GDP and Inflation



Note: Impulse response functions confirm that in these models both real output and inflation are positively responded to money supply shocks and negatively to interest rate shocks. These were consistent with previous studies.

3.3.10 Estimation of the Model

The prior parameter distributions used to estimate the benchmark model follow the settings in Smets and Wouters (2007). The estimation is conducted in two steps. In the first step all frictions are shut down so that a flexible price model is estimated. The purpose is to obtain the potential output level. In the estimation of the second step the output gap is computed with the aid of the potential output level.

Five Chinese quarterly series, namely real GDP, consumption, investment, CPI ,

M2, and seven-day repo rate from 1994 to 2009, are used for estimation. CPI and M2 are from International Financial Statistics. Nominal GDP, consumption, and investment are from Statistics Bureau of China. Quarterly GDP deflator is taken from Zhang (2011) to compute real GDP. Results are shown in Tables 3.3 and 3.4.

Table 3.3: Parameter Values—Estimated Parameters

		Prior Distribution			Posterior Recursive Estimates		
		Type	Mean	St. Dev.	Min.	Mean	Max.
Calvo prices	ξ_s^P	beta	0.84	0.10	0.56	0.61	0.66
Calvo wages	ξ_s^W	beta	0.84	0.10	0.54	0.58	0.66
Labor supply elas.	σ_L	normal	1.61	0.75	0.40	0.55	0.72
Discount factor	β	gamma	0.99	0.10	0.90	0.95	0.99
Wage index.	γ_W	beta	0.76	0.15	0.54	0.82	0.84
Price indexa.	γ_P	beta	0.47	0.15	0.19	0.33	0.54
Consumption habit	h	beta	0.76	0.10	0.45	0.51	0.60
Consumption elas.	σ_c	normal	1.50	0.37	1.26	1.46	1.59
Capital share	α	normal	0.30	0.05	0.15	0.26	0.27
Output gap coeff.	r_y	normal	0.99	0.1	0.86	0.87	0.92
Inflation coeff.	r_π	normal	1.34	0.20	0.97	0.99	1.05
Cap. adj. cost	ψ	beta	5.92	1.50	4.99	5.23	5.46
Inv. adj. cost	φ	normal	0.15	1.50	0.19	0.21	0.26
Int. rate inflation	r_π	normal	1.50	0.25	1.76	1.87	1.97
Int. rate smoothing	ρ	beta	0.75	0.10	0.80	0.82	0.84
Int. rate output	r_y	normal	0.12	0.05	0.09	0.10	0.12
S.S. inflation	$\bar{\pi}$	gamma	0.62	0.10	0.63	0.65	0.67

Source: Smets and Wouters (2007), and Mehrotra et al. (2011).

: Note: Ideally a set of China-specific parameters should be better, but unfortunately relevant studies were scarce.

Table 3.4: Parameter Values—Shock Processes

		Prior Distribution			Posterior Recursive Estimates		
		Type	Mean	St.Dev	Min.	Mean	Max.
Productivity	$\rho_{\epsilon\alpha}$	beta	0.82	0.10	0.99	0.99	1.00
	$\sigma_{\epsilon\alpha}$	inv. gam.	1.85	2.00	1.83	1.88	1.92
Preference	$\rho_{\epsilon b}$	beta	0.85	0.20	0.83	0.86	0.86
	$\sigma_{\epsilon b}$	inv. gam.	0.34	2.00	0.20	0.46	0.66
Gov. Spending	ρ_G	beta	0.95	0.10	0.90	0.91	0.99
	σ_G	inv. gam.	0.33	2.00	0.33	0.33	0.34
Investment	$\rho_{\epsilon i}$	beta	0.93	0.10	0.70	0.89	0.99
	$\sigma_{\epsilon i}$	inv. gam.	0.09	2.00	0.08	0.08	0.09
Interest Rate	$\rho_{\epsilon r}$	beta	0.00	0.20	0.00	0.00	0.01
	$\sigma_{\epsilon r}$	inv. gam.	0.08	2.00	0.07	0.07	0.08
Price Markup	ρ_{λ_P}	beta	0.50	0.20	0.97	0.98	0.99
	σ_{λ_P}	inv. gam.	0.50	0.20	0.79	0.84	0.89
Risk Premium	$\rho_{\epsilon q}$	beta	0.50	0.10	0.43	0.56	0.66
	$\sigma_{\epsilon q}$	inv. gam.	0.10	2.00	0.60	0.79	1.12
Money Agg.	$\rho_{\epsilon m}$	beta	0.50	0.20	0.14	0.23	0.25
	$\sigma_{\epsilon m}$	inv. gam.	0.10	2.00	0.21	0.23	0.25

Source: Smets and Wouters (2007),and Mehrotra et al. (2011).

: Note: Ideally a set of China-specific parameters should be better, but unfortunately relevant studies were scarce.

