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ESSAYS ON MACROECONOMICS AND FORECASTING

A Dissertation

by

DANDAN LIU

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2005

Major Subject: Economics

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Approved by:

Chair of Committee,	Dennis W. Jansen
Committee Members,	David A. Bessler
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ABSTRACT

Esssays on Macroeconomics and Forecasting. (August 2005)

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Chair of Advisory Committee: Dr. Dennis W. Jansen

This dissertation consists of three essays. Chapter II uses the method of structural factor analysis to study the effects of monetary policy on key macroeconomic variables in a data rich environment. I propose two structural factor models. One is the *structural factor augmented vector autoregressive* (SFAVAR) model and the other is the *structural factor vector autoregressive* (SFVAR) model. Compared to the traditional vector autogression (VAR) model, both models incorporate far more information from hundreds of data series, series that can be and are monitored by the Central Bank. Moreover, the factors used are structurally meaningful, a feature that adds to the understanding of the "black box" of the monetary transmission mechanism. Both models generate qualitatively reasonable impulse response functions. Using the SFVAR model, both the "price puzzle" and the "liquidity puzzle" are eliminated.

Chapter III employs the method of structural factor analysis to conduct a forecasting exercise in a data rich environment. I simulate out-of-sample real time forecasting using a *structural dynamic factor forecasting* model and its variations. I use several structural factors to summarize the information from a large set of candidate explanatory variables. Compared to Stock and Watson (2002)'s models, the models

proposed in this chapter can further allow me to select the factors structurally for each variable to be forecasted. I find advantages to using the *structural dynamic factor forecasting* models compared to alternatives that include univariate autoregression (AR) model, the VAR model and Stock and Watson's (2002) models, especially when forecasting real variables.

In chapter IV, we measure U.S. technology shocks by implementing a dual approach, which is based on more reliable price data instead of aggregate quantity data. By doing so, we find the relative volatility of technology shocks and the correlation between output fluctuation and technology shocks to be much smaller than those revealed in most real-business-cycle (RBC) studies. Our results support the findings of Burnside, Eichenbaum and Rebelo (1996), who showed that the correlation between technology shocks and output is exaggerated in the RBC literature. This suggests that one should examine other sources of fluctuations for a better understanding of the business cycle phenomena.

To my parents and my husband, Pingshan Li

for their unconditional support,

and to my beloved son, David Li

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CHAPTER I

INTRODUCTION

Chapter II studies the effects of monetary policy using a structural factor analysis approach. Sims (1980) suggests the use of a vector autoregression (VAR) to derive the impulse responses of key macroeconomic variables to monetary policy shocks, based on a recursiveness identification assumption. Since then, this VAR approach has been the fundamental tool in the literature, either using different sets of variables or applying different identification schemes.

However, the traditional VAR approach suffers from a limited information problem. Constrained by the degrees of freedom, only a small number of variables can be included. There is a potential "missing information" problem and the identified monetary shocks could be seriously contaminated by using the traditional VAR approach.

In this chapter, I reexamine the effects of monetary policy using a factor analysis approach in a data rich environment. In the first model—a *structural factor augmented vector autoregressive* (SFAVAR) model, I use several structural residual factors to summarize information that is left over by the variables typically used in traditional

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This dissertation follows the style and format of the Journal of Monetary Economics.

VARs such as industrial production, the consumer price index and the federal funds rate. I then propose a more general *structural factor vector autoregressive* (SFVAR) model. In the SFVAR model, instead of taking any arbitrary stand on choosing specific series, I treat all series in the same subset equally without any prior preference. Some of them explain the general real economic conditions, so I call them “real activity factors”. And some of them are “inflation/price factors” that determine the inflation or price levels. Meanwhile, I use a “monetary policy factor” to represent the stand of monetary policy instead of any individual series (e.g. the federal funds rate or the non-borrowed reserve).

The advantages of these two factor model are quite obvious. First of all, they still have the advantages of the traditional VAR approach. Second, they carry more information about the dynamics of the economy. Third, instead of using hundreds or even thousands of data series, they use several factors to summarize and preserve the structure among them. Finally, the factors used have more meaningful structural interpretations, a feature that adds to the understanding of the “black box” of monetary transmission mechanism.

Chapter III uses a dynamic structural factor model and its variations to forecast some key macroeconomic variables. An important application of the structural factor analysis relates to the forecasting literature. Stock and Watson (1998, 1999 and 2002) are the pioneer papers in the literature. However, using their factor models, one can not choose estimated factors or forecasting models structurally based on some standard theories. Given the shortcomings of the non-structural dynamic factor forecasting model, in this chapter, I propose a general *structural factor forecasting model* and its variations to forecast some key macroeconomic variables. Since the factors used in the models are structurally meaningful, one can choose the factors according to some widely-accepted theories depending on the variable to be forecasted.

Chapter II and chapter III both employ factor models. The literature on factor models in macroeconomics both for estimation and forecasting is relatively small but is growing rapidly. Sargent and Sims (1977) first propose a general form of dynamic factor model or index model to analyze the U.S. business cycle. They argue that many existing models can be fitted into their factor/index model. Afterwards, various versions of Sargent and Sims' model have been used to study the dynamic covariation among different sets of variables, e.g., Geweke (1977), Singleton (1980), Engel and Watson (1981), Stock and Watson (1989,1991), Quah and Sargent (1993), and Forni and Reicnlin (1996,1998). Recently, Bernanke, Boivin and Eliasz (2004) combine the factor analysis with VAR. Stock and Watson (1998, 1999, 2002) apply the factor analysis into forecasting literature.

Chapter IV re-examines the role of technology shocks using a dual approach. The real-business-cycle RBC theory singles out the real shocks, technology shocks, as the main source of aggregate fluctuations. To demonstrate the role of technology shocks in generating business cycles, people use the primal Solow residual as a measure of the rate of technological progress, i.e., the growth rate of total factor productivity or technology shocks. But the use of the primal Solow residual remains a controversial issue. There are several measurement problems that can make the primal Solow residual a poor measure of productivity at cyclical frequencies. First, it is labor hoarding, the phenomenon in which firms may continue to employ workers they do not need during recession. This means that labor input is overestimated in recession, and productivity as measured by the primal Solow residual falls even if there is no technology regress. As a result, the primal Solow residual is more cyclical than the available productivity technology. Second, people also question the standard assumption used in calculating the primal Solow residual in the real-business-cycle literature: the capital service is proportional to the capital stock. Finally, the measures of the primal Solow residual in RBC literature are based on aggregate national accounts data. As is well known, the task of computing reliable national statistics is an extremely difficult one, and even under the best circumstances such statistics are plagued with errors.

Motivated by the criticism of the measures of technology shocks used in the RBC literature, this chapter uses a price-based dual approach to measure the Solow residual. The dual Solow residual is measured as the share-weighted average of real factor prices. Rather than using the aggregate quantity data employed in the primal approach, the use of dual Solow residuals allows for us to utilize more accurate and easily accessed price-based data. Therefore, the dual approach avoids many of the problems of the primal approach mentioned above and measures the technology shock more accurately. In this chaper, we re-examine the role of technology shocks in RBC using the dual Solow residual approach, and compare it with the primal approach.

CHAPTER II

THE EFFECTS OF MONETARY POLICY USING STRUCTURAL FACTOR ANALYSIS

2.1 Introduction

There has been a great deal of interest in identifying and measuring the effects of monetary policy shocks on macroeconomic variables , both for the purpose of policy analysis and for the purpose of assessing the empirical fitness of structural models.

The traditional VAR approach that was first propsed by Sims(1980) has the advantage of being statistically simple but unfortunately, because of the constraint on the degrees of freedom, only a small number of variables can be included. However, the Central Bank actually monitors and analyzes thousands of data series and the policy makers consider the information contained in these series when making their decisions. Obviously, there is a potential “missing information” problem and the identified monetary shocks could be seriously contaminated by using the traditional VAR approach.

To solve this problem, recent research has combined the VAR approach with factor analysis, e.g., Bernanke and Boivin (2003) and Bernanke, Boivin and Eliasz (2004). In this new approach, Bernanke et al. use a small set of estimated factors or indexes summarizing large amounts of information about the economy and use these factors to augment standard VARs. This new so-called *factor augmented vector autoregressive* (FAVAR) approach not only conserves the advantages of traditional VAR, but it also allows us to employ a significant larger number of data series. However, it is hard to give any structural interpretation to these factors and therefore it is impossible for us to study the monetary transmission mechanism using this FAVAR model.

In this chapter, I go a step further by seeking structural interpretations to these common factors. The structural factor models that I propose in this chapter can help us have a better structural understanding of the forces that are driving the evolution of the economy and display more traceable information for policy making. They also open the door for us to study the monetary transmission mechanism with richer information.

I first propose a *structural factor augmented vector autoregressive* (SFAVAR) model by augmenting the traditional VAR with structural factors. The traditional VAR typically uses variables such as industrial production, the consumer price index and the federal funds rate. However, one could expect that there are "real activity residual factors", "inflation/price residual factors" and "monetary policy residual factors" that contain important information that is not explained by the typical VAR variables. Then, one can improve on the traditional VAR by using these extra "hidden" residual structural factors and estimate the effects of monetary policy shocks. The advantages of the *structural factor augmented VAR* (SFAVAR) model are quite obvious. First of all, it still has the advantage of the traditional VAR approach, since it is computationally easy to estimate. Second, it carries more information about the dynamics of the economy. Third, instead of using hundreds or even thousands of data series, it uses several factors to summarize and preserve the structure among them. Finally, compared to Bernanke, Boivin and Eliasz (2004)'s FAVAR model, the factors I propose have more meaningful structural interpretations. Moreover, the SFAVAR model nests the traditional VAR model totally, so that it is possible to make a direct comparison between them.

I then propose a more general *structural factor vector autoregressive* (SFVAR) model. In the traditional VAR literature, the choice of variables that are included is quite arbitrary. There are no prior theoretical reasons for choosing them, except that sometimes they are the most often used ones (e.g. IP, the CPI and the federal funds rate) or that they help to produce "reasonable" dynamic responses (e.g. the commodity price index). Moreover, some theoretical constructs, for instance, the "real economic activity", may not be adequately presented by any specific individual series. Meanwhile, many "observable" series are contaminated by measurement errors. Therefore, in the SFVAR model, instead of taking any arbitrary stand on choosing specific series, I treat all series in the same subset equally without any prior preference. These individual series only reflect different aspects of some economy condition on the "surface" and what matters are the unobservable underlying factors that drive the evolution of the economy. These factors not only explain common movement among these series but also average away idiosyncratic errors. Some of them explain the general real economic conditions, so I call them "real activity factors". And some of them are "inflation/price factors" that determine the inflation or price levels. Meanwhile, I use a "monetary policy factor" to represent the stand of monetary policy instead of any individual series (e.g. the federal funds rate or the non-borrowed reserve). The general SFVAR model has all the advantages of the SFAVAR model. Moreover, it is more general and more flexible. By using the SFVAR model, one can generate impulse response functions of any variable of interest.

The data set I use in this chapter consists of 308 monthly U.S. macroeconomic time series. Each series covers the period from January 1972 to December 2003, therefore 383 observations per variable. To my knowledge, this data set has the largest number of series and is the most updated one.

The rest of the chapter is organized as follows. In section 2.2, I outline the *structural factor augmented vector autoregressive* (SFAVAR) model and the *structural factor vector autoregressive* (SFVAR) model used to evaluate the effects of monetary policy. Section 2.3 describes the data set and the identification schemes applied to identify the monetary policy shocks for the SFAVAR model and the SFVAR model. Section 2.4 reports the estimation results and studies the effects of a monetary policy shock. In this section, I also compare both models with the traditional VAR model and the FAVAR model proposed by Bernanke, Boivin and Eliasz (2004). Section 2.5 summarizes the main conclusions of this chapter.

2.2 The Models

In this section, I propose two models to study the effects of monetary policy on the economy. The first model, the *structural factor augmented VAR* (SFAVAR) model is a natural extension of the traditional 3-variable VAR model. I use three groups of residual factors to summarize information that is left over by industrial production, the consumer price index inflation rate and the federal funds rate. The 3-variable VAR is then augmented by the residual factors. I then propose a more general model—the *structural factor VAR* (SFVAR) model. In this model, I assume all the variables only reflect the economy on the surface and what matters are the underlying factors. I classify all the variables into a small number of categories. In this chapter, I look at 3 categories—real, inflation and monetary categories, based on the fundamental conditions of the economy. I then use factors to summarize the common information in each category and estimate a factor VAR model.

2.2.1 The SFAVAR Model

Following the notation of Bernanke, Boivin and Eliasz (2004), let Y_t be a vector of observable variables with dimension $M \times 1$. We can think of them as those either closely in the control of the Central Bank (e.g., the federal funds rate) or readily "observable" (e.g., industrial production). Also, these are the variables frequently studied in the traditional VAR approach. Among the most typical variables, we have industrial production (IP) to indicate the real activity, the consumer price index (CPI) to indicate the inflation pressure and the federal funds rate (FFED) to represent monetary policy. However, there are more forces that drive the dynamic behavior of the economy. For example, one could think of many other series that are related to the real activity besides industrial production; series that provide information about different aspects or different sectors of the real economy, such as retail sales, real personal consumption, housing starts and industrial production or capacity utilization of individual industries, etc. Similarly, there are also a lot of other series that may represent the inflation pressure besides the consumer price index, such as average hourly earning, the producer price index, etc. Moreover, even though the federal funds rate is a very good indicator of monetary policy, it does not capture completely the stand of the monetary authority. All these variables other than industrial production, the consumer price index and the federal funds rate contain very important information about the economy: not using this information, as is common in traditional VARs, can have serious consequences. Meanwhile one can not include all these variables in the VAR either due to statistic reasons: it seriously reduces the degrees of freedom.

An alternative approach, and the one I propose in this chapter, is to use a small number of factors that summarize the information contained in these additional variables. Moreover, by construction, these factors contain structural information that is very helpful in understanding and interpreting the results. These factors can be thought of as the "hidden" factors behind the scene.

As a natural step to extend the typical three-variable VAR model, one can think of three groups of factors: "real activity residual factors", "inflation/price residual factors" and "monetary policy residual factors". These residual factors cover the "space" of the economy that is left over or can not be explained by the three original variables—industrial production, the consumer price index and the federal funds rate. Then, one can augment the typical three-variable VAR with these "hidden" residual structural factors and estimate the effects of a monetary policy shock. I call this model the *structural factor augmented* VAR or SFAVAR, as illustrated in equation (2.1).

$$A \bullet \begin{bmatrix} RF^{R}{}_{t} \\ IP_{t} \\ RF_{t}^{I} \\ CPI_{t} \\ RF_{t}^{M} \\ FFED_{t} \end{bmatrix} = C(L) \bullet \begin{bmatrix} RF_{t-1}^{R} \\ IP_{t-1} \\ RF_{t-1}^{I} \\ CPI_{t-1} \\ RF_{t-1}^{M} \\ FFED_{t-1} \end{bmatrix} + \varepsilon_{t} \qquad (2.1)$$

where matrix A is the contemporaneous coefficient matrix, $C(L)$ is a conformable lag polynomial of finite order d, telling us the intertemporaneous relationships among these residual factors and variables, and ε_t is the vector of the structural shocks with mean zero and identity variance-covariance matrix . In equation (2.1), RF^R denotes the "real activity residual factors" vector that covers the real activity space that is not covered by industrial production (*IP*); RF^I denotes the "inflation/price residual factors" vector that covers the inflation or price space that can not be explained by the consumer price index inflation rate (*CPI*); and RF^M denotes the "monetary policy residual factors" vector that covers the monetary policy space left over by the federal funds rate (*FFED*). Thus, we use these three sets of structural residual factors to summarize the extra information that can not be explained by the typical three variables in VAR— industrial production, the consumer price index inflation rate and the federal funds rate. By construction, the "real activity residual factors" are orthogonal to industrial production, the "inflation/price residual factors" are orthogonal to the consumer price index inflation rate, and the "monetary policy residual factors" are orthogonal to the federal funds rate contemporaneously.