The estimation and forecasting are conducted in Dynare and Matlab.[1] The inflation forecasts generated with the specification of each monetary policy rules are stored and reported in Table 3.5. The true inflation data are shown in the same table for comparison purpose. Bench1 to Bench4 stand for the benchmark models with the original McCallum rule, the modified McCallum rule, the original Taylor rule, and the modified Taylor rule, respectively.

Table 3.5: Inflation Forecasts—The Benchmark Model

Horizon	TRUE	Bench1	Bench2	Bench3	Bench4
1	2.229	4.711	2.330	4.413	1.831
2	2.865	4.396	3.502	3.792	2.556
3	3.665	4.047	4.273	3.242	2.881
4	4.533	3.196	4.791	2.277	3.037

Source: Author's calculation.

3.4 Alternative Models

To examine the robustness of the results that are derived from benchmark model, I also check two other well-cited DSGE models. For each of these models, alternative monetary policy rules mentioned in previous section are taken into consideration. And the inflation forecasts are computed from each specification of these models.

The first model is similar to (Clarida, Gali and Gertler 1999) with the money-in-utility specification and the associated budget constraint. And I add a hybrid Phillips Curve with endogenous inflation persistence in inflation as in Wieland et al. (2009). The government spending is not explicitly modeled. Four shocks are presented, namely the cost-push shock, the demand shock, the technological shock, and

[1]The Dynare codes are modified from Wieland, Cwik, Müller, Schmidt and Wolters (2009).

the monetary policy shock. Thus the data series used for estimation are the real GDP, CPI, M2, and repo rate. The parameterizations are the same as in the benchmark model. Forecasts of inflation are summarized in Table 3.6. CGG1 to CGG4 are the models with original Taylor rule, modified Taylor rule, original McCallum rule, and modified McCallum rule, respectively.

Table 3.6: Inflation Forecasts—The CGG(1999) Model

Horizon	TRUE	CGG1	CGG2	CGG3	CGG4
1	2.229	1.241	1.831	3.431	2.209
2	2.865	1.931	2.556	6.442	2.537
3	3.665	9.661	2.881	8.476	2.492
4	4.533	10.505	3.037	8.909	3.551

Source: Author's calculation.

The second alternative model is similar to the ones in Rotemberg and Woodford (1997) and Zhang (2009). The equations for estimation are derived from the optimization behavior of the agents. I modify the money-in-utility assumption to make it consistent with the ones in the benchmark and the other alternative model. This model has both standard New Keynesian IS curve and Phillips Curve. Shocks specified in this model include the cost-push shock, the monetary shock, the fiscal shock, and the technological shock. Data used for estimation and the parameterization are the same as in the first alternative model. Inflation forecasts are presented in Table 3.7. RW1 to RW4 stand for the models with original Taylor rule, modified Taylor rule, original McCallum rule, and modified McCallum rule, respectively.

Table 3.7: Inflation Forecasts—The RW(1997) Model

Horizon	TRUE	RW1	RW2	RW3	RW4
1	2.229	2.007	1.994	5.179	2.127
2	2.865	1.540	2.587	5.301	4.308
3	3.665	2.463	2.783	5.053	4.047
4	4.533	1.879	2.583	4.683	4.385

Source: Author's calculation.

3.5 Time Series Models

To evaluate the inflation forecast performance of proposed DSGE models, I construct two time series models, namely the vector autoregressive (VAR) and the Bayesian VAR model to obtain the data-generated inflation forecasts. These are quarterly models, which differ from the ones with monthly data in the previous chapter. I do not consider the ARIMA model due to the fact that multivariate time series models provide as accurate inflation forecasts (Zhao 2011). Two specifications are made for VAR and BVAR. One is with money supply as the monetary policy instrument and the other is with short-term interest rates. The purpose of doing so is to compare the forecasting accuracy of VAR or BVAR to the ones of DSGE models with the same policy instrument.

To be consistent with proposed DSGE models, I choose 1994Q1 to 2009Q4 as the estimation period. The 1-to-4-steps-ahead forecasts are computed and compared with the actual inflation data in 2010. The variables I used in VARs are real GDP, CPI inflation, foreign reserves, and monetary policy instrument (either the money supply or the short-term interest rate). The variables are placed in this sequence, because monetary policy actions are assumed to react to information about output and price at the current month, and should have impact on these variables only the

next month. Price is placed after output, because inflation is assumed to be influenced mainly through the output gap. Foreign reserves is an important variable in that it also captures part of the monetary policy in China. If not sterilized, foreign exchange inflows result in an increase in the money supply of a country with a fixed exchange rate. Given the sheer size of the recent influx of foreign capital, it would be most interesting to see whether such increase in foreign reserves would have an impact on money supply, i.e. whether sterilization was successful, and the subsequent impact on real economic activities.

The unit root tests suggest that real GDP, foreign reserves, and money supply are integrated of order one. Thus the first differences of these series are used. Both CPI inflation and the short-term interest rate is I(0), the level of which are used in the VAR. The lag length selection is based on Akaike Information Criterion and Hannan–Quinn Criterion. Both criteria indicate that the optimal number of lags should be one. For the BVAR models, the Minnesota Prior is used.