To obtain these structural residual factors, I collect all the real activity series except industrial production in the vector RX_t^R, all the series related to prices or inflation except the consumer price index in the vector RX_t^I and all the interest rate series or money aggregate series except the federal funds rate in the vector RX_t^M. I then estimate equation (2.2) by the ordinary least squares method.

$$\begin{bmatrix} \mathrm{RX}_t^R \\ \mathrm{RX}_t^I \\ \mathrm{RX}_t^M \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \bullet \begin{bmatrix} IP_t \\ CPI_t \\ FFED_t \end{bmatrix} + \begin{bmatrix} ru_t^R \\ ru_t^I \\ ru_t^M \end{bmatrix} \tag{2.2}$$

where the coefficient matrix b is block diagonal. Afterwards, I estimate the structural residual factors by the *principal components* method[1] from the residuals as shown in (2.3).

---

[1] Principal components method: suppose a factor model is represented as $X_{it} = \lambda_i' F_t + e_{it}$, where X_{it} is the observed datum for the ith series at time t (i=1,…., N; t = 1,….,T); F_t is a vector ($r \times 1$) of common factors; λ_i is a vector ($r \times 1$) of factor loadings; and e_{it} is the idiosyncratic component of X_{it}. The right hand side variables are not observed. The method of principal components minimizes $V(r) = \min_{\Lambda,F} (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i' F_t)^2$, where $\Lambda=(\lambda_1,\ldots,\lambda_N)$. Concentrating out Λ and using the normalization that $F'F/T = I_r$ (an $r \times r$ identity matrix), the problem is identical to maximizing $tr(F'(XX')F)$. The estimated factor matrix, denoted by $\widetilde{F}$, is $\sqrt{T}$ times eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix XX', and $\widetilde{\Lambda}' = (\widetilde{F}'\widetilde{F})^{-1}\widetilde{F}X = \widetilde{F}X/T$ is the corresponding loading matrix. Refer to Bai (2003) for more details.

$$\begin{bmatrix} ru_t^{\ R} \\ ru_t^{\ I} \\ ru_t^{\ M} \end{bmatrix} = \begin{bmatrix} R\lambda_{11}^{\ R} & 0 & 0 \\ 0 & R\lambda_{22}^{\ I} & 0 \\ 0 & 0 & R\lambda_{33}^{\ M} \end{bmatrix} \bullet \begin{bmatrix} RF_t^{\ R} \\ RF_t^{\ I} \\ RF_t^{\ M} \end{bmatrix} + u_t \tag{2.3}$$

where the block diagonal loading matrix $R\lambda$ and the residual factors are unknown. By imposing the loading matrix is block diagonal, I assume that each set of residuals is influenced only by the corresponding set of factors. Therefore, one can interpret each set of factors structurally depending on the common characteristic of corresponding residuals. As the residuals from equation (2.2) are contemporaneously orthogonal to industrial production, the consumer price index inflation rate and the federal funds rate respectively, so are the estimated structural residual factors from equation (2.3).

2.2.2 The SFVAR Model

In this section, I propose a more general version of *structural factor VAR* (SFVAR) model. As many of us have noticed, the choice of variables that are included in traditional VAR seems to be ad-hoc. For example, it is hard to prove industrial production can represent real activity better than other variables, such as the unemployment rate, the capital utilization rate, etc.

In the SFVAR model, instead of assuming that these typical variables, e.g., industrial production and the consumer price index inflation rate, are the only indicators for the real condition and nominal condition of the economy respectively, I treat them equally with other real and nominal series. All these series including industrial production and the consumer price index only reflect the phenomena on the “surface”.

What matters are those common factors behind them. Some of them are “real activity factors” that decide the way of the real economy and some of them are “inflation/price factors” that determine the price level and its growth rate.

Moreover, there is also no consensus about which variable is the best indicator for monetary policy or even if there is such a variable. In the beginning, many researchers supported the use of some broad monetary aggregate variables (M1, M2 and M3). Friedman and Schwartz (1963) first show that comovement of money and output is not due to the passive response of money to the developments in the economy and argue that rates of change in money are good approximations to monetary policy disturbances. However, identifying monetary policy shocks with innovations in money aggregates has led to the “liquidity puzzle”—positive innovations in money aggregates appear to be associated with increases in interest rates, which are only expected in monetary contractions.[2] To solve the “liquidity puzzle”, some studies, e.g., McCallum (1983), Bernanke and Blinder (1992) and Sims (1986, 1992), suggest using the federal funds rate. They argue institutionally that the federal funds rate is something that is controlled closely by the Center Bank and any shock to it should reflect shocks to money demand rather than shocks to money supply. There are also some authors who suggested using some narrow money aggregates or their ratio to solve the “liquidity puzzle”. For examples, Eichenbaum (1992) and Christiano and Eichenbaum (1992) show evidences that innovations to non-borrowed reserves reflect exogenous shocks to monetary policy.

[2] See Reichenstein (1987) and Leeper and Gordon (1992).

Kim (2001) uses innovations in the ratio of non-borrowed reserves to total reserves to represent monetary policy shocks. After eliminating the "liquidity puzzle", all these studies suffer from another puzzle— the "price puzzle", that is, positive innovations in interest rates and negative innovations in narrow aggregates or their ratio are associated with increases in the price level, which are expected in monetary expansion.[3] And when one looks at the practice of the Fed, it is true that the Fed has adopted the federal funds rate—the interest rate that banks charge one another for overnight loans—as its policy instrument. The changes in the federal funds rate affect changes in other interest rate subsequently. However, behind the changes of the interest rates are the necessary changes in money supply—changes in money aggregates. The Fed affects the federal funds rate through open market operation by selling or buying government bonds. Selling bonds decreases money supply and increases the federal funds rate and vice versa. So, it is really hard and not quite appropriate to choose a single variable to summarize monetary policy. Even Sims (1992) acknowledges that the traditional VAR analysis relies heavily on "postulating" that innovations in a particular variable represent monetary disturbances.

In the SFVAR model, instead of choosing any individual variable arbitrarily, I use "monetary policy factors", which are estimated from all kinds of interest rate series, money aggregate series and outstanding credit series, as indicators of monetary policy. And I treat the innovations to the monetary policy factors as shocks to monetary policy.

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[3] Some authors have tried to solve the "prize puzzle" by adding variables such as commodity price indexes, but except sometimes they "work', there are no solid theoretical explanations for including these variables.

I assume that there are three vectors of variables: the vector of "real activity" variables X_t^R that includes industrial production and other real activity variables, the vector of "inflation/price" variables X_t^I that includes the consumer price index and other price variables, and the vector of "monetary policy" variables X_t^M that includes the federal funds rate and other monetary policy variables. I then estimate the underlying factors from the three groups of "observable" series using principal components method. I further assume that variables in each group are only influenced by the state of the economy through the corresponding underlying factors. So, we have,

$$\begin{bmatrix} X_t^R \\ X_t^I \\ X_t^M \end{bmatrix} = \begin{bmatrix} \lambda^R & 0 & 0 \\ 0 & \lambda^I & 0 \\ 0 & 0 & \lambda^M \end{bmatrix} \bullet \begin{bmatrix} F_t^R \\ F_t^I \\ F_t^M \end{bmatrix} + \begin{bmatrix} e_t^R \\ e_t^I \\ e_t^M \end{bmatrix} \tag{2.4}$$

where F_t^R are the factors affecting the real state of the economy, F_t^I are the factors driving the inflation rate or price levels and F_t^M are the factors explaining the monetary policy of the economy.[4] And the loading matrix λ is block diagonal.

In this chapter, I further assume that there are exactly one real activity factor, one inflation/price factor and one monetary policy factor deciding the big picture of the

[4] In this paper, I consider these three categories of factors representing the "real", "nominal" and "monetary policy" conditions of the economy. Further dividing these factors into more detailed categories will violate the purpose of using factor analysis to reduce dimensions. For some small open economies, I believe there are extra "external" factors that should be considered. But given that the U.S. is a large open economy, I assume that these external factors are relatively unimportant. Given the ongoing debate about asset prices, I also consider the case when there is an extra set of "asset price factors" which are estimated from a large number of asset price series. The estimated impulse responses after a monetary policy shock from the SFVAR model with four groups of structural factors are almost identical qualitatively to the ones using only the above three groups of factors.

overall economy. As the next step, in order to understand the dynamic behavior of the economy, I estimate a *structural factor VAR* (SFVAR) model as shown in equation (2.5):

$$A^F \bullet \begin{bmatrix} F_t^R \\ F_t^I \\ F_t^M \end{bmatrix} = C^F(L) \bullet \begin{bmatrix} F_{t-1}^R \\ F_{t-1}^I \\ F_{t-1}^M \end{bmatrix} + \varepsilon_t^F \qquad (2.5)$$

where A^F is the contemporaneous coefficient matrix, $C^F(L)$ is a conformable lag polynomial of finite order d^F, telling us the intertemporaneous relationship among these factors, and $\varepsilon^F{}_t$ is the vector of the structural shocks with mean zero and identity variance-covariance matrix, $\varepsilon_t^F = A^F \bullet \upsilon_t$.

2.3 The Data and Estimation

2.3.1 The Data

The data set consists of 308 monthly U.S. macroeconomic time series. The period starts in January 1972 and ends in December 2003 with 383 observations for each variable. The original data series are taken from the Haver USECON data set. All these series are then transformed to be stationary.[5] Among all these series, there are 172 real activity variables, 80 inflation or price variables and 56 monetary variables. The list of the series and their transformation is listed in Appendix A at the end of the paper. The real activity group consists of variables about industrial production, capacity utilization,

[5] The theoretical work for factor analysis using principal components is limited to I(0) framework up to now. Only in a I(0) framework, factors estimated by principal components can be consistent estimators. See Stock and Watson (1998) for reference.

manufacturers' inventories, retail inventories, retail sales, real personal consumption, real personal income, new housing starts, employment and average working hours. The inflation or price group is composed of variables related to the consumer price index, the producer price index, the personal consumption expenditure deflator and average hourly earnings. The last group of variables is closely related to monetary policy and it includes money aggregate variables, all kind of interest rates, credit outstanding, etc.

2.3.2 Estimation and Identification

2.3.2.1 The SFAVAR model

In this part, first of all, I first estimate equation (2.2) using the ordinary least squares method. Then I obtain residual vectors that are orthogonal to industrial production, the consumer price index and the federal funds rate respectively. Finally, I estimate the common factors from these residual vectors using the method of *principal components*, as shown in (2.3). As discussed in Stock and Watson (1998), the *principal components* can consistently recover the space spanned by those "surface" series when the number of series is large enough even in the case of having small amounts of data contamination. I further assume that there is only common structural factor for each residual vector. [6]

[6] I assume that there is only one factor from each group of series in the SFAVAR model and SFVAR model in this paper. I examine the validity of this assumption by looking at the variances of each group of variables that are explained by the factors estimated by principal components. The results show that in each group the first principal component or factor corresponding to the biggest eigenvalue of the correlation matrix explains most of the variance. There is an obvious "threshold" between the first factor and the rest in each group in terms of variance explained. This confirms the robustness of my assumption. I also use the criteria suggested by Bai and Ng (2002) to choose the optimal number of factors for each group. Without being imposed any restriction, their criteria tend to select very large number of factors, which violates the purpose of reducing dimensions.

Then I use these three structural residual factors to augment the traditional three-variable VAR and estimate a reduced-form *structural factor augmented VAR* (SFAVAR) model as shown in equation (2.6).

$$\begin{bmatrix} RF^{R}_{t} \\ IP_{t} \\ RF_{t}^{I} \\ CPI_{t} \\ RF_{t}^{M} \\ FFED_{t} \end{bmatrix} = \beta(L) \bullet \begin{bmatrix} RF_{t-1}^{R} \\ IP_{t-1} \\ RF_{t-1}^{I} \\ CPI_{t-1} \\ RF_{t-1}^{M} \\ FFED_{t-1} \end{bmatrix} + v_{t} \qquad (2.6)$$

where $\beta(L) = A^{-1} \bullet C(L)$ and $v_t = A^{-1} \bullet \varepsilon_t$ (or $A \bullet v_t = \varepsilon_t$). Both $\beta(L)$ and the variance-covariance matrix of the residual vector v_t—Q can be estimated directly. However, if we want to derive the impulse response functions of structural shocks, we need to go back to equation (2.1) which takes the contemporaneous relationships among these variables and residual factors into consideration. Since there are more parameters in equation (2.1) than in equation (2.6), we need to impose some restrictions on matrix *A*.

I now describe the assumptions made with regard to identification. First, I assume that the innovations to the federal funds rate are the monetary policy shocks, as much of the previous literature. Second, I assume that the federal funds rate and the other monetary variables that are summarized by a monetary policy residual factor react to real economic activity and inflation/price conditions within a month. Third, I assume that the consumer price index inflation and other price related variables contained in the inflation residual factor respond to real economic condition within a month but respond to monetary policy after a month. Fourth, for industrial production and other real economic conditions which are driven by the real activity residual factor, I assume that they are exogenous contemporaneously. As a result, the order or preference of the three variables and the remaining three structural factors is as follows: the real activity residual factor, industrial production, the inflation/price residual factor, the CPI inflation rate, the monetary policy residual factor and the federal funds rate.[7] This order is same as showed in equation (2.6). Recall also that, by construction, each structural residual factor is contemporaneously orthogonal to the corresponding variable. Therefore, I can write the identification matrix A as

$$A = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & 0 & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & 0 & a_{66} \end{bmatrix} \tag{2.7}$$

From $v_t = A^{-1} \bullet \varepsilon_t$, we can derive that the variance-covariance matrix of v_t,

$$Q = A^{-1}(A^{-1})' \tag{2.8}$$

where Q can be estimated directly from the reduced-form SFAVAR model.

I then further test the covariances or correlations between each two variables or factors in the SFAVAR to derive more structural restrictions for the elements in matrix A. I do so in the spirit of direct acyclic graph (DAG) method as proposed by Spirtes,

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[7] The order between each "observable" variable and the corresponding residual factor can be switched. For instance, I can put industrial production first and the real activity residual factor second. That will only cause the switch of the first row of matrix A with the second row of matrix A in equation (2.7). The identified innovations and the impulse response functions will not be affected.

Glymour and Scheines (1993) and Swanson and Granger (1997).[8] I use Fisher's z statistic to test whether correlations or covariances are significantly different from zero or not.

$$z[\rho(i,j)] = \left[\frac{1}{2}\sqrt{n-3}\right]\ln\left[\frac{|1+\rho(i,j)|}{|1-\rho(i,j)|}\right] \tag{2.9}$$

where n is the number of observations used to estimate the correlations, $\rho(i,j)$ is the unconditional population correlation between series i and series j. If $r(i,j)$ is the unconditional sample correlation between series i and series j, then $z[\rho(i,j)] - z[r(i,j)]$ has a standard normal distribution, provided that series i and j are normally distributed. The null hypothesis of the test is that the correlation between series i and series j is zero. By testing those correlations, I further derive an extra restriction on A: a_{31} has to be zero. Then the final identification scheme is:

$$\begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & a_{22} & 0 & 0 & 0 & 0 \\ 0 & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & 0 & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & 0 & a_{66} \end{bmatrix} \bullet v_t = \varepsilon_t \tag{2.10}$$

[8] For more details on the DAG approach, readers can refer to Bessler and Yang (2002).