The inflation forecasts are shown in Table 3.8. M2 is the monetary policy instrument in VAR1 and BVAR1, and the repo in VAR2 and BVAR2.

Table 3.8: Inflation Forecasts—Time Series Models

Horizon	TRUE	VAR1	VAR2	BVAR1	BVAR2
1	2.229	1.979	1.410	0.918	1.867
2	2.865	3.054	3.192	2.504	2.881
3	3.665	3.409	4.164	2.845	3.583
4	4.533	3.257	4.658	3.406	3.811

Source: Author's calculation.

Table 3.9: RMSEs—The Benchmark Model and Time Series Models

Horizon	VAR1	VAR2	BVAR1	BVAR2	Bench1	Bench2	Bench3	Bench4
1	0.249	0.819	1.310	0.361	2.482	0.101	2.184	0.397
2	0.221	0.623	0.961	0.255	2.062	0.456	1.677	0.356
3	0.233	0.585	0.916	0.214	1.698	0.511	1.391	0.538
4	0.669	0.510	0.973	0.405	1.615	0.462	1.650	0.881

Note: RMSE statistics for different forecast horizons. Lower value means more accurate forecast.

3.6 Forecasting Performance

The root mean squared error (RMSE) for inflation forecasts of the benchmark models and the time series models are computed and reported in Table 3.9. For the two VAR models, M2 seems to be more informative in forecasting Chinese inflation in the first three out-of-sample periods. The BVAR model with short-term interest rates outperforms other three time series models in forecasting inflation.

The RMSEs of the benchmark model with modified Taylor rule are smaller than the ones in BVAR2 in the first forecasting period. On average the forecasting errors are comparable. This can be interpreted as showing that the proposed benchmark model has similar power in forecasting inflation in China, given the specification of the appropriate monetary policy rule. The original Taylor rule and the McCallum rule relatively are not as good as the modified rules.

The other interesting finding is that models with price rules generate smaller forecast errors than the ones with quantity rules. This result contradicts many other studies in the same area, where money supply seems to be more informative. One possible explanation can be that those studies are with much shorter data horizons. Economic agents in China have become more sensitive to the changes in short-term

Table 3.10: RMSEs—Alternative Models

Horizon	CGG1	CGG2	CGG3	CGG4	RW1	RW2	RW3	RW4
1	1.201	0.020	0.987	0.397	2.950	0.101	0.222	0.235
2	2.668	0.232	0.961	0.356	2.705	1.023	0.949	0.257
3	3.530	0.703	3.549	0.538	2.350	0.864	1.040	0.550
4	3.759	0.782	4.285	0.881	2.036	0.751	1.603	1.085

Note: RMSE statistics for different forecast horizons. Lower value means more accurate forecast.

interest rates in the recent years as the economy keeps growing.

RMSEs of the inflation forecasts from alternative models show similar results. In CGG type of models, the forecast errors of the ones with modified rules are comparable to the VAR and BVAR models. And models with price rules generate more accurate inflation forecasts than the ones with quantity rules in most cases. The pattern is less clear in RW type of models, where quantity rules seem to have better forecast performance but the forecast errors are of the same magnitude.

3.7 Conclusion

DSGE models have lacked forecasting power until Smets and Wouters (2007). Recent studies show that in forecasting inflation DSGE models compare well with other empirical methods. But few studies, if not none, have used DSGE models to forecast Chinese inflation. It is natural to ask whether or not DSGE models are useful in forecasting inflation in China. Also it is interesting to know whether the forecast performance will be affected by the choice of monetary policy rules given that China does not have an official one.

This chapter has estimated several DSGE models and conducted inflation forecasts using recent Chinese data. The forecast errors are comparable to time series models such as VAR and BVAR. The forecast performance is affected by the choice of monetary policy rules. Price rules, using interest rates as the policy instrument, are more informative in forecasting Chinese inflation than quantity rules that use money supply as the policy instrument.

The results should be more promising when the inflation forecasts from DSGE models can be compared to the professional forecasts. Unfortunately professional forecasts are relatively new in China. I have not found a good source of trackable professional inflation forecasts. Structural models such as the four-equation one proposed by IMF are used by the People's Bank of China to project policy consequences. However, the inflation forecasts from this model are not publicly available. A DSGE model designed specifically for China should also help to provide better forecasts in that the nature of the Chinese economy is quite different from typical developed and developing countries.

Despite the facts that there is scope for improving the forecasting performance, DSGE models are worth considering when forecasting inflation in China. The results provide robust support for the conclusion that DSGE models should belong in the inflation forecasting toolbox of Chinese monetary policy makers.