2.3.2.2 The SFVAR model

For the more general *structural factor VAR* (SFVAR) model, first of all, I estimate the structural factors from the 308 time series. By assuming a block diagonal loading matrix, I estimate the common factors by *principal components* as shown below.

$$\begin{bmatrix} X_t^R \\ X_t^I \\ X_t^M \end{bmatrix} = \lambda \bullet \begin{bmatrix} F_t^R \\ F_t^I \\ F_t^M \end{bmatrix} + e_t \tag{2.11}$$

where λ is the block diagonal loading matrix:

$$\lambda = \begin{bmatrix} \lambda^R & 0 & 0 \\ 0 & \lambda^I & 0 \\ 0 & 0 & \lambda^M \end{bmatrix} \tag{2.12}$$

In equation (2.11), X_t^R is the vector composed of 172 series related to real activity, X_t^I is the vector of 80 price/inflation series and X_t^M is the vector of 56 monetary policy "indicator" series. I further assume that there is exactly one structural factor from each structural vector[9]—the real activity factor F_t^R, the inflation/price factor F_t^I and the monetary policy factor F_t^M. I then estimate a reduced-form *structural factor* VAR model as shown in equation (2.13).

$$\begin{bmatrix} F_t^R \\ F_t^I \\ F_t^M \end{bmatrix} = \beta^F(L) \bullet \begin{bmatrix} F_{t-1}^R \\ F_{t-1}^I \\ F_{t-1}^M \end{bmatrix} + \upsilon_t \tag{2.13}$$

[9] See footnote 6 for a discussion on this assumption.

where $\beta^F(L) = (A^F)^{-1} \bullet C^F(L)$ and the variance-covariance matrix of the residual vector $\upsilon_t = (A^F)^{-1} \bullet \varepsilon_t^{\ F}$ — Q^F can be estimated directly.

Following much of the literature in traditional VAR models, I identify the system by means of the Cholesky decomposition. That is, I recursively order these three structural factors with the real activity factor first and the monetary policy factor last. I then can specify the identification scheme as

$$A^F \bullet \upsilon_t = \varepsilon_t^{\ F} \tag{2.14}$$

with

$$A^F = \begin{bmatrix} a_{11}^{\ F} & 0 & 0 \\ a_{21}^{\ F} & a_{22}^{\ F} & 0 \\ a_{31}^{\ F} & a_{32}^{\ F} & a_{33}^{\ F} \end{bmatrix} \tag{2.15}$$

where υ_t is the estimated residue vector from equation (2.13) with mean zero and a positive definite variance-covariance matrix Q^F ,and $\varepsilon_t^{\ F}$ is the identified vector of structural innovations with mean zero and identity variance-covariance matrix.

This recursive identification scheme is a reasonable assumption given the short frequency of the data. The economy's real activity is contemporaneously exogenous with respect to both the monetary policy factor and the inflation/price factor, and it usually takes longer than a month for the real activity to adjust to either changes in monetary policy or changes in the cost of living. However, monetary policy, which is designed to intervene and influence both the real activity and the price level, should be endogenous contemporaneously, so that it reacts quickly to the real and nominal conditions of the economy. So, as I mentioned before, in the SFVAR model, I order the real activity factor first and the monetary policy factor last.

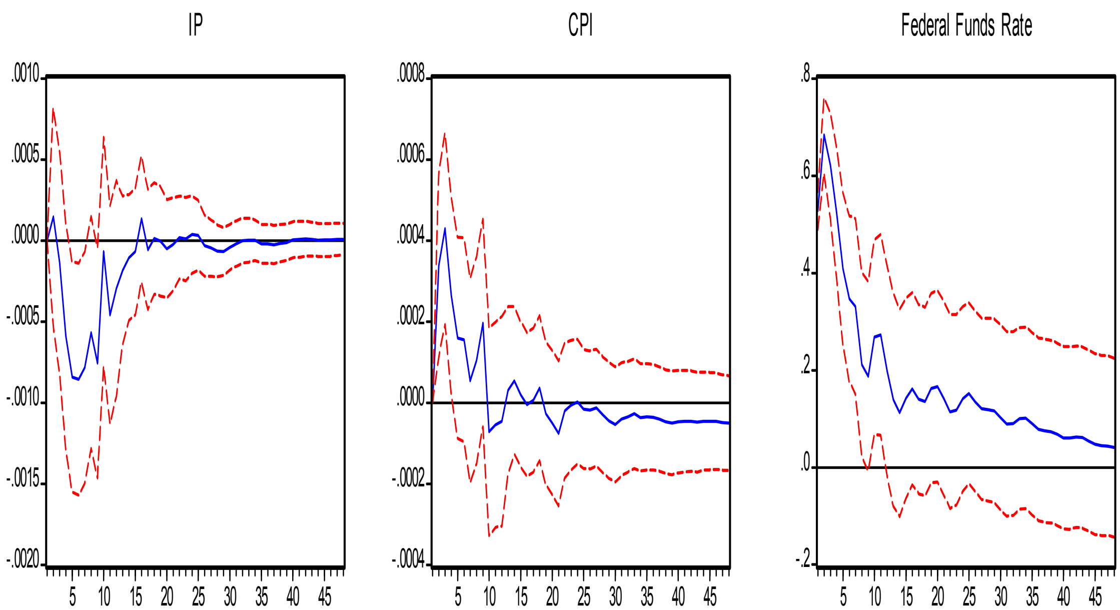
2.4 Empirical Results of the Effects of Monetary Policy

In order to evaluate the advantages of the *structural factor augmented VAR (*SFAVAR) model and the *structural factor VAR* (SFVAR) model that I propose in this the paper, I compare the impulse responses generated from these two models with those from the conventional VAR model and Bernanke, Boivin and Eliasz (2004)'s FAVAR model.

First, I look at the impulse responses to a federal funds rate monetary policy shock from the conventional 3-variable (industrial production, the CPI and the federal funds rate) VAR as shown in Figure 2.1. We observe a strong example of the so-called "price puzzle"—prices go up significantly after a contractionary monetary policy shock (the federal funds rate rises). According to Sims's (1992) explanation, this could be the results that the data in the standard VAR may not adequately capture the signals of future inflation and what appears to be a monetary policy shock could be just a response to future inflation. So, the results could be seriously contaminated because of information missed in the VAR.

Bernanke, Boivin and Eliasz (2004) suggest a factor augmented VAR (FAVAR) model. In their model, they treat the federal funds rate as an observed factor and they estimate other factors from a total of 120 time series. I implement the same exercise using my new data set. My data set has 188 additional variables and it is more updated (till December 2003). I estimate the factors using the method of *principal components*.[10]

Figure 2.2 reports the impulse responses from the FAVAR model with five factors.[11]



Note: The three variables are industrial production, the CPI and the federal funds rate. The first two variables are taken first difference of logarithm to be stationary. The solid line is the impulse response of each variable, and the dash lines are the upper and lower bounds of the two-standard deviation confidence interval.

Fig. 2.1. The Impulse Responses to a Federal Funds Rate Monetary Policy Shock from a 3-Variable VAR.

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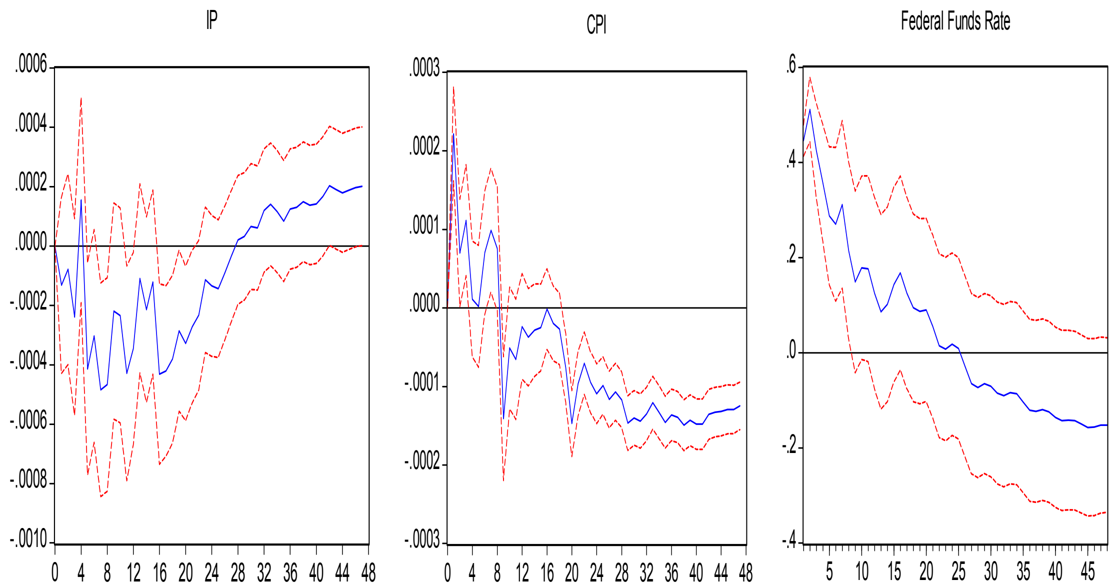
[10] In Bernanke, Boivin and Eliasz (2004), they also use Gibbs sampling procedure to estimate the factors and the dynamic behavior of the economy simultaneously. But they find that the likelihood-based estimation method suffers from the additional structure restrictions it imposes and produces factors that do not successfully capture information about real-activity and prices.

[11] In Bernanke, Boivin and Eliasz (2004) also estimate a three-factor FAVAR model. They find that these two models basically suggest the same conclusion and further increasing the number of factors does not change the qualitative nature of their results.

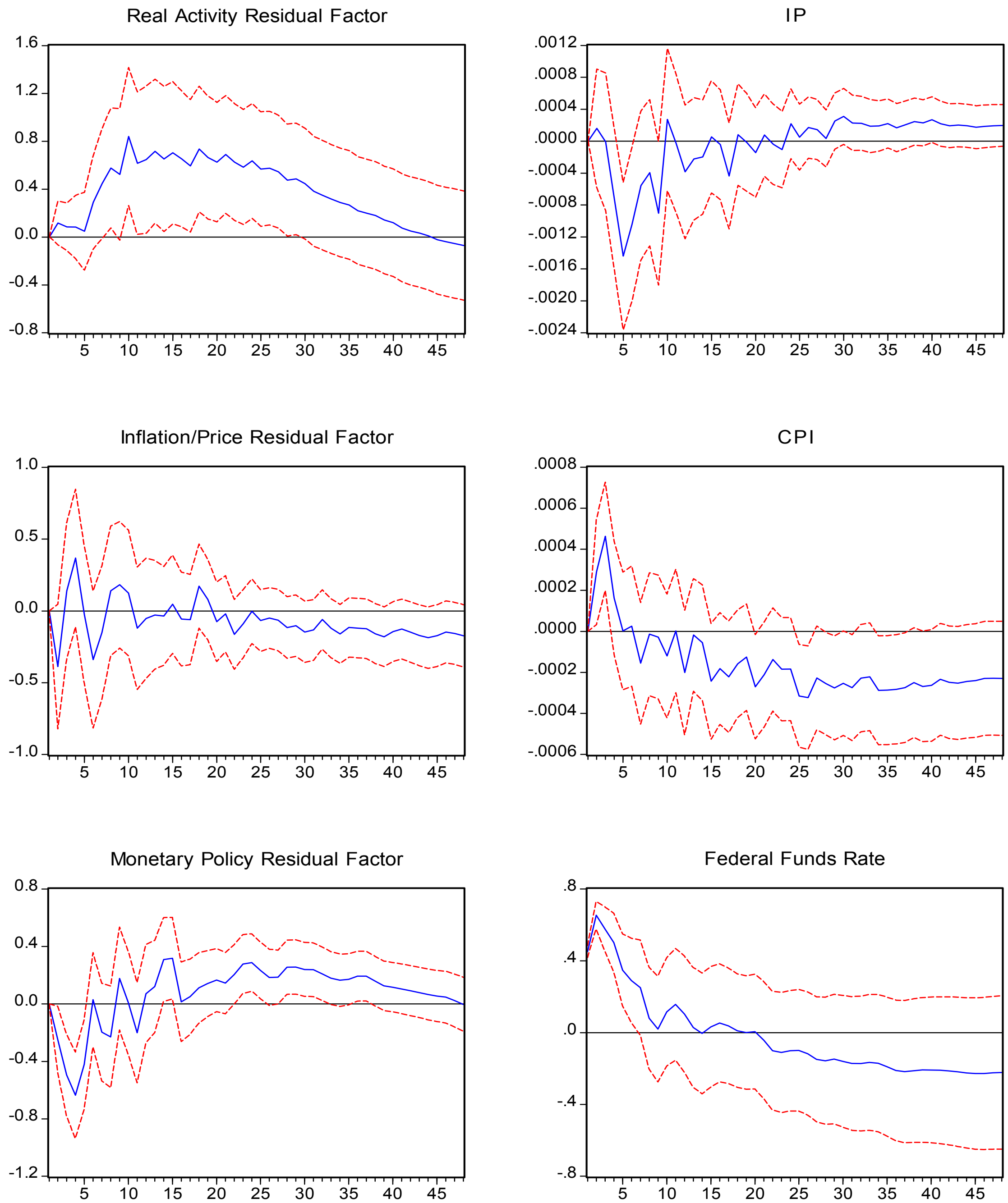


Note: The impulse responses in the figure are generated from the FAVAR model with 5-factors as Bernanke, Boivin and Eliasz (2004). The solid line is the impulse response of each variable, and the dash lines are the upper and lower bounds of the two-standard deviation confidence interval.

Figure 2.2. The Impulse Responses to a Federal Funds Rate Monetary Policy Shock from the FAVAR Model with Five-Factors.

One can observe that the "price puzzle" is reduced considerably compared to the VAR model but it still exists. So, it seems that the factors do capture more information about the economy but not quite adequately. More importantly, just as I mentioned before, it is hard to give any structural interpretation to these factors, and this prevents us from understanding the structure of the economy as well as the very important monetary transmission mechanism.

Figure 2.3 shows the impulse responses generated from the *structural factor augmented VAR* (SFAVAR) model with three factors and three variables. I still treat the



Note: The solid line is the impulse response of each variable, and the dash lines are the upper and lower bounds of the two-standard deviation confidence interval.

Figure 2.3. The Impulse Responses to a Federal Funds Rate Monetary Policy Shock from the SFAVAR Model.

innovations to the federal funds rata as monetary policy shocks in this model. The three "residual" factors capture the extra information about the real activity, the inflation pressure and monetary conditions that are not covered by industrial production, the CPI and the federal funds rate respectively.

To assure the information captured by these three residual factors is important, I apply a model specification test. The unrestricted model is

$$\begin{bmatrix} IP_t \\ CPI_t \\ FFED_t \end{bmatrix} = \beta_{11}(L) \bullet \begin{bmatrix} IP_{t-1} \\ CPI_{t-1} \\ FFED_{t-1} \end{bmatrix} + \beta_{12}(L) \bullet \begin{bmatrix} RF_{t-1}{}^{R} \\ RF_{t-1}{}^{I} \\ RF_{t-1}{}^{M} \end{bmatrix} + v_{1t} \tag{2.16}$$

I test $\beta_{12}(L) = 0$ or not. The likelihood ratio test statistic that has a χ^2 distribution strongly rejects the null hypothesis at 5 percent significance level.[12] It suggests that the information contained in the residual factors can not be neglected. I also apply the likelihood ratio test to test the inclusion of these three variables is important or not. The unrestricted model is

$$\begin{bmatrix} RF_t{}^{R} \\ RF_t{}^{I} \\ RF_t{}^{M} \end{bmatrix} = \beta_{21}(L) \bullet \begin{bmatrix} IP_{t-1} \\ CPI_{t-1} \\ FFED_{t-1} \end{bmatrix} + \beta_{22}(L) \bullet \begin{bmatrix} RF_{t-1}{}^{R} \\ RF_{t-1}{}^{I} \\ RF_{t-1}{}^{M} \end{bmatrix} + v_{2t} \tag{2.17}$$

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[12] The likelihood ration test statistic is equal to -2 times the difference between the log likelihood of the restricted model and that of the unrestricted model. It has a χ^2 distribution with the degree of freedom that equals to the number of restrictions. In this test, the test statistic is 337.396, while the critical value at 5 percent with the degree of freedom that equals to 36 is 51. The number of lags is 12.

The null hypothesis that $\beta_{21}(L)$=0 is also strongly rejected at 5 percent significance level.[13] Both tests justify the model specification of the SFAVAR model that includes information both from these three traditional variables and the corresponding three residual factors.