Chapter 4

Inflation Forecast with Optimal Monetary Policy in a Sudden Stop: The Role of Capital Accumulation

Abstract

The previous two chapters discussed methods to forecast inflation in 'normal' periods, where links between inflation and other macroeconomic variables are relatively robust. However, these methods may be less reliable as such links cease to exist in crisis periods. In this chapter, I attempt to explore possible ways to forecast inflation during crisis periods. There are two related questions. The first one is to determine how monetary policy should react to financial crises. Emerging economies are often exposed to 'sudden stops' that triggers economic crises. In the Asian Financial Crisis the interest rates in several crisis countries were raised immediately and then reduced sharply. Some existing models taking financial frictions as 'reverse accelerator' have illustrated that this is the optimal monetary policy. But this type of model usually overestimates the inflation reaction and leads to biased inflation forecasts. One possible reason is that many of such models ignore capital accumulation. In this chapter I examine the role of the physical investment in a sudden stop scenario, to address this

caveat. The inflation responses generated from this proposed model get closer to the actual Korean data. And this model outperforms the one without capital accumulation in terms of inflation forecasts. If this is true in Korea, given the similarities of economic structures in China and Korea, this model not only confirms what optimal monetary policy should be, but also has the potential to be used to forecast inflation in China during a crisis.

Keywords: Inflation Forecasting, Sudden Stops, Optimal Monetary Policy, Collateral Constraint, Current Account Adjustment.

4.1 Introduction

Forecasting inflation is no easy job in normal times, and it can be even more difficult in economic crises. As observed in crisis periods in many emerging economies, inflation can become extremely volatile within very short periods. There are a number of possible explanations for this. First, policy response can be sub-optimal. For instance, should central banks raise interest rates to slow down capital outflows, or lower them to stimulate domestic demands as in normal times? Second, economic agents may react irrationally facing crises. The problem of asymmetric information, and the change of decision-making horizons, are likely to lead to 'irrational' responses even if each and every agent makes rational decisions individually.

I attempt to address the following questions in this chapter: What is the optimal monetary policy response during a crisis? And how to forecast inflation during a crisis assuming the optimal monetary policy is adopted? Although China has not experienced a full-scale economic crisis in the last three decades or so, learning from other economies with similar economic structures can be potentially beneficial. A natural experiment is the Asian Financial Crisis. What is the optimal monetary policy for that period? And is there any model that can explain this optimal policy? And more importantly, can that model be applied to forecast inflation changes during and after the crisis period? Following these questions, the paper first explores the optimal monetary policy that should be applied in crisis, followed by its quantitative implications compared with empirical data. Then I use this model to test its power in forecasting inflation.

In the financial crisis of 1997–1998 the short-term interest rates in several Asian countries rose sharply, and then ultimately fell to the pre-crisis level. This contradicted the traditional monetary transmission mechanism, where a cut in interest rates, rather than a rise, was needed to boost the economy after the realization of adverse

shocks.

However, raising interest rates might be welfare-improving, given the balance-sheet mismatch. Firms in many emerging economies use their assets as collateral to borrow from foreign markets. The assets are denominated in domestic currency but the liabilities are in foreign currency. An exchange rate depreciation will reduce the borrowing capacity of those firms. And a hike in interest rates helps to prevent the exchange rate moving in unfavorable direction.

Braggion, Christiano and Roldos (2009) use a standard small open economy model with tradeable and non-tradeable goods sectors to show that the observed interest rate movement in Korea during the Asian Financial Crisis is essentially the optimal monetary policy response. This model introduces one real friction and two financial frictions. The real friction is that firms in the traded goods sector choose labor prior to the realization of the crisis. The portfolio allocation friction in the limited participation model, and collateral constraint that captures the balance-sheet effects are the two financial frictions. This model explains well *qualitatively* the Korean experience in 1997–1998. But *quantitatively* it leaves several caveats. The magnitude of the simulated current account movement is underestimated. And the inflation response of the model is overestimated.

The underestimation of current account movement may stem from the model assumption of fixed working capital. When the collateral constraint is binding due to the sudden stop ((Calvo 1998)), a firm can choose to import less or borrow less to reduce the interest payment. Adding the capital accumulation may help to address this problem. A reduction in investment provides firms with another margin from which to spend resources that can be used to pay off international debt. But on the other hand, if the capital is costly to adjust, the marginal product of capital, which is used to value firms' assets as collateral, will be lower than the case where capital

stock is fixed in the crisis episode. This means that firm's borrowing ability in this framework is reduced, comparing to Braggion et al. (2009).

Some earlier work that incorporates the capital accumulation fits well the empirical data of current account reversal in some emerging countries. Mendoza (2005) uses a dynamic stochastic general equilibrium model to explain the three stylized facts of sudden stops: sudden current account reversals, sharp decline in output and investment, and collapses in domestic asset prices. He extends the standard real business cycle (RBC) model of small open economies (SOE) and calibrates the parameters to the Mexican case in the 1990s. Two types of constraint are assumed in this model: the collateral constraint and the working capital constraint. This model reproduces the current account reversal in Mexico. But this model does not include monetary policy, hence it cannot address the issue of optimal monetary policy during financial crisis.

The overshooting inflation responses, on the other hand, are due to the lack of stickiness in the transmission mechanism. In the original setup of Braggion et al. (2009), prices are flexible. Adding capital adjustment process can partly address this issue. As when firms are facing collateral constraint and make optimal decisions accordingly, they also make price changes stickier. That provides another reason to add the capital accumulation channel.

In this chapter I examine a model that adds the capital accumulation channel to Braggion et al. (2009). The capital stock in the tradeable sector is allowed to vary, subject to a capital adjustment costs. Here I am allowing the minimal increase in real frictions relative to the benchmark model. When investment and capital accumulation decision is considered, capital adjustment costs are needed. And this model does include the monetary authority so that I can explain the optimal monetary policy in the wake of the financial crisis.

This chapter is organized as follows. The next section presents the model. Then Section 4.3 discusses the quantitative results, followed by tests of its power in forecasting inflation. Concluding remarks are offered in the last section.

4.2 The Model

This section presents the details of the model.

4.2.1 Households

Households choose consumption c_t, deposit D_t, and labor L_t (all in real terms) to maximize the life-time utility:

$$\sum_{t=0}^{\infty} \beta^t u(c_t, L_t) \tag{4.1}$$

The representative household derives utility from consumption and disutility from labor following:

$$u(c_t, L_t) = \frac{\left[c_t - \frac{\psi_0}{1+\psi} L_t^{1+\psi}\right]^{1-\sigma}}{1-\sigma} \tag{4.2}$$

Here ψ_0, ψ and σ are all positive.

The household faces the following cash constraint on consumption expenditure:

$$P_t^T p_t c_t \leq P_t^T w_t L_t + \tilde{M}_t - D_t \tag{4.3}$$

$\tilde{M}_t$ represents the stock of liquid assets at the beginning of period t, D_t is the deposits, and N_t is the labor units. w_t denotes the wage rate, p_t denotes the price of final goods. Both of them are denominated in units of tradeable goods. P_t^T denotes

the domestic currency prices of tradeable goods. There is a no-Ponzi games condition, so that the problem is well defined.

Note here the household makes the deposit decision before the realization of the adverse shocks. This is equivalent to the portfolio allocation friction in the limited participation model, such as Lucas (1990) and Fuerst (1992).

The law of motion of the household's assets is given by

$$\tilde{M}_{t+1} = R_t(D_t + X_t) + P_t^T \pi_t + \left[P_t^T w_t L_t + \tilde{M}_t - D_t - P_t^T p_t c_t\right] \tag{4.4}$$

R_t is the gross domestic nominal interest rate, π_t is firm profits and is measured in units of tradeable goods. X_t is a liquidity injection from the monetary authority.

4.2.2 Firms

Final Goods Firm

Following Braggion et al. (2009), one representative, competitive firm produces the final goods, using intermediate goods following a CES aggregate function:

$$c = \left(\left[(1-\gamma)c^T\right]^{\frac{\eta-1}{\eta}} + \left[\gamma c^N\right]^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \tag{4.5}$$

where $\eta \geq 0$ and $0 < \gamma, 1$.

η is the elasticity of substitution between tradeable c^T, and non-tradeable intermediate goods c^N, respectively.

The final good firm maximizes profits:

$$p_t c_t - c_t^T - p_t^N c_t^N \tag{4.6}$$

where $p_t^N = \frac{P_t^N}{P_t^T}$. P_t^N is the domestic currency price of non-tradeable goods. Note that the final good firm is a price taker and the zero profit condition hold here.

Intermediate Inputs Firm

One representative, competitive firm produces the traded and non-traded intermediate goods. The firm borrows at the beginning of period to purchase a foreign input, and repays these loans at the end of the period.

The firm's optimization problem is

$$\max \sum_{t=0}^{\infty} \beta_{t+i}^{t} E_t \Lambda_{t+1} \pi_t \tag{4.7}$$

where

$$\pi_t = p_t^N y_t^N + y_t^T - w_t R_t L_t^T - R^* z_t - r^* B_t + (B_{t+1} - B_t) \tag{4.8}$$

Here β_{t+i} is the stochastic discount factor, π_t is the profit, B_t is the stock of external debt at the beginning of period t, R^* is the gross interest rate on loans for purchasing z_t, r^* is the interest rate on the outstanding stock of external debt. Λ_{t+1} is the price taken by firms, and it is the Lagrangian multiplier of the household problem.