Appendix B shows the descriptive statistics of these residual factors. I find these residual factors almost follow a normal distribution, which justifies the use of Fisher's *z* statistic in the estimation and identification part. I also examine the correlation of these factors as shown in Table 2.1. It is a little surprising to see the real activity residual factor is more correlated with the monetary policy residual factor than with the inflation/price residual factor according to conventional Philips curve and the notion that money or monetary policy does not matter in the long run.

Table 2.1
Correlation Matrix of the Structural Residual Factors

	Real Activity Residual Factor	Inflation/Price Residual Factor	Monetary Policy Residual Factor
Real Activity Residual Factor	1	0.086	0.350
Inflation/Price Residual Factor	0.086	1	0.056
Monetary Policy Residual Factor	0.350	0.056	1

Let us look at the impulse response functions in Figure 2.3. Industrial production decreases significantly after a delay and goes back to its original level in the long run after a positive shock in the federal funds rate, which is consistent with the conventional

[13] The test statistic is 513.298.

wisdom that money is neutral.[14] However, the real activity residual factor shows a reverse pattern. Table 2.2 shows the explanatory power of the real activity residual factor for each real variable listed. I find the real activity residual factor has the biggest explanatory power (*R*-squares) for those capacity utilization variables and it also has quite high explanatory power for unemployment rate. Moreover, this real activity residual factor is negatively correlated with capacity utilization and positively correlated with the unemployment rate. This explains this reverse "U" shape of the response of this real activity residual factor to a federal funds rate shock. When we examine the responses of the CPI, we notice that the "prize puzzle" is reduced considerably compared to the traditional 3-variable VAR but it is still there. However, turning to the inflation/price residual factor, I notice the " price puzzle" disappears totally as the inflation/money residual factor decreases immediately after the shock even though not significantly. Overall, the inflation/price residual factor displays stickiness after this monetary policy shock. As shown in Table 2.3, this inflation/price residual factor is more correlated with another two important measures of cost of living: the producer price index (PPI) for finished consumer non-durable goods less food, and the personal consumption expenditure (PCE) deflator less food and energy. This suggests that a single variable (e.g. the CPI) may not be enough to measure the price effect and it is also

[14] Strictly, the claim that money is neutral is made with regard to changes in the quantity of money. However, according to open market operations, changes in the federal funds rate are achieved through necessary changes in the quantity of money. Therefore, one can still say "money" is neutral here.

Table 2.2
Explanatory Power of the Real Activity Residual Factor

Variable	Coefficient	R^2
Capacity utilization: industry	-0.5583*	0.8456
	(0.0000)	
Capacity utilization: manufacturing	-0.6237*	0.8482
	(0.0000)	
Capacity utilization: durable goods manufacturing	-0.8155*	0.8550
	(0.0000)	
Capacity utilization: non-durable goods manufacturing	-0.3980*	0.6003
	(0.0000)	
Manufactures' inventories	-0.0006*	0.1577
	(0.0000)	
Manufactures' shipments	-0.0002	0.0072
	(0.0974)	
Retail inventories	-0.0003*	0.0750
	(0.0000)	
Retail sales	0.0000	0.0003
	(0.7261)	
Personal consumption: durable goods	0.0006*	0.0218
	(0.0137)	
Personal consumption: non-durable goods	0.0001	0.0054
	(0.1520)	
Personal consumption: services	0.0000	0.0030
	(0.2840)	
Disposal personal income	0.0000	0.0000
	(0.9288)	
New private housing authorized	-0.0145*	0.1262
	(0.0000)	
Manufactures' shipment of mobile homes	-0.0347*	0.4148
	(0.0000)	
Housing starts	-0.0163*	0.1938
	(0.0000)	
All employees: total nonfarm	-0.0002*	0.2188
	(0.0000)	
Civilian employment	-0.0001*	0.0436
	(0.0000)	
Index of help wanted in newspapers	-0.0003	0.0034
	(0.2579)	
Unemployment rate	0.1493*	0.3905
	(0.0000)	
Average weekly hours: total private industries	-0.0690*	0.2381
	(0.0000)	
Average weekly hours: manufacturing	-0.0536*	0.2173
	(0.0000)	

Note: In this table, I regress each variable in the first column on the real activity residual factor which is estimated by the principal component method. The second column shows the coefficient before the factor in each regression and the numbers in the brackets are the *p*-values. I use asterisk (*) to denote significant at the 5 percent level. The last column is the R-square of each regression.

Table 2.3
Explanatory Power of the Inflation/Price Residual Factor

Variable	Coefficient	R^2
PPI: finished goods	-0.0005*	0.1083
	(0.0000)	
PPI: finished consumer goods	-0.0007*	0.1770
	(0.0000)	
PPI: finished consumer durable goods	0.0002*	0.0255
	(0.0017)	
PPI: finished consumer non-durable goods less foods	-0.0013*	0.2599
	(0.0000)	
Average hourly earning: total private industries	0.0002*	0.0197
	(0.0059)	
Average hourly earning: goods-producing industries	0.0003*	0.1464
	(0.0000)	
Average hourly earning: manufacturing	0.0003*	0.1273
	(0.0000)	
Average hourly earning: durable goods manufacturing	0.0003*	0.1004
	(0.0000)	
Average hourly earning: non-durable goods manufacturing	0.0003*	0.1077
	(0.0000)	
Average hourly earning: private service-providing industries	0.0002*	0.1112
	(0.0000)	
PCE	0.0000	0.0038
	(0.2273)	
PCE: less food and energy	0.0003*	0.2104
	(0.0000)	
PCE: durable goods	0.0003*	0.1331
	(0.0000)	
PCE: non-durable goods	-0.0004*	0.1477
	(0.0000)	
PCE: services	0.0003*	0.1835
	(0.0000)	

not quite appropriate to look at it solely.Instead we should look at other measures as well to have a complete picture of the price effect. The monetary policy residual factor is significantly positively correlated with money aggregates (M1 and M2) as shown in Table 2.4, and that is why we observe that it goes down significantly after a contractionary monetary policy shock. Thus, no “liquidity puzzle” is observed.

Finally, let us look at the *structural factor VAR* (SFVAR) model with structural factors only. As I argued before, there are no specific reasons to separate industrial production and the CPI from other real activity and price variables, except that people "believe" they could be good indicators for real activity and inflation conditions. Given the means of factor analysis in hand, one can just use the underlying structural factors

Table 2.4
Explanatory Power of the Monetary Policy Residual Factor

Variable	Coefficient	R^2
3-Month treasury bill rate	0.1098* (0.0054)	0.0201
6-Month treasury bill rate	0.1390* (0.0003)	0.0334
Non-borrowed reserve	0.0000 (0.9115)	0.0000
Monetary base	0.0001 (0.0980)	0.0072
M1	0.0003* (0.0007)	0.0296
M2	0.0001* (0.0075)	0.0186
M3	0.0000 (0.3747)	0.0021
Non-revolving consumer credit outstanding	0.0001 (0.1259)	0.0061
Consumer credit outstanding	0.0002* (0.0008)	0.0291

Note: In table 2.3 and 2.4, I regress each variable in the first column on the monetary policy residual factor which is estimated by the principal component method. The second column shows the coefficient before the factor in each regression and the numbers in the brackets are the *p*-values. I use asterisk (*) to denote significant at the 5 percent level. The last column is the R-square of each regression.

which have more information than any single variable to represent the dynamics of the economy. I also use a monetary policy factor instead of the federal funds rate to indicate monetary policy given the long time on-going debate about shocks to which variable are better to be interpreted as innovations to monetary policy.

First of all, let us examine these three structural factors estimated by the *principal components* method. The descriptive statistics are shown in Appendix C. From Table 2.5, I find that the real activity factor has a very low correlation with the monetary policy factor, consistent with the widely-accepted theory that money is neutral. Meanwhile, I observe that the inflation/price factor and the monetary policy factor are highly correlated, just as most people have expected. Tables 2.6-2.8 display the explanatory power of each structural factor respectively. I notice that the real activity factor has a quite large explanatory power for all these "important" real activity variables, e.g., industrial production, capacity utilization, housing starts and employment. And this real activity factor is positively correlated with all of these real activity variables except the unemployment rate. For the inflation/price factor, I find that it is highly positively correlated with the consumer price index (CPI), the personal

Table 2.5
Correlation Matrix of the Structural Factors

	Real Activity Factor	Inflation/Price Factor	MonetaryPolicy Factor
Real Activity Factor	1	0.121	0.010
Inflation/Price Factor	0.121	1	0.568
Monetary Policy Factor	0.010	0.568	1

Table 2.6 Explanatory Power of the Real Activity Factor

Variable	Coefficient	R^2
Industrial production	0.0007* (0.0000)	0.4255
IP: durable consumer goods	0.0009* (0.0000)	0.0876
IP: non-durable consumer goods	0.0003* (0.0000)	0.0491
IP: manufacturing	0.0008* (0.0000)	0.4189
Capacity utilization: industry	0.4387* (0.0000)	0.6109
Capacity utilization: manufacturing	0.5000* (0.0000)	0.6375
Capacity utilization: durable goods manufacturing	0.6275* (0.0000)	0.5923
Capacity utilization: non-durable goods manufacturing	0.3581* (0.0000)	0.5685
Manufactures' inventories	0.0002* (0.0016)	0.0259
Manufactures' shipments	0.0010* (0.0000)	0.1677
Retail inventories	0.0004* (0.0000)	0.1109
Retail sales	0.0004* (0.0004)	0.0322
Personal consumption: durable goods	0.0004 (0.1058)	0.0069
Personal consumption: non-durable goods	0.0001* (0.0449)	0.0105
Personal consumption: services	0.0000 (0.2092)	0.0041
Disposal personal income	0.0002* (0.0109)	0.0169
New Private housing authorized	0.0208* (0.0000)	0.3023
Manufactures' shipment of mobile homes	0.0338* (0.0000)	0.4589
Housing starts	0.0212* (0.0000)	0.3822
All employees: total nonfarm	0.0003* (0.0000)	0.6678
Civilian employment	0.0002* (0.0000)	0.1935
Index of help wanted in newspapers	0.0019* (0.0000)	0.1321
Unemployment rate	-0.1014* (0.0000)	0.2110
Average weekly hours: total private industries	0.0576* (0.0000)	0.1943
Average weekly hours: manufacturing	0.0628* (0.0000)	0.3487

Table 2.7
Explanatory Power of the Inflation/Price Factor

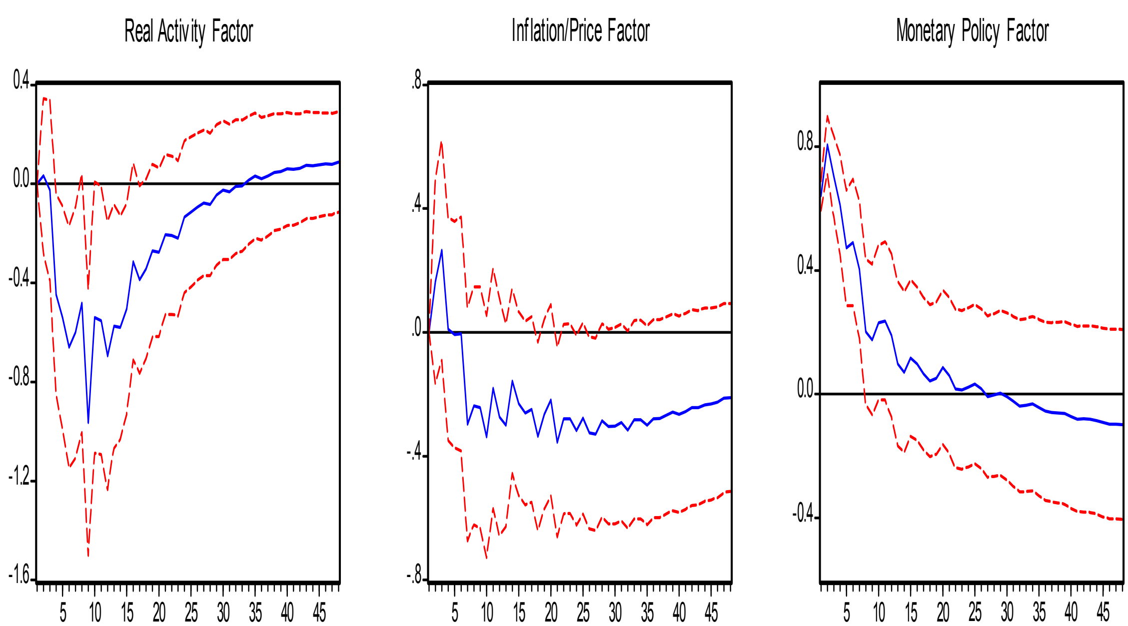
Variable	Coefficient	R^2
CPI: all items	0.0005*	0.8681
	(0.0000)	
CPI: commodities	0.0007*	0.7303
	(0.0000)	
CPI: durables	0.0005*	0.4667
	(0.0000)	
CPI: non-durables	0.0007*	0.5607
	(0.0000)	
CPI: services	0.0004*	0.5469
	(0.0000)	
CPI: gasoline	0.0031*	0.2782
	(0.0000)	
PPI: finished goods	0.0008*	0.5444
	(0.0000)	
PPI: finished consumer goods	0.0008*	0.4638
	(0.0000)	
PPI: finished consumer durable goods	0.0005*	0.2500
	(0.0000)	
PPI: finished consumer non-durable goods less foods	0.0013*	0.4679
	(0.0000)	
Average hourly earning: total private industries	0.0003*	0.4172
	(0.0000)	
Average hourly earning: goods-producing industries	0.0004*	0.3466
	(0.0000)	
Average hourly earning: manufacturing	0.0004*	0.3231
	(0.0000)	
Average hourly earning: durable goods manufacturing	0.0004*	0.2610
	(0.0000)	
Average hourly earning: non-durable goods manufacturing	0.0004*	0.2811
	(0.0000)	
Average hourly earning: private service-providing industries	0.0003*	0.3571
	(0.0000)	
PCE	0.0004*	0.8450
	(0.0000)	
PCE Less food and energy	0.0003*	0.5535
	(0.0000)	
PCE: durable goods	0.0004*	0.4604
	(0.0000)	
PCE: non-durable goods	0.0007*	0.6701
	(0.0000)	
PCE: services	0.0003*	0.4483
	(0.0000)	

Table 2.8
Explanatory Power of the Monetary Policy Factor

Variable	Coefficient	R^2
Federal funds rate	0.7314* (0.0000)	0.9356
3-Month treasury bill rate	0.6217* (0.0000)	0.9621
6-Month treasury bill rate	0.6151* (0.0000)	0.9769
Non-borrowed reserves	-0.0001 (0.6654)	0.0005
Monetary base	-0.0001 (0.2702)	0.0032
M1	-0.0000 (0.8323)	0.0001
M2	0.0001* (0.0047)	0.0208
M3	0.0003* (0.0000)	0.0003
Non-revolving consumer credit outstanding	0.0001 (0.0838)	0.0078
Consumer credit outstanding	0.0002* (0.0034)	0.0223

consumption expenditure deflator (PCE) and the producer price index (PPI). When I look at Table 2.8, I notice the monetary policy factor is highly positively correlated with those short-run interest rates, e.g. the federal funds rate and the Treasury bill rates. And this monetary factor is negatively correlated with high powered money—the monetary base and the non-borrowed reserves.