For the traded goods sector, production function is

$$y_t^T = \left(\theta V_t^{\frac{\xi-1}{\xi}} + (1-\theta)[\mu z_t]^{\frac{\xi-1}{\xi}} \right)^{\frac{\xi}{\xi-1}} - CAC(I_t, K_t) \tag{4.9}$$

$$V_t = A(K_t^T)^v (L_t^T)^{1-v} \tag{4.10}$$

where ξ is the elasticity of substitution between value-added V_t in the traded good sector and the imported intermediate good z_t. The capital stock in this sector K^T is allowed to vary over time through physical investment and depreciation. It relaxes the strict assumption that capital stock in the traded goods sector is constant and there is no physical investment in Braggion et al. (2009). This is the key difference of these two models. K_t is assumed to be costly to adjust. $CAC(I_t, K_t)$ is the capital adjustment cost which exists only in the tradeable goods sector and not in the non-traded sector. Here I am allowing the minimal increase in real frictions relative to the benchmark model. When investment and capital accumulation decision is considered, capital adjustment costs are needed, otherwise the rate of investment is infinite.[1] Here I assume a quadratic adjustment cost and consider the following form:

$$CAC(I_t, K_t) = \frac{\varepsilon}{2}\left(\frac{I_t^2}{K_t^T}\right) \tag{4.11}$$

And the capital accumulation in this sector is

$$I_t = K_t^T - (1-\delta)K_{t-1}^T \tag{4.12}$$

For the non-traded goods sector, the production function takes the form

$$y_t^N = (K^N)^\alpha (L_t^N)^{1-\alpha} \tag{4.13}$$

K^N is the capital non-traded good sectors. It is assumed to be fixed in the non-traded good sector, following Braggion et al. (2009).

[1]Alternatively an investment adjustment cost term, which captures the changes of the flow of investment and is commonly used in DSGE models, can be added. The intuition is similar to models in Chapter 3 of the dissertation.

Employment in the traded and non-traded sectors, L_t^T and L_t^N, satisfy the following constraint:

$$L_t = L_t^T + L_t^N \tag{4.14}$$

In equilibrium, the following borrowing restriction exists:

$$\frac{B_{t+1}}{(1+r^*)^t} \to 0, \text{ as } t \to \infty \tag{4.15}$$

In case of a sudden stop, the following collateral constraint is imposed:

$$\tau^N q_t^N K^N + \tau^T q_t^T K_t^T \geq R^* z_t + (1+r^*)B_t \tag{4.16}$$

Here q^N and q^T are the value of one unit of capital in the non-traded and traded good sectors, respectively. τ^N and τ^T are the fractions of these stocks accepted as collateral by international creditors.

In the absence of capital accumulation, the firm can adjust the right-hand side of the constraint only by importing less and borrowing less. Adding investment provides the agent the ability to adjust from its total assets, the left-hand side of the equation. For instance, the firm can make investment decisions to change the level of K_t^T.

Adding investment with capital adjustment cost can lower the unit value of the capital. q_t^i satisfies

$$q_t^i = \frac{VMP_{k,t}^i + \beta \frac{\Lambda_{t+2}}{\Lambda_{t+1}} q_{t+1}^i}{1 - \lambda_t \tau^i}, \; i = N, T. \tag{4.17}$$

Here $VMP_{k,t}^i$ is the marginal product of capital in sector i. When $\lambda_t \equiv 0$, the collateral constraint is not binding. With capital adjustment cost,$VMP_{k,t}^T$ is lower than the case of fixed capital stock.

If the firm chooses to reduce its investment, given the lower unit value of capital, the firm has to reduce its imports even further than the case of fixed capital stock. This leads to a potentially larger magnitude of current account reversal than Braggion et al. (2009).

4.2.3 Monetary Authority

The financial intermediary takes domestic deposits from the households, and receives the liquidity injection from the monetary authority at the beginning of period t. Then it lends all its domestic funds to intermediate goods firms to finance the wage bills.

$$D_t + X_t = P_t^T w_t L_t. \tag{4.18}$$

Scaling by aggregate money stock at the beginning of period t,

$$d_t + x_t = p_t^T [w_t L_t^N + w_t L_t^T]. \tag{4.19}$$

where $d_t = \frac{D_t}{M_t}$.

4.2.4 Market Clearing

Actual money balances M_t must equal $\tilde{M}_t$ in equilibrium. In other words, money supplied to this economy always meets the demand. Combining this with the household budget constraint, the equilibrium cash constraint is obtained:

$$p_t^T p_t c_t = 1 + x_t. \tag{4.20}$$

Market clearing in the traded good sector requires

$$y_t^T - R^* z_t - r^* B_t - c_t^T - I_t = -(B_{t+1} - B_t). \tag{4.21}$$

The left-hand side of the equation is the current account, which equals the output in the traded good sector at period t, less the consumption, investment, and foreign interest payment. The right-hand side is the movement of net foreign debt.

Market clearing in the non-traded good sector requires

$$y_t^N = c_t^N. \tag{4.22}$$

4.3 Quantitative Results

4.3.1 Data Parameter Calibration

Korean data are taken from International Financial Statistics at IMF. All parameters used in this chapter, except the depreciation rate and capital adjustment cost parameter, are from Braggion et al. (2009), in order to match the Korea data. The depreciation rate is taken from standard real business cycle literature and has been converted to semi-annual rate. The capital adjustment cost parameter varies from country to country. For instance, Groth (2008) reported a higher value for the UK than the ones reported for the US (Hall 2005). I have not found any empirical assessment of the magnitude of such a parameter for Korea. Hence I leave ε as a free parameter. Other parameter values are listed in Table 4.2.