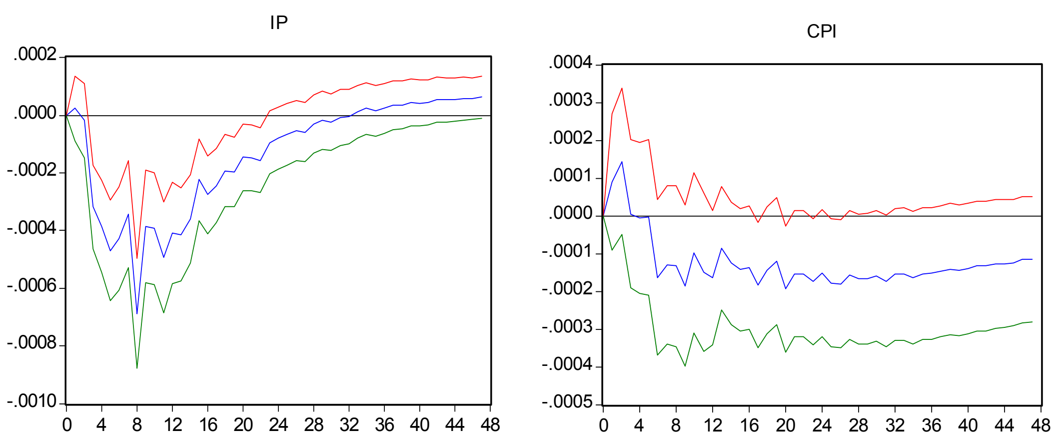
Figure 2.4 displays the impulse responses of all these three factors to a monetary policy factor shock. I observe a negative monetary policy shock, which means increases in short-run interest rates and decreases in money aggregates. This contractionary monetary policy shock causes the inflation/price factor to increase insignificantly right after the shock then decline gradually. The pattern does not show any “price puzzle” which troubles most of the previous research. And it is consistent with the popular argument that prices are sticky. In response to the contractionary monetary shock, the real activity factor rises immediately but not significantly. Then it drops significantly afterwards and persists for about a year. Later it returns to its previous level, which is consistent with the long-run monetary neutrality. It is also consistent with the general agreement that the real activity should show a "U" shape response after a contractionary monetary policy shock. The *structural factor VAR* (SFVAR) model also has the advantage of allowing us to derive the dynamic behavior of each of the 308 variables in the data set after any kind of shocks, i.e. real shocks, price shocks or monetary policy



Note: The solid line is the impulse response of each variable, and the dash lines are the upper and lower bounds of the two-standard deviation confidence interval.

Figure 2.4. The Impulse Responses to a Monetary Policy Factor Shock from the SFVAR Model

shocks. In Figure 2.5, I plot the impulse responses of various key variables to a monetary policy factor shock derived from the SFAVAR model. These responses functions are all consistent with what people would have expected. The federal funds rate goes up and the money aggregates go down right after the shock, which is a contrationary monetary shock. Thus, no "liquidity puzzle" is observed. All these real activity variables show a "U" shape after the shock except the unemployment rate which displays a reverse "U" shape. The "price" puzzle totally disappears regardless of whether we look at the CPI, the PCE or the PPI and these price indexes show stickiness after the shock



Note: The middle solid line is the impulse response of each variable, and the other two lines are the upper and lower bounds of the two-standard deviation confidence interval.

Figure 2.5. The Impulse Responses of Various Variables to a Monetary Policy Factor Shock from the SFVAR Model.

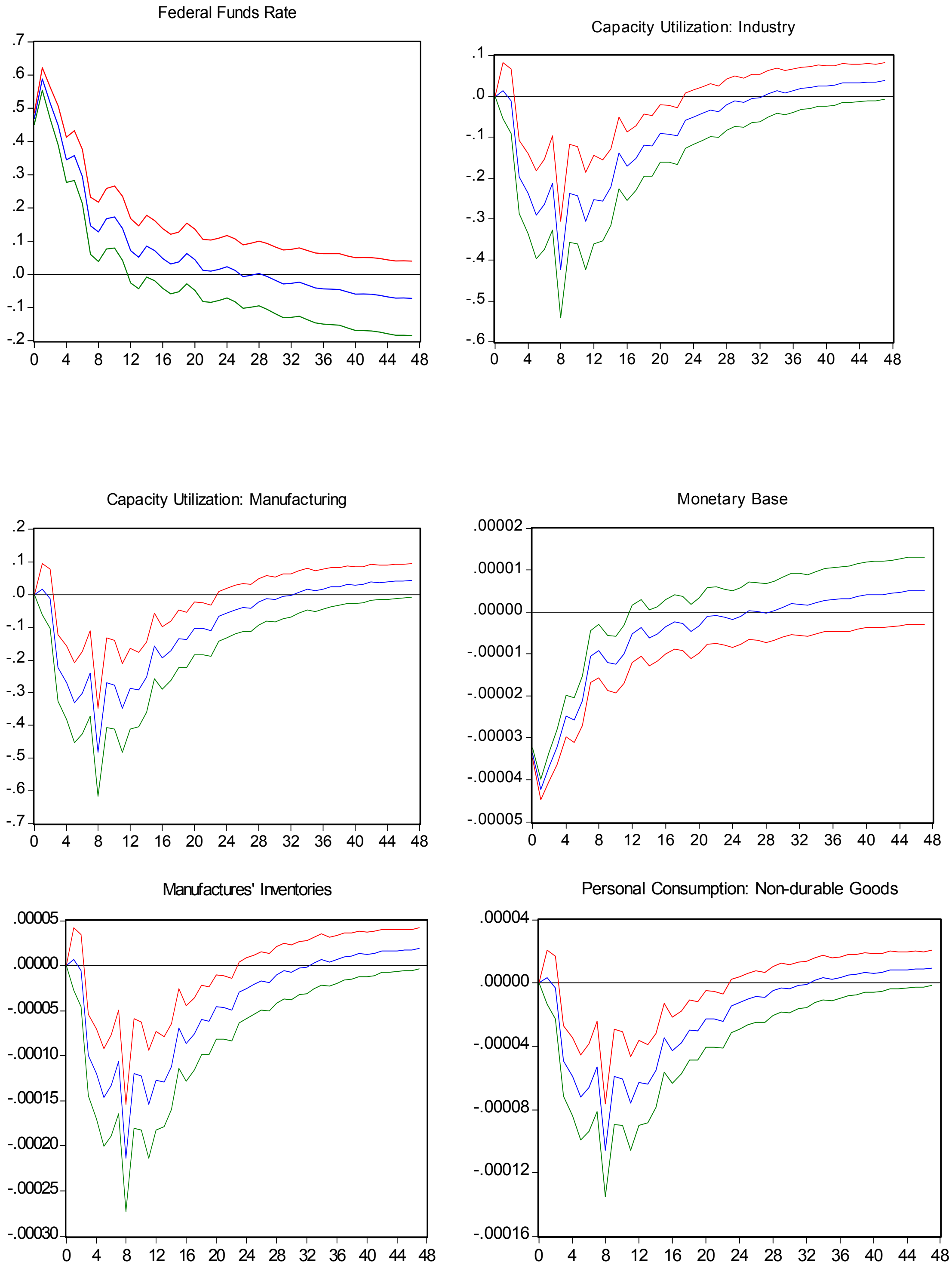


Figure 2.5.(Continued)

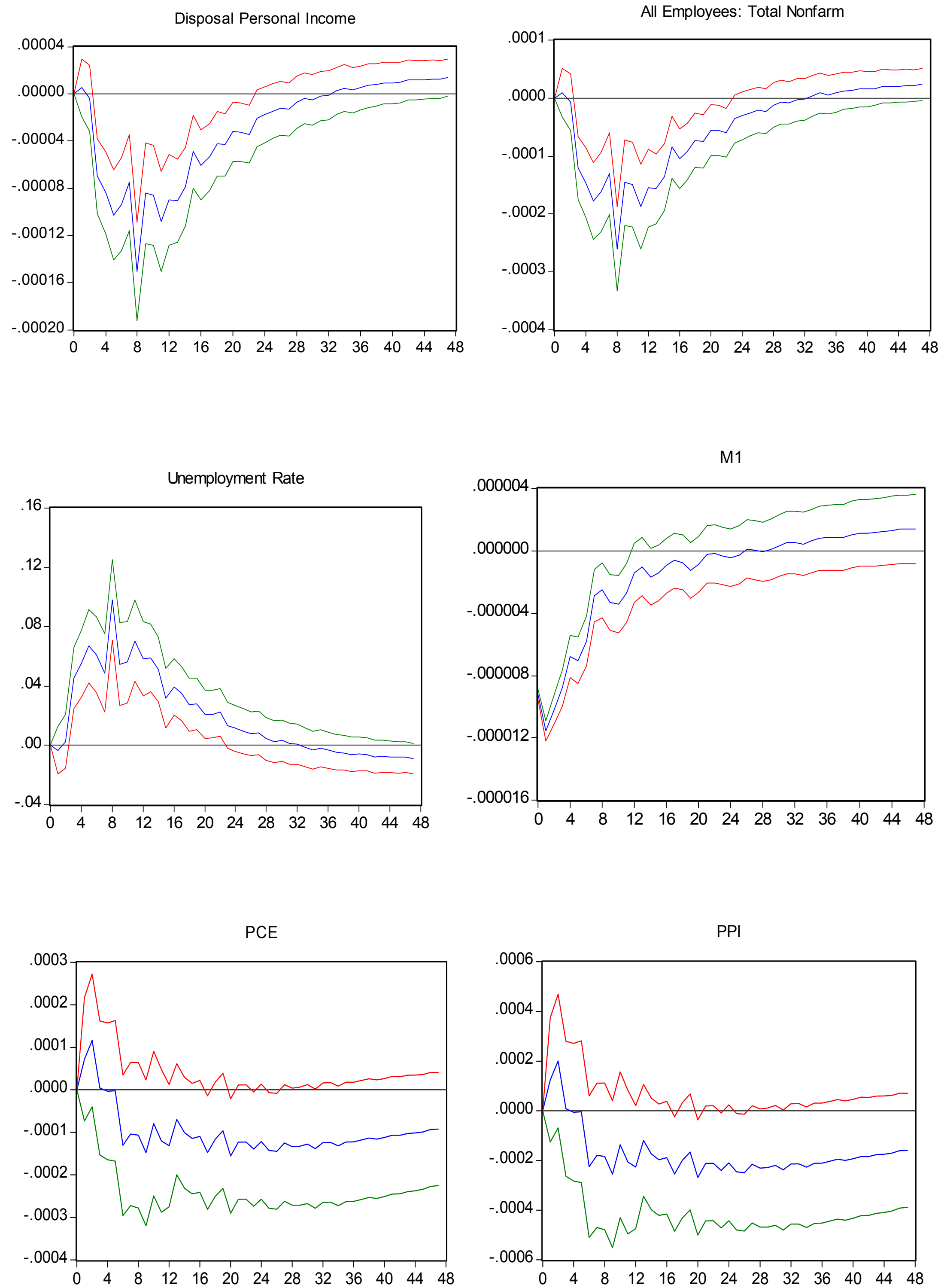


Figure 2.5.(Continued)

From the above analysis, the advantages of the SFAVAR model and SFVAR model compared to both the traditional VAR and the newly proposed FAVAR model seem evident. One can not only employ more information using these two models than using the VAR model, but can also interpret the models structurally. By using the models, especially the SFVAR model, I generate impulse responses all consistent with the conventional theories. Moreover, the “price puzzle” and the “liquidity puzzle” are eliminated totally.[15] The results confirm Sims’s (1992) missing information explanations for the “puzzles” observed using the traditional VAR. By using the SFVAR, we can also derive impulse response function for any variable that we are interested in and to any kind of shocks (real shocks, inflationary shocks or monetary policy shocks).

2.5 Conclusions

In this chapter, I use the method of structural factor analysis to evaluate the effects of monetary policy and forecast some key macroeconomic variables in a data rich environment. This allows me to employ the information from a very large data set, and at the same time I can still interpret the underlying factors estimated by *principal components* structurally.

To evaluate the effects of monetary policy, I propose two structural factor models. One is the *structural factor augmented vector autoregressive* (SFAVAR) model,

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[15] It is worth noting that the aim of this part of the paper is to propose appropriate ways to examine the effects of monetary policy shocks in a data rich environment, instead of just eliminating the “puzzles”. There are other ways of “fixing” the “puzzles”, for instance, by including a commodity price index in a conventional VAR, but they are not really directly relevant to the comparison.

where shocks to the federal funds rate are treated as innovations to monetary policy as much of the previous literature and the other is the *structural factor vector autoregressive* (SFVAR) model, where an underlying monetary factor is used to represent monetary policy. Compared to the traditional VAR models, both models contain more information from hundreds of data series which can be and are actually monitored by the Center Bank. Also, the factors used are structurally meaningful, a feature that adds to the understanding the "black box" of the monetary transmission mechanism. Under reasonable identification schemes, both models generate qualitatively reasonable impulse response functions. Especially, using the SFVAR model, both the "price puzzle" and the "liquidity puzzle" are eliminated. This model also has the flexibility to allow us to generate the impulse response function for any variable of interest.

CHAPTER III

MACROECONOMIC FORECASTING USING STRUCTURAL FACTOR ANALYSIS

3.1 Introduction

The use of several underlying factors to summarize the information from a relatively large set of explanatory variables is a new frontier of the forecasting literature. Stock and Watson (1998, 1999 and 2002) are the pioneer papers in the area. Bernanke and Boivin (2003) also apply the factor analysis to study U.S. monetary policy by forecasting monetary policy reaction rules.

The dynamic factor forecasting model proposed by Stock and Watson can employ the information from all the available predictor variables and make forecasts in a data rich environment. Stock and Watson (2002) have shown that the use of underlying factors can lead to improved forecasting performance for some key macroeconomic variables. However, these factors can not be interpreted structurally as those factors in Bernanke, Boivin and Eliasz (2004). Therefore, one can not choose estimated factors or forecasting models structurally based on some standard theories. For example, real activity series are often used to predict inflation according to the so-called Philips curve. Accordingly, in a factor model, one would like to choose some real activity factors to forecast inflation. However, using Stock and Watson's model, one can not realize that.

Given the shortcomings of the non-structural dynamic factor forecasting model, in this chapter, I propose a general *structural factor forecasting model* and its variations to forecast some key macroeconomic variables. Since the factors used in the models are structurally meaningful, one can choose the factors according to some widely-accepted theories depending on the variable to be forecasted. To analyze the advantages of the *structural factor forecasting model*, I compare its forecasting performance with some baseline models including the AR model and the standard VAR model, as well as Stock and Watson (2002)'s non-structural factor forecasting model. The results show that the *structural factor forecasting model* I propose performs significantly better, especially for real activity variables at short-horizons.

The rest of the chapter is organized as follows. In section 3.2 I briefly review Stock and Watson's model and introduce the structural dynamic factor forecasting model proposed in this chapter. Section 3.3 outlines the forecasting framework. Section 3.4 reports the forecasting results. And section 3.5 briefly concludes this chapter.

3.2 A Structural Dynamic Factor Forecasting Model

Stock and Watson (1998, 1999 and 2002) propose a dynamic factor forecasting model using several common factors to summarize the information from a huge set of explanatory variables. Bernanke and Boivin (2003) forecast the monetary policy reaction rules to analyze U.S. monetary policy using this factor analysis too.

In brief, Stock and Watson adopt a dynamic factor model to forecast some economic variables. Following the notations of Stock and Watson (2002), let y_{t+1} denote the scalar series to be forecasted and let X_t be an N-dimensional multiple time series of predictor variables, one can write the dynamic factor forecasting model as

$$y_{t+1} = \beta' F_t + \gamma(L) y_t + \varepsilon_{t+1} \tag{3.1}$$

$$X_t = \Lambda F_t + e_t \tag{3.2}$$

where $F_t = (f_t{}', ... f_{t-q}{}')'$ is the vector of common factors with dimension $r \times 1$, where $r \le (1+q)\bar{r}$, by assuming the factor vector has finite lag order of at most q and $\bar{r}$ is the true number of common factors, $\beta = (\beta_{0,} \beta_{1,} .... \beta_q)$, $\gamma(L)$ is a lag polynomial, Λ is the factors loading matrix, and e_t is the $N \times 1$ idiosyncratic disturbance matrix. In equation (3.2), the factors are estimated from the whole panel of all the available predictor variables using *principal components*. This dynamic factor forecasting model can employ the information from all the available predictor variables and make the forecasting more efficient. But just as Bernanke, Boivin and Eliasz's (2004) FAVAR model, one can not interpret these factors structurally. Therefore, this model restricts us from choosing these factors structurally based on the characteristics of the variable to be forecasted. Let us suppose we want to forecast industrial production, we use the above dynamic factor forecasting model and the optimal number of factors is chosen by some Bayesian information criterion, e.g., Schwarz Bayesian information criterion (SIC), as Stock and Watson (2002). Ideally, one wants to have factors that are closely related to the real activity or the ones explaining inflation pressure given the conventional Philips curve. However, the factors chosen by BIC may only explain the monetary structure, e.g., interest rates, and have very low correlations with real variables or price variables which are more related with industrial production. Obviously, these factors are not desirable predictors. But with this non-structural dynamic factor forecasting model, one can not prevent this from happening and the choice of the best forecasting model may vary greatly with different data set X_t.

So, in this section, I propose a *structural dynamic factor forecasting* model. One can write this model as

$$y_{t+1} = \beta^{R}{}'F_t^R + \beta^{I}{}'F_t^I + \beta^{M}{}'F_t^M + \gamma(L)y_t + \varepsilon_{t+1}{}^S \tag{3.3}$$

$$X_t = \begin{bmatrix} X_t^R \\ X_t^I \\ X_t^M \end{bmatrix} = \begin{bmatrix} \Lambda^R & 0 & 0 \\ 0 & \Lambda^I & 0 \\ 0 & 0 & \Lambda^M \end{bmatrix} \bullet \begin{bmatrix} F_t^R \\ F_t^I \\ F_t^M \end{bmatrix} + e_t^S \tag{3.4}$$

In this model, I assume the loading matrix Λ is block diagonal and assume that there are three groups of structural factors explaining real activity variables X_t^R, inflation/price variables X_t^I and monetary variables X_t^M respectively. These structural factors that are estimated using *principal components* can then be used in equation (3.3) for forecasting. So I call this model *structural dynamic factor forecasting* model in the similar spirit of the SFVAR model proposed in chapter II. This structural factor model not only allows me to summarize a huge set of predictor variables using several factors but also makes it possible to choose the factors structurally according to the variable to be forecasted based on some well-accepted theories.

3.3 Forecasting Framework

3.3.1 Forecasting Design and Forecasting Models

Next, I simulate a real time forecasting exercise using the s*tructural dynamic factor forecasting* model, Stock and Watson's non-structural dynamic factor forecasting model and two benchmark models, i.e., the AR model and the VAR model.

The data set I use consists of 308 monthly U.S. macroeconomic time series from January 1972 till December 2003 with 383 observations for each variable. The original data series are taken from the Haver USECON data set. All these series are then transformed to be stationary. Among all these series, there are 172 real activity variables, 80 inflation or price variables and 56 monetary variables. The list of the series and their transformation is listed in Appendix A.

The original estimation period is from January 1972 to December 1989. And the forecasting period is from January 1990 till December 2003. Forecasting is made at the 1-, 3-, 6-, 12- and 24-month forecasting horizons. And I forecast four key macroeconomic variables—industrial production, real personal income, nonagricultural employment and the consumer price index. For these four predicted variables, I treat them all as being $I(1)$ series in logarithm and transform them from monthly data to annual data. For example, suppose I predict industrial production, then

$$y_{t+h}{}^{h} = (1200/h)\ln(IP_{t+h}/IP_t) \quad \text{and} \quad y_t = 1200\ln(IP_t/IP_{t-1}) \tag{3.5}$$

where h is the forecasting horizon. And the multistep-ahead forecasting regression models are projections of an h-step-ahead variable y_{t+h}^{h} onto t-dated predictors.[16]

The forecasting models used are:

- *Autoregressive Forecast*. The benchmark autoregressive forecasting function is

$$\hat{y}_{T+h|T}^{h} = \hat{\alpha}_h + \sum_{j=1}^{p} \hat{\gamma}_{hj}\, y_{T-j+1} \tag{3.6}$$

where the optimal lag order p of the autoregressive term is chose by Schwarz information criterion (SIC) with $1 \le p \le 6$.

- *Vector Autoregressive Forecast.* Another benchmark model is a three-variable vector autoregression (VAR). These three variables are industrial production, the consumer price index and the federal funds rate. When I forecast real personal income or nonagricultural employment, industrial production is replaced by them respectively. And the optimal lag length is chosen by SIC too.

- *Dynamic Factor Forecasts.* These models are the ones proposed by Stock and Watson (2002) and they call them Diffusion index forecasts. One can write the general forecasting function as

$$\hat{y}_{T+h|T}^{h} = \hat{\alpha}_h + \sum_{j=1}^{m} \hat{\beta}_{hj}\, \hat{F}_{T-j+1} + \sum_{j=1}^{p} \hat{\gamma}_{hj}\, y_{T-j+1} \tag{3.7}$$

where $\hat{F}_t$ is the vector of k common factors estimated from the whole panel of candidate predictor series X_t using *principal components*. There are three variations of

[16] For multistep-ahead forecasting, I can roll the forecasts and estimated factors forward period by period also. But this involves a large number of parameters to be estimated and could erode forecast performance.

this model. The first, denoted by DF-AR-LAG, includes lags of the estimated factors and lags of y_t. The optimal number of factors k and the optimal lag length m and p are chosen by SIC with $1 \le k \le 4$, $1 \le m \le 3$ and $1 \le p \le 6$. The second model, denoted as DF-AR, excludes lags of factors. So, I set $m = 1$. And p and k are chosen by SIC with $1 \le k \le 12$ and $1 \le p \le 6$. The third, denoted as DF, includes contemporaneous estimated factors only and excludes all autoregressive terms. That is,

$$\hat{y}^{h}_{T+h|T} = \hat{\alpha}_h + \hat{\beta}_h \hat{F}_T \tag{3.8}$$

where the number of factors chosen by SIC with $1 \le k \le 12$. As I pointed out before, it is hard to interpret these factors structurally and more importantly, the factors chosen may not be quite suitable for forecasting y.

- *Structural Dynamic Factor Forecasts.* Given the shortcomings of the above dynamic factor or diffusion index model, the proposed *structural dynamic factor forecasting* model takes the structure of underlying predictor series into consideration. The general form of the *structural dynamic factor forecasting* function is

$$\hat{y}^{h}_{T+h|T} = \hat{\alpha}_h + \sum_{j=1}^{m} \hat{\beta}^{R}_{hj} \hat{F}^{R}_{T-j+1} + \sum_{j=1}^{m} \hat{\beta}^{I}_{hj} \hat{F}^{I}_{T-j+1} + \sum_{j=1}^{m} \hat{\beta}^{M}_{hj} \hat{F}^{M}_{T-j+1} + \sum_{j=1}^{p} \hat{\gamma}_{hj}\, y_{T-j+1} \tag{3.9}$$

where $\hat{F}^{R}_{t}$, $\hat{F}^{I}_{t}$ and $\hat{F}^{M}_{t}$ are the vectors of real activity factors, inflation/price factors and monetary factors estimated using *principal components* from the real activity related variables X_t^R, inflation/price variables X_t^I and monetary variables X_t^M respectively. Corresponding to dynamic factor forecasting models, I also have three variations of the structural factor model. The first, denoted as SDF-AR-LAG, includes lags of the estimated structural factors and lags of y_t. And the optimal number of structural factors k from each group and the optimal lag length m and p are chosen by SIC with $1 \le k \le 3$, $1 \le m \le 3$ and $1 \le p \le 6$. The second model, denoted as SDF-AR, excludes lags of all structural factors. So, I set $m = 1$. And p and k are chosen by SIC with $1 \le k \le 4$ and $1 \le p \le 6$. The third, denoted as SDF, includes contemporaneous estimated structural factors only and excludes all autoregressive terms. That is,

$$\hat{y}^{h}_{T+h|T} = \hat{\alpha}_h + \hat{\beta}^{R}_{h} \hat{F}^{R}_{T} + \hat{\beta}^{I}_{h} \hat{F}^{I}_{T} + \hat{\beta}^{M}_{h} \hat{F}^{M}_{T} \tag{3.10}$$

where the number of structural factors from each group k chosen by SIC with $1 \le k \le 4$. One can also put restrictions on the coefficients of equation (3.10) and generate many kinds of structural factor forecasting models. For example, one can restrict all the coefficients before F^{M}_{t} to be zeros when forecasting real activity variables given the very low correlations between real activity variables and monetary variables most of the time and the wide-accepted theory of money neutrality, one ends up a forecasting model with real activity factors and inflation/price factors in the sprite of Philips curve. So I call this model *real activity-inflation/price dynamic factor* (RIDF) forecasting model. And correspondingly, I have RIDF-AR-LAG model, RIDF-AR model and RIDF model. When I forecast the CPI, these general Philips curve models are also used. When foresting real variables, I also consider the model where the factors are selected from the group of variables related to real activity only and I call this model as a *real activity dynamic factor forecasting* model (RDF) as a generalized AR model in factor form. When foresting the CPI, I also use the model where the factors are selected from the group of variables related to inflation/prices only and I call this model as an *inflation/price dynamic factor forecasting* model (IDF). As the general *structural dynamic factor* model, these models each also have three variations and I label them as RDF-AR-LAG, RDF-AR and RDF for the *real activity dynamic factor forecasting* model (RDF) and IDF-AR-LAG, IDF-AR and IDF for the *inflation/price dynamic factor forecasting* model (IDF).

My forecasting exercise is a simulated real time forecasting. I estimate factors, estimate model parameters and select models recursively. The first out-of-sample forecast is made for January 1990. For instance, I predict *h*-step ahead. To predict $y^{h}_{1990:01}$, data from 1972:01 to1990:01-*h* is used to estimate factors, to estimate parameters of forecasting models and to select models using SIC. To make forecast for 1990:02, then data at 1990:02-*h* is included, factors are then reestimated, information criterion is recomputed and models are reselected, etc. So, I increase my estimation window every period. When I forecast for the last period 2003:12, the data from 1972:01 to2003:12-*h* is used for estimation. All these predictor series are transformed to be stationary. Moreover, they are fully standardized to have zero mean and unit variance when they are used to estimate factors.

3.3.2 Forecasting Comparison

In order to choose the best out-of-sample forecasting model, I compare each model with the baseline AR model. I report the relative forecasting mean square error

(RMSE) of each model relative to the benchmark AR model. The forecasting mean square error (MSE) for each model is calculated as

$$MSE = \frac{1}{P}\sum_{t=1990:01}^{2003:12}(\hat{y}_t - y_t)^2 \tag{3.11}$$

where $\hat{y}$ is the forecasted value , y is the true value and P is the number of forecasts. In this paper, the number of forecasts equals 168 from January 1990 till December 2003. In order to draw more accurate inference, I consider the F-statistic for testing equal forecast accuracy proposed by McCracken (2000) and the F-type encompassing test proposed by Clark and McCracken (2001). Clark and McCracken (2001,2002a,b) have shown them to be more powerful than the t-statistics for equal MSE test developed by Diebold and Mariano (1995) and West(1996) and the t-statistics for encompassing test developed in Harvey, Leybourne, and Newbold (1998) and West(2001).

If I denote the AR model as model 1 and any of the other models, e.g., the VAR model, as model 2, and I use $\hat{u}_{1t}$ and $\hat{u}_{2t}$ to denote the two sequences of forecast errors from model 1 and model 2 respectively, then the F-type test statistic of equal MSE takes the following form

$$MSE\text{-}F = P \times \frac{MSE_1 - MSE_2}{MSE_2} \tag{3.12}$$

where P is the number of forecasts , MSE_1 and MSE_2 are forecast mean square errors from model 1 and model 2 respectively. Under the null, these two models have equal forecast accuracy, and the test statistic equals zero. Under the alternative hypothesis,

$MSE_1 \geq MSE_2$ .So, this test is one-sided to the right. The encompassing test developed by Clark and McCracken (2001) takes the form

$$ENC-F = P \times \frac{\bar{c}}{MSE_2} \tag{3.13}$$

where $\hat{c}_t = \hat{u}_{1t}(\hat{u}_{1t} - \hat{u}_{2t})$ and $\bar{c} = P^{-1} \sum_{t=1990:01}^{2003:12} \hat{c}_t$. For this encompassing test, as Harvey, Leybourne and Newbold (1998) point out, under the alternative, model 2 contains added information, so the covariance in the numerator of the encompassing test should be positive. Under the null that model 1 encompasses model 2, the covariance will be less or equal zero. So this encompassing test is also one-sided, to the right.

Since the distributions of these two tests are non-standard for multi-step forecasts, I use a bootstrap procedure which is similar to the one proposed by Kilian (1999) to yield the critical values for these tests. Clark and McCracken (2002a) show that the simple bootstrap algorithm yields good size and power properties for a range of realistic data generating processes. The bootstrap algorithm consists of resampling with replacement from the residual vector of a simple AR model for the variable of interest for the whole period from 1972:01 to 2003:12. Then a pseudo series is generated. I also replace the original series with this pseudo series when estimating factors. Then I implement the same forecasting procedure with the new pseudo sample. Pseudo forecast errors are generated and the two pseudo test-statistics are computed. I do this for 200 times. Then I sort the 200 pseudo test-statistics for each test in an ascending order. The

90 percentile, 95 percentile and 99 percentile are the critical values at 10 percent, 5 percent and 1 percent significance level respectively.

3.4 Forecasting Results

The simulated out-of-sample forecasting results are reported from Table 3.1 to Table 3.4. Since the critical values for the MSE-F and ENC-F test derived using the bootstrap algorithm may not be accurate, I draw the conclusions carefully based on both tests instead of just one of them. I pick the best model at each horizon for all these four variables. Moreover, I compare specifically my favorite structural factor model in mind—the generalized factor version of Philips curve model, the *real activity and inflation/price dynamic factor* model including lags of the factors and lags of the forecasted variable (RIDF-AR-LAG), with its nonstructural corresponding one, Stock and Watson's DF-AR-LAG model. First, let us look at the forecasting results for industrial production in Table 3.1. I notice that at short horizons, the general *structural factor forecasting* model or some restricted versions of it outperforms the AR model, the VAR model and the dynamic factor models proposed by Stock and Watson. For instance, at the 1-month horizon, the best model is my *real activity dynamic factor* model including lags of the factors and lags of the forecasted variable (RDF-AR-LAG)—the factor version of the AR model. Both MSE-F test and ENC-F test reject the nulls at 1% significance level and the MSE is reduced by 10% compared to the benchmark AR model. At the 3-month and 6-month horizons, my *real activity and inflation/price dynamic factor* model including lags of the factors and lags of the

Table 3.1
Simulated Out-of–Sample Forecasting Results: Industrial Production

Industrial Production									
h=1									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1.00	-	-	-	-	-	-	-	-
VAR	1.11	-17.31	66.18	60.90	49.82	2.44	60.79	55.20	50.31
DF-AR-LAG	0.93	12.60***	3.99	1.68	0.75	24.04***	3.12	2.18	1.92
DF-AR	1.00	0.04**	3.66	-0.93	-1.39	21.78***	5.92	5.00	3.79
DF	1.01	-2.07***	-8.93	-16.97	-21.38	16.46***	8.49	7.57	6.22
SDF-AR-LAG	0.98	3.97***	3.66	1.27	0.33	16.40***	6.69	4.15	3.25
SDF-AR	0.98	3.24**	3.76	-1.41	-1.89	15.32***	6.14	4.50	4.11
SDF	1.00	0.50***	-2.73	-11.51	-18.15	12.38**	17.46	10.72	7.79
RIDF-AR-LAG	0.92	13.80***	2.76	1.70	0.27	18.83***	4.41	2.28	1.21
RIDF-AR	0.93	13.37***	1.93	0.65	-0.37	18.89***	5.09	3.07	1.82
RIDF	0.96	7.87***	-8.25	-15.17	-17.03	13.44***	11.82	10.24	7.53
RDF-AR-LAG	0.90	17.66***	2.18	1.25	0.41	31.74***	4.15	2.17	1.76
RDF-AR	1.00	0.56**	0.92	-0.86	-2.09	30.73***	6.52	5.06	3.16
RDF	1.00	0.72***	-8.88	-16.09	-19.19	26.89***	9.73	8.23	5.94
h=3									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1.00	-	-	-	-	-	-	-	-
VAR	1.35	-43.70	37.70	29.07	23.81	12.40	30.30	26.69	24.51
DF-AR-LAG	0.97	5.35**	6.18	4.67	2.45	37.80***	8.61	5.72	4.80
DF-AR	1.10	-15.31	4.28	-1.60	-3.87	33.41***	14.96	9.30	8.37
DF	1.11	-16.95	-8.01	-9.62	-12.58	25.51***	15.35	9.68	7.60
SDF-AR-LAG	1.05	-8.19	12.76	0.72	-2.14	32.53***	12.05	10.15	8.18
SDF-AR	1.07	-10.76	11.12	1.44	-4.00	31.53***	17.88	11.08	8.21
SDF	1.11	-16.47	-2.67	-11.64	-14.25	21.45**	31.05	15.78	9.20
RIDF-AR-LAG	0.89	21.23***	4.04	1.18	-1.01	41.73***	7.55	4.34	2.83
RIDF-AR	0.91	17.20***	7.04	4.05	1.56	42.37***	10.88	8.52	5.99
RIDF	0.95	8.06***	7.30	-1.47	-7.15	24.10***	23.13	11.65	7.12