4.3.2 Simulation Results

The model is simulated to compare with the results from Braggion et al. (2009) and the actual data in Korea. I focus on the comparison of the current account reversal and the inflation response, which are the two caveats mentioned earlier.

Simulation results in 4.1 illustrate the magnitude of current account reversal. Adding investment results in a larger degree of current account movement, which gets closer to the real data in Korea. In the wake of the financial crisis where the collateral constraint is binding, the firm has three options: adjust the collateral value by changing its capital stock level, import less, or borrow less. The high capital adjustment cost lowers the marginal product of capital. The firm is less willing to invest comparing to the pre-crisis level. The shrinking capital stock makes the firm's collateral less valuable. Compared to the case of fixed capital stock, the firm has to import even less and borrow even less, raising the value of the left-hand side of 4.21, which is the current account.

The simulated inflation in the aftermath of the crisis also becomes less extreme as in the model without capital simulation. This is largely due to the fact that the capital accumulation process introduces additional frictions into the system. In other words, price changes are relatively less flexible. Hence under the same optimal monetary policy responses, the problem of the inflation overshooting is partly addressed.

4.4 Inflation Forecasts

From the comparison of IRFs of models with and without capital accumulation, we see the former generates closer inflation responses to empirical data using the eyeball approach. Thus adding capital accumulation should improve the forecasting power. Results (RMSEs) are shown in Table 4.1.

Table 4.1: Inflation Forecasting Performance: RMSEs

Forecasting Periods	without capital accumulation	with capital accumulation
1	5.490	3.357
2	6.473	3.327
3	6.484	3.470
4	6.579	3.006
5	7.358	3.858
6	6.346	4.246
7	7.542	6.335
8	7.732	5.344

Note: Lower value means more accurate forecast.

As we can see from this table, the original model in Braggion et al. (2009) does not provide good inflation forecasts. Adding capital accumulation improves its forecastability. The possible reason comes from different frictions included in both models. In terms of inflation responses, adding investment lowers the magnitude of the inflation response after the realization of collateral shocks. The original model produces the hyperinflationary scenario. This may due to the lack of nominal rigidities in the model setup. Many real business cycle models, which also lack nominal frictions, have weak internal propagation mechanism and must depend on the external sources of dynamics (Cogley and Nason (2005)). The model presented in this chapter, as well as the one in Braggion et al. (2009), is similar to those RBC models in modeling. Hence it is no surprise that the responses of nominal variables are so extreme. This paper adds another friction, the capital adjustment cost, on top of the case of fixed capital stock. This additional friction may explain why the inflation response after adding investment is closer to reality. Hence the extended model generates better inflation forecasts.

4.5 Conclusion

This chapter extends the model in Braggion et al. (2009) by examining the role of the physical investment in a sudden stop, especially on how it may improve the inflation forecastability.

When capital stock is fixed, a firm has two instruments to respond to the binding collateral constraint: to import less or to borrow less to pay off the international debt. Adding the capital accumulation enables the firm to adjust the value of its collateral. On one hand, a reduction in investment provides firms another margin from which to spend resources that can be used to pay off international debt. On the other hand, if the capital is costly to adjust, the marginal product of capital, which is used to value firms' assets as the collateral, will be lower than the case where capital stock is fixed in the crisis episode. Less capital stock and lower unit value of capital reduce the value the firm's collateral. In this case the firm has even less incentive to import or borrow. Thus this framework can generate a current account reversal with much larger magnitude comparing to the case of fixed capital stock.

This model produces less extreme inflation reaction than Braggion et al. (2009). The original model generates the counterfactual hyperinflationary scenario. It is caused by the lack of nominal rigidities, as appears in many models with flexible price setups. The weak internal propagation mechanism forces the model to depend on external sources of dynamics, which produces the extreme responses of inflation. By adding the capital accumulation process (another friction), the extended model is able to improve inflation forecasting power substantially.

The collateral shock is exogenously determined in this chapter. It is natural to extend the model to endogenously determined collateral constraint triggered by unexpected shocks from domestic market as well as the international market. It will help

to estimate the possibility of a sudden stop even if the economic fundamentals look sound. This is particularly meaningful considering the fast-growth Asian economies before the financial crisis in 1997–1998.

This chapter also has important implications for China. Since China has not experienced a full-scale economic crisis in the past three decades, existing literature on inflation forecasting seems to focus on normal periods. If economic slowdown occurs, including possible 'sudden stops,' these studies may fall short of providing good inflation forecasts with certain policy response. This chapter, at least on two fronts, contributes to the existing literature. First, this chapter confirms that the optimal monetary policy rules in crisis should be a combination of raising and lowering policy rates. And second, this chapter proposes a model that improves on existing papers on forecasting inflation during and shortly after crisis periods. Admittedly the model is using Korean data for quantitative comparison, but it should be easily modified to fit Chinese data when they become available.

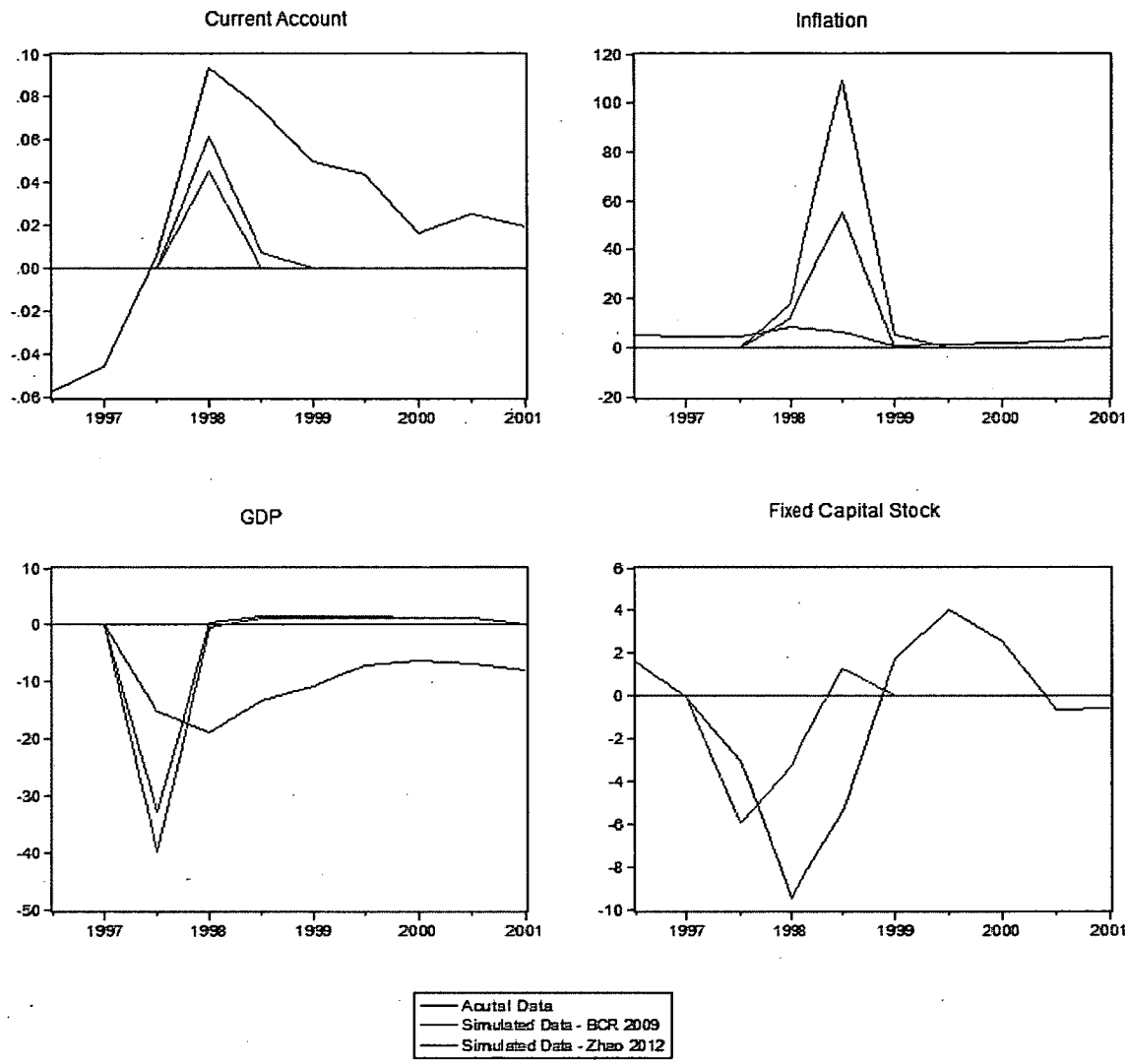
This model can also serve as a benchmark for further extensions. For instance, one can incorporate nominal rigidities in Mendoza (2006). It should also strengthen the internal prorogation mechanism and is likely to improve inflation forecasting performance.

Table 4.2: Parameter Values

β	0.093	η	0.015
ψ	1	γ	0.26
R^*	1.06	R	1.12
α	0.36	r^*	0.06
ν	0.5	μ	3.5
τ^T, τ^N	0.05	θ	0.7
ψ_0	0.0036	σ	4
A	1.5	ξ	0.9
ε	12	δ	0.024
K^N	10		

Note: Parameters are from Braggion et al. (2009). Here β, R^* and r^* are expressed in annualized terms.

Figure 4.1: Simulation Results



Note: Adding capital accumulation helps to produce simulated output and inflation data which are closer to true Korea data after the financial crisis, comparing to Braggion et al. (2009).

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