Table 3.1 (Continued)

Industrial Production									
h=3									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
RDF-AR-LAG	1.08	-12.64	7.72	3.32	1.78	35.51***	15.37	7.66	4.53
RDF-AR	1.15	-22.29	2.65	-2.37	-5.39	36.71***	15.21	10.66	7.43
RDF	1.12	-17.85	-4.22	-12.05	-16.01	35.29***	13.69	8.86	7.88
h=6									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1.00	-	-	-	-	-	-	-	-
VAR	1.50	-56.12	21.19	12.43	10.75	22.65**	27.03	19.09	16.67
DF-AR-LAG	1.10	-14.71	15.02	6.87	5.28	39.36***	16.93	11.17	9.58
DF-AR	1.56	-60.58	10.97	3.06	-6.72	25.81**	29.37	21.88	16.24
DF	1.55	-59.85	-3.26	-10.38	-13.26	20.60**	22.92	16.30	11.31
SDF-AR-LAG	1.28	-36.81	22.24	2.02	-0.89	29.30***	26.51	20.82	17.20
SDF-AR	1.30	-38.64	22.85	3.15	-6.46	28.33**	37.63	27.20	13.45
SDF	1.32	-40.41	5.98	-5.03	-11.81	22.95*	39.34	26.55	15.65
RIDF-AR-LAG	0.94	10.51***	10.43	5.60	-0.81	42.68***	12.34	7.86	6.24
RIDF-AR	1.01	-1.90	15.17	9.28	3.63	39.07***	23.73	16.32	11.52
RIDF	1.02	-3.52	29.97	9.53	-1.70	25.29**	32.58	19.61	13.36
RDF-AR-LAG	1.29	-37.49	13.90	4.79	3.15	24.93**	31.22	11.18	8.99
RDF-AR	1.41	-49.08	11.04	2.34	-7.42	33.32***	30.04	21.36	17.65
RDF	1.39	-47.07	14.13	-9.89	-15.42	33.04***	24.52	15.01	11.62
h=12									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1.00	-	-	-	-	-	-	-	-
VAR	1.52	-57.79	47.75	20.63	11.55	29.32*	59.63	34.65	23.09
DF-AR-LAG	1.53	-58.15	41.95	23.55	10.16	18.08	36.63	26.57	20.39
DF-AR	1.75	-72.25	25.90	7.58	-0.10	12.21	72.32	41.29	31.05
DF	1.74	-71.67	27.67	3.12	-11.44	11.87	56.54	28.44	21.03
SDF-AR-LAG	1.83	-76.42	44.54	18.63	-0.09	14.96	53.71	38.86	26.59
SDF-AR	1.85	-77.19	47.87	4.74	-8.89	9.55	83.82	56.69	27.60
SDF	1.84	-76.87	37.16	1.35	-8.96	9.47	73.57	37.81	27.15

Table 3.1 (Continued)

Industrial Production									
h=12									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
RIDF-AR-LAG	1.12	-17.41	25.00	11.50	0.18	19.81**	26.16	15.86	12.62
RIDF-AR	1.22	-30.60	35.78	11.03	4.34	17.44	39.58	29.51	19.59
RIDF	1.22	-30.74	41.98	11.65	0.52	11.76	46.38	31.81	23.51
RDF-AR-LAG	1.76	-72.72	22.98	16.04	4.14	1.04	57.70	24.83	24.83
RDF-AR	2.04	-85.71	57.52	8.86	-10.48	13.59	78.58	40.14	32.28
RDF	2.02	-84.94	21.86	-6.75	-10.56	13.62	66.27	33.44	22.66
h=24									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1.00	-	-	-	-	-	-	-	-
VAR	1.07	-11.40	74.66	48.13	37.84	41.43*	163.2	63.36	39.20
DF-AR-LAG	1.34	-42.17	93.69	59.16	27.45	14.74	121.0	56.24	39.35
DF-AR	1.39	-47.25	41.13	14.32	-14.94	8.81	75.63	57.80	48.67
DF	1.38	-46.54	52.37	14.12	-0.09	10.27	189.2	75.61	53.24
SDF-AR-LAG	1.54	-59.03	61.41	30.17	-1.10	24.33	86.84	72.75	49.29
SDF-AR	1.80	-74.65	88.11	24.81	3.10	14.65	187.6	61.13	40.66
SDF	1.81	-75.21	48.59	-2.36	-9.17	14.11	101.6	49.61	43.03
RIDF-AR-LAG	1.41	-49.17	76.23	12.37	-7.86	5.13	107.5	34.47	30.07
RIDF-AR	1.34	-42.76	66.51	35.59	6.28	10.12	81.70	65.48	43.98
RIDF	1.40	-47.64	48.85	15.36	3.52	6.78	88.61	54.44	32.58
RDF-AR-LAG	1.71	-69.61	63.78	33.41	12.08	0.47	97.66	65.82	30.83
RDF-AR	1.59	-62.50	49.60	8.45	-5.87	-2.89	102.5	69.30	47.03
RDF	1.59	-62.15	147.7	25.78	8.53	-2.85	147.2	65.59	38.07

Note: 1. Entries of the first column are the lists of forecasting models used; the second column is the relative MSE of each model with regard to the AR model; the third column is the MSE-F test statistic; columns four to six are the simulated critical values of MSE-F test at the 1% , 5% and 10% significance level respectively; the seventh column is the ENC-F test statistic and columns eight to ten are the simulated critical values of ENC-F test at the 1% , 5% and 10% significance level respectively.

2. *, **, and *** indicate significant at the 10%, 5% and 1% level respectively.

Table 3.2
Simulated Out-of–Sample Forecasting Results: Real Personal Income

Real Personal Income									
h=1									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.00	0.45	10.60	6.98	4.89	1.42	11.36	7.04	6.59
DF-AR-LAG	0.93	12.43***	4.81	3.71	1.38	7.73***	6.18	3.76	2.86
DF-AR	0.94	9.81***	2.57	0.20	-1.85	9.46***	9.33	5.43	4.12
DF	0.94	10.47***	1.25	-1.30	-2.74	10.74***	7.68	6.54	5.75
SDF-AR-LAG	0.94	10.83***	1.57	0.62	-0.82	9.19***	5.75	3.81	2.51
SDF-AR	0.95	9.20***	-0.72	-1.65	-2.74	9.10***	6.54	3.93	2.78
SDF	0.93	11.84***	4.08	-0.96	-3.18	11.91***	9.40	6.38	3.81
RIDF-AR-LAG	0.93	12.86***	5.70	2.60	1.33	10.29***	7.07	4.08	2.39
RIDF-AR	0.94	11.63***	4.53	1.97	0.58	10.04***	7.10	5.44	3.73
RIDF	0.92	14.66***	2.06	1.60	0.33	12.72***	5.95	4.79	4.27
RDF-AR-LAG	0.93	11.81***	4.05	2.92	1.08	8.15***	5.18	3.86	2.23
RDF-AR	0.97	5.15***	2.91	0.07	-1.80	5.61*	8.49	5.71	4.04
RDF	0.97	4.71***	-1.02	-2.49	-3.51	7.32**	11.07	5.16	3.91
h=3									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.04	-6.36	8.55	2.95	2.39	2.55	12.50	8.43	5.79
DF-AR-LAG	0.86	28.49***	12.93	7.79	4.24	20.49***	15.88	10.99	8.48
DF-AR	0.82	37.19***	1.72	-1.40	-4.68	32.38***	16.80	10.86	8.62
DF	0.86	26.89***	4.89	-3.28	-5.87	22.17***	16.42	11.85	8.50
SDF-AR-LAG	0.82	36.65***	4.20	1.44	-0.32	31.01***	17.82	9.73	6.68
SDF-AR	0.82	36.86***	4.27	-1.42	-4.60	33.88***	11.66	9.15	6.55
SDF	0.86	27.93***	4.05	-1.35	-2.78	25.72***	13.09	8.21	5.87
RIDF-AR-LAG	0.79	45.27***	11.76	7.78	4.54	35.10***	19.19	10.18	6.77
RIDF-AR	0.80	41.40***	4.31	2.13	-0.64	33.68***	10.75	10.11	6.81
RIDF	0.84	32.93***	6.36	2.05	-0.61	25.21***	11.14	9.40	7.03

Table 3.2 (Continued)

Real Personal Income									
h=3									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
RDF-AR-LAG	0.88	23.92***	12.20	6.02	3.15	20.75***	16.48	8.72	6.77
RDF-AR	0.89	19.76***	6.43	1.99	-1.71	21.58***	21.36	14.44	12.02
RDF	0.93	12.63***	6.74	-0.01	-2.54	15.26**	23.98	12.02	9.21
h=6									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.20	-28.45	17.82	9.04	3.78	-3.21	29.10	16.71	9.18
DF-AR-LAG	1.00	-0.58	23.73	13.06	7.49	9.00	25.25	17.87	15.85
DF-AR	1.01	-1.19**	8.17	-3.77	-7.68	18.01*	30.08	18.53	15.14
DF	1.03	-5.43*	10.75	-3.95	-8.83	10.60	35.01	21.49	18.95
SDF-AR-LAG	1.06	-8.76	10.97	3.01	-3.41	9.68	28.07	14.69	11.83
SDF-AR	1.02	-2.99*	20.71	-0.10	-3.98	17.39*	26.32	19.62	12.01
SDF	1.04	-6.84	14.20	7.00	-5.05	11.07	25.68	16.52	13.08
RIDF-AR-LAG	0.90	18.15**	21.63	15.12	4.54	22.66**	43.58	19.45	8.10
RIDF-AR	0.87	25.48***	9.16	2.26	-2.37	28.24***	21.48	14.99	10.98
RIDF	0.89	21.69***	10.08	5.27	-0.98	20.72**	20.86	17.50	11.13
RDF-AR-LAG	0.98	3.37*	26.82	12.71	2.91	21.39**	29.08	18.24	12.64
RDF-AR	1.03	-4.48	24.68	4.92	0.35	19.93	57.15	30.89	25.07
RDF	1.04	-6.73	15.97	5.92	-0.28	12.97	38.53	19.59	13.79
h=12									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.20	-28.52	74.31	20.25	11.91	-1.35	81.77	35.83	18.50
DF-AR-LAG	1.15	-22.39	61.69	32.76	21.75	3.16	57.23	43.48	28.49
DF-AR	1.26	-35.11	13.30	-3.38	-9.79	-1.30	52.20	33.57	26.12
DF	1.26	-35.10	29.57	3.38	-4.23	-2.38	75.35	54.01	32.44
SDF-AR-LAG	1.31	-40.06	16.12	5.56	-1.76	-5.02	84.23	26.56	15.72
SDF-AR	1.32	-40.25	32.22	-0.71	-11.00	-1.35	61.18	34.81	27.43
SDF	1.31	-39.95	53.54	15.99	-3.11	-0.90	66.47	38.93	23.61

Table 3.2 (Continued)

Real Personal Income									
h=12									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
RIDF-AR-LAG	1.01	-1.41	53.33	17.73	5.80	14.99*	88.75	19.93	14.24
RIDF-AR	1.05	-8.13	18.70	-0.33	-4.39	15.00	50.14	21.26	15.56
RIDF	1.05	-7.36	26.99	14.13	-0.03	13.64	41.20	27.86	17.98
RDF-AR-LAG	1.15	-21.55	61.76	29.72	8.29	11.07	61.05	33.11	25.43
RDF-AR	1.23	-31.48	74.75	17.48	-7.46	9.30	116.0	63.52	41.04
RDF	1.22	-29.95	53.74	11.87	-3.80	7.39	73.34	37.43	20.68
h=24									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.14	-20.15	161.6	57.96	26.56	-1.66	132.3	86.68	53.10
DF-AR-LAG	1.40	-47.76	199.7	104.61	39.97	-10.00	187.7	92.90	65.92
DF-AR	1.74	-71.65	62.92	6.69	-16.73	-18.16	141.5	73.12	45.26
DF	1.69	-68.76	70.44	28.39	-0.29	-17.37	141.5	89.59	72.67
SDF-AR-LAG	1.65	-66.15	43.11	18.32	-5.01	-16.60	193.4	35.77	31.09
SDF-AR	2.03	-85.30	66.51	17.43	-19.44	-14.63	129.9	70.74	46.07
SDF	2.03	-85.08	110.1	36.65	2.43	-14.52	165.7	66.33	39.57
RIDF-AR-LAG	1.41	-48.94	148.7	35.45	9.48	-6.71	156.1	41.70	29.51
RIDF-AR	1.52	-57.39	158.7	-2.64	-14.07	-2.32	155.4	52.92	26.36
RIDF	1.50	-56.04	70.85	36.24	7.33	-1.80	91.75	47.45	38.37
RDF-AR-LAG	1.49	-55.14	133.8	35.50	20.13	-0.46	128.2	104.3	41.28
RDF-AR	1.51	-57.05	177.6	77.26	2.21	-11.37	209.8	121.1	103.7
RDF	1.46	-53.26	78.75	43.32	3.36	-10.10	127.9	70.61	48.14

Note: 1. Entries of the first column are the lists of forecasting models used; the second column is the relative MSE of each model with regard to the AR model; the third column is the MSE-F test statistic; columns four to six are the simulated critical values of MSE-F test at the 1% , 5% and 10% significance level respectively; the seventh column is the ENC-F test statistic and columns eight to ten are the simulated critical values of ENC-F test at the 1% , 5% and 10% significance level respectively.

2. *, **, and *** indicate significant at the 10%, 5% and 1% level respectively.

forecasted variable (RIDF-AR-LAG), the factor version of Philips curve model, is the best. But at longer horizons, the AR model outperforms all the others for industrial production forecasts. Comparing the proposed structural models and Stock and Watson's non-structural models specifically, I notice that my favorite model in mind—the generalized factor Philips curve model (RIDF-AR-LAG) performs much better than its non-structural corresponding model (DF-AR-LAG) consistently for four out of five horizons. And for two horizons, my RIDF-AR-LAG model is the best among all. Similar to industrial production, for real personal income forecasts (Table 3.2), variations of my *real activity and inflation/price dynamic factor* model (RIDF), or put in another way, variations of factor Philips curve model, perform best at short horizons. Moreover, my RIDF-AR-LAG model outperforms the non-structural DF-AR-LAG model most of the time. Regarding the forecasts of nonagricultural employment (Table 3.3), the restricted *structural factor forecasting* models perform best at the 1-month, 6-month and 24-month horizons. More importantly, my RIDF-AR-LAG model generates better forecasts than the DF-AR-LAG model at all horizons. Finally, turning to the forecasts of the CPI inflation rate (Table 3.4), the advantages of the proposed *structural factor forecasting* models are not as obvious as the above three real variables relative to Stock and Watson's factor forecasting models. At the 1-month horizon, both my restricted *structural factor forecasting* model (IDF-AR-LAG) and Stock and Watson's dynamic factor model (DF) generate the best forecasts. At the 3-month horizon, the best model is my structural factor model (RIDF-AR). But at longer horizons, one variation of Stock and Watson's model (DI-AR) outperforms all the other models. But turning to these two

Table 3.3
Simulated Out-of–Sample Forecasting Results: Nonagricultural Employment

Nonagricultural Employment									
h=1									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.37	-45.59	174.2	159.89	143.11	-6.46	167.6	144.0	134.0
DF-AR-LAG	1.08	-13.09	3.34	1.82	0.21	19.59***	3.84	2.18	1.48
DF-AR	1.11	-17.21	2.08	-0.65	-0.99	28.05***	7.53	5.41	3.74
DF	1.19	-27.08***	-36.7	-40.36	-47.65	18.82***	16.19	11.93	9.32
SDF-AR-LAG	1.26	-34.83	6.72	1.25	0.27	15.55***	9.48	5.09	4.18
SDF-AR	1.17	-24.08	6.58	0.21	-2.16	23.38***	9.79	4.37	3.24
SDF	1.26	-35.06**	-31.2	-41.49	-49.20	15.61***	15.52	10.20	7.56
RIDF-AR-LAG	1.03	-5.67	3.72	2.82	0.79	23.80***	5.08	2.84	2.13
RIDF-AR	1.00	0.69*	3.03	1.03	0.24	26.87***	5.86	3.84	2.63
RIDF	1.03	-4.46***	-36.4	-43.67	-45.44	22.12**	18.36	12.71	9.52
RDF-AR-LAG	0.97	5.01***	2.29	1.22	0.66	29.92***	5.33	2.55	1.84
RDF-AR	1.17	-23.96	7.41	-1.32	-3.26	23.77***	12.94	5.89	3.28
RDF	1.37	-45.46*	-40.2	-44.64	-46.41	12.38**	12.91	9.39	8.75
h=3									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.87	-78.00	103.5	88.15	80.68	-9.54	86.42	77.31	68.69
DF-AR-LAG	1.37	-45.06	8.92	2.99	1.86	7.63**	11.64	6.35	4.22
DF-AR	1.12	-18.07	5.00	3.22	-0.85	27.85***	19.23	13.38	8.41
DF	1.29	-37.41	-11.8	-22.57	-29.69	20.41**	25.20	16.93	13.86
SDF-AR-LAG	1.52	-57.17	10.01	1.15	-2.91	6.07	21.84	10.20	8.00
SDF-AR	1.34	-43.00	10.04	-0.84	-4.47	12.31**	19.34	12.29	7.48
SDF	1.50	-55.88	-22.1	-25.78	-31.17	9.74	21.14	14.44	10.76
RIDF-AR-LAG	1.01	-1.06	10.14	3.18	0.14	25.54***	11.18	6.03	4.22
RIDF-AR	0.98	3.46**	3.66	0.78	-3.19	27.01***	10.94	5.97	4.75
RIDF	1.05	-7.53***	-16.2	-23.27	-26.64	24.62***	18.64	16.57	10.81

Table 3.3 (Continued)

Nonagricultural Employment									
h=3									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
RDF-AR-LAG	1.00	0.61	8.30	5.85	2.17	29.57***	11.67	7.72	5.91
RDF-AR	1.00	-0.13*	11.52	2.26	-4.62	47.12***	17.01	10.07	7.89
RDF	1.21	-28.86*	-15.8	-23.74	-30.71	29.48***	21.05	18.75	12.23
h=6									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	2.24	-93.15	53.81	43.23	37.51	-11.73	54.00	37.65	34.60
DF-AR-LAG	1.75	-72.19	14.61	4.87	2.91	-4.71	19.44	12.15	8.00
DF-AR	1.73	-70.97	21.08	2.58	-7.32	-3.30	34.19	25.67	15.83
DF	1.83	-76.14	14.19	4.39	-16.58	-4.78	44.77	26.58	18.94
SDF-AR-LAG	1.90	-79.61	23.20	7.88	-3.46	-7.72	34.67	18.70	13.52
SDF-AR	1.68	-67.83	11.17	-1.59	-6.30	-6.36	29.18	20.36	12.81
SDF	1.77	-73.27	1.87	-9.72	-14.09	-5.76	27.74	22.43	18.06
RIDF-AR-LAG	1.10	-15.81	27.52	6.75	0.91	11.39*	25.11	11.44	8.16
RIDF-AR	1.07	-11.55	6.96	2.76	-1.47	12.48*	21.93	14.30	8.64
RIDF	1.11	-16.37	1.60	-6.86	-15.48	11.68	31.79	22.19	14.85
RDF-AR-LAG	1.15	-22.31	18.35	9.34	0.33	18.93**	24.05	15.55	7.82
RDF-AR	1.37	-45.47	23.17	9.68	-6.82	18.78*	43.80	23.67	16.11
RDF	1.55	-59.68	-10.2	-17.22	-20.96	9.80	33.48	21.44	14.26
h=12									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	2.40	-98.11	37.35	26.24	20.73	-14.09	55.96	38.46	26.27
DF-AR-LAG	1.76	-72.50	30.58	8.93	1.33	-6.69	31.18	21.40	15.66
DF-AR	1.60	-63.20	40.20	15.62	1.93	-7.26	83.88	44.85	32.67
DF	1.62	-64.10	37.78	6.32	-1.18	-6.53	65.79	40.59	29.45
SDF-AR-LAG	2.02	-84.93	50.43	4.91	-0.81	-11.19	52.35	34.95	25.85
SDF-AR	1.84	-76.89	25.55	9.33	-3.55	-13.47	62.51	40.12	30.25
SDF	1.85	-76.97	43.00	12.05	-9.03	-11.78	62.21	36.24	29.08

Table 3.3 (Continued)

Nonagricultural Employment									
h=12									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
RIDF-AR-LAG	1.02	-4.07	55.33	13.79	2.79	11.93	50.54	27.60	18.00
RIDF-AR	1.07	-10.51	19.47	1.99	-5.33	11.48	46.21	25.60	17.94
RIDF	1.05	-8.42	24.35	6.03	-6.51	12.47	71.23	42.27	18.02
RDF-AR-LAG	1.19	-27.29	32.66	9.13	0.19	24.61*	46.95	27.43	19.77
RDF-AR	1.59	-62.44	32.54	-2.41	-8.76	9.10	65.73	36.86	31.09
RDF	1.72	-70.19	26.63	-7.44	-16.55	2.93	58.22	42.82	25.59
h=24									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.84	-76.90	93.03	53.79	29.08	-7.66	112.6	70.97	44.09
DF-AR-LAG	1.16	-22.68	101.3	32.51	17.87	13.76	86.02	45.78	26.95
DF-AR	1.05	-8.55	181.2	44.69	4.83	22.45	197.3	133.5	45.74
DF	1.07	-10.26	76.45	30.99	-6.15	17.26	151.5	77.23	56.59
SDF-AR-LAG	1.37	-45.07	117.7	11.34	-5.60	14.85	99.32	64.10	45.40
SDF-AR	1.44	-51.67	102.5	28.82	3.74	11.03	144.7	79.11	63.39
SDF	1.45	-52.29	65.30	34.35	7.04	9.52	120.6	80.31	54.79
RIDF-AR-LAG	0.95	8.11	124.0	42.13	25.11	39.40	108.1	58.85	41.40
RIDF-AR	1.00	-0.16*	36.04	30.20	-8.17	37.83	106.9	57.10	42.27
RIDF	1.03	-4.51	51.38	30.53	11.09	35.16	136.3	72.17	45.88
RDF-AR-LAG	1.26	-34.50	51.32	32.10	5.19	48.45*	72.35	52.83	41.59
RDF-AR	1.07	-10.41	39.13	5.74	-8.12	17.49	94.00	58.56	45.79
RDF	1.18	-25.06	40.60	21.63	-16.96	7.61	138.8	56.19	51.01

Note: 1. Entries of the first column are the lists of forecasting models used; the second column is the relative MSE of each model with regard to the AR model; the third column is the MSE-F test statistic; columns four to six are the simulated critical values of MSE-F test at the 1% , 5% and 10% significance level respectively; the seventh column is the ENC-F test statistic and columns eight to ten are the simulated critical values of ENC-F test at the 1% , 5% and 10% significance level respectively.

2. *, **, and *** indicate significant at the 10%, 5% and 1% level respectively.

Table 3.4
Simulated Out-of–Sample Forecasting Results: Consumer Price Index Inflation Rate

Consumer Price Index Inflation Rate									
h=1									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	0.91	51.27	266.9	232.30	199.65	11.04	239.8	209.1	185.6
DF-AR-LAG	0.90	18.37***	4.33	2.65	1.70	38.98***	5.38	3.88	2.12
DF-AR	0.94	27.44***	1.79	-1.36	-1.90	45.10***	4.75	4.31	3.62
DF	0.85	30.54***	-42.9	-58.43	-64.41	44.40***	15.70	9.59	7.44
SDF-AR-LAG	0.92	15.14***	6.02	3.04	-0.02	39.90***	8.77	5.59	3.40
SDF-AR	0.95	8.69***	5.01	0.33	-1.19	31.11***	12.41	4.87	4.14
SDF	0.94	10.80***	-33.0	-47.27	-54.75	29.15***	17.96	10.16	7.73
RIDF-AR-LAG	0.90	18.34***	5.56	0.36	-0.34	20.99***	4.98	3.10	1.34
RIDF-AR	0.89	21.17***	4.17	1.00	0.25	19.30***	6.42	3.14	2.22
RIDF	0.88	22.66***	-49.1	-54.13	-56.74	22.69***	14.12	10.89	9.57
IDF-AR-LAG	0.85	29.54***	4.48	0.51	-0.39	28.10***	3.86	1.83	1.31
IDF-AR	0.94	10.07***	3.90	1.87	-0.42	17.59***	7.14	4.22	2.99
IDF	0.95	8.49***	-45.0	-53.74	-56.70	19.91**	23.61	10.75	7.94
h=3									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	0.91	16.86	136.4	116.06	108.66	17.43	117.8	103.5	97.13
DF-AR-LAG	1.02	-3.84	12.89	7.27	4.10	49.98***	12.62	9.79	5.83
DF-AR	1.03	11.07***	2.20	-0.75	-2.78	70.70***	12.14	10.13	6.22
DF	0.91	16.21***	-25.0	-31.88	-41.28	69.62***	24.13	16.55	11.94
SDF-AR-LAG	1.13	-18.91	10.64	4.96	-0.62	51.91***	26.25	12.12	8.21
SDF-AR	1.08	-12.65	10.06	1.01	-4.02	52.04***	17.47	12.73	10.10
SDF	1.05	-8.31***	-24.9	-28.78	-38.98	51.44***	27.64	18.95	14.88
RIDF-AR-LAG	0.93	13.43**	13.46	1.87	-0.29	38.58***	12.53	5.92	3.22
RIDF-AR	0.83	34.23***	6.17	2.11	0.15	47.77***	13.28	9.06	6.00
RIDF	0.86	28.20***	-21.3	-31.68	-35.40	39.37***	21.21	13.75	10.74

Table 3.4 (Continued)

Consumer Price Index Inflation Rate									
h=3									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
IDF-AR-LAG	0.86	27.75***	5.29	2.97	0.59	33.69***	5.72	4.39	2.78
IDF-AR	1.06	-9.56	5.51	1.61	-1.30	21.96***	10.93	5.37	4.23
IDF	1.10	-15.59**	-10.6	-22.79	-33.88	19.22**	32.08	16.26	12.78
h=6									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.20	-28.15	87.35	80.63	54.88	-4.09	75.34	67.45	53.87
DF-AR-LAG	0.92	13.64**	22.89	11.03	7.34	52.16***	22.65	15.79	10.78
DF-AR	0.77	13.74***	5.13	0.54	-8.10	65.40***	23.45	16.96	12.66
DF	1.00	-0.29***	-15.7	-18.29	-21.52	75.88***	28.43	22.88	15.89
SDF-AR-LAG	1.09	-14.43	16.83	5.10	0.44	54.16***	43.48	16.22	12.69
SDF-AR	1.18	25.24***	10.31	2.89	-5.82	43.33***	24.86	21.87	14.48
SDF	1.30	-38.77	-5.16	-14.03	-21.27	44.40***	35.72	27.67	15.36
RIDF-AR-LAG	0.90	17.91**	17.98	4.74	1.82	52.35***	22.99	11.62	7.13
RIDF-AR	0.86	26.77***	10.70	5.28	2.77	52.34***	25.13	15.88	11.99
RIDF	1.01	-0.92***	-5.29	-16.80	-23.45	35.38***	17.38	15.21	11.74
IDF-AR-LAG	1.18	-25.41	13.18	5.74	2.23	8.49**	15.04	7.51	3.57
IDF-AR	1.43	-50.49	8.08	-0.76	-2.81	-2.21	11.58	7.82	6.35
IDF	1.54	-58.61	11.28	-10.83	-18.65	3.58	38.83	17.90	12.62
h=12									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.40	-48.17	61.79	50.47	35.59	-15.62	53.23	43.90	35.83
DF-AR-LAG	0.83	35.10**	40.27	32.56	11.14	55.44***	45.41	28.30	15.74
DF-AR	0.47	85.09***	26.06	7.94	-8.63	123.46***	59.15	39.21	27.81
DF	0.70	72.24***	41.18	17.17	-6.99	127.39***	71.61	46.92	31.22
SDF-AR-LAG	0.92	14.02*	36.48	16.13	2.81	67.52***	60.37	34.38	27.90
SDF-AR	0.98	3.24**	46.57	-7.44	-13.68	65.33***	49.43	29.24	19.92
SDF	1.11	-16.44	37.16	-0.77	-12.24	57.90**	60.30	34.20	28.13

Table 3.4 (Continued)

Consumer Price Index Inflation Rate									
h=12									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
RIDF-AR-LAG	0.79	44.64***	23.13	11.70	1.88	77.87***	43.80	22.96	17.16
RIDF-AR	0.74	58.09***	22.92	13.36	2.72	95.72***	42.13	25.80	17.19
RIDF	0.84	32.65***	16.99	-0.04	-7.07	62.04***	48.74	25.58	17.81
IDF-AR-LAG	0.98	3.02	30.50	14.06	3.51	33.33***	26.27	18.20	5.11
IDF-AR	1.31	-40.22	11.17	3.37	-3.03	3.19	25.12	13.56	7.13
IDF	1.46	-53.21	29.97	19.85	3.20	0.90	38.53	25.67	20.01
h=24									
	RMSE	MSE-F	1%	5%	10%	ENC-F	1%	5%	10%
AR	1	-	-	-	-	-	-	-	-
VAR	1.73	-70.98	79.29	37.89	23.55	-24.97	120.3	47.78	32.68
DF-AR-LAG	0.72	66.79**	83.94	51.49	37.65	60.27*	92.77	66.39	48.06
DF-AR	0.31	148.64***	81.21	32.46	14.19	159.72**	177.2	72.48	52.36
DF	0.51	163.30***	111.0	7.35	-4.23	171.44***	147.0	73.20	51.27
SDF-AR-LAG	0.72	66.68**	172.2	33.05	3.94	75.24*	184.8	88.40	51.48
SDF-AR	0.76	53.58***	20.34	-0.06	-11.54	76.05**	80.15	51.71	28.49
SDF	0.89	21.53**	40.44	-2.55	-18.38	55.62*	70.20	60.87	48.59
RIDF-AR-LAG	0.53	149.04***	46.20	23.63	-1.21	138.36***	73.29	55.23	39.64
RIDF-AR	0.53	146.13***	46.61	24.09	2.33	131.92***	91.71	58.96	39.10
RIDF	0.53	148.07***	75.82	31.54	8.64	133.59***	115.0	71.52	37.63
IDF-AR-LAG	0.97	5.00	57.45	37.17	17.57	35.18*	58.58	37.99	20.48
IDF-AR	1.34	-42.88	39.08	22.72	2.13	-1.46	51.22	27.03	14.56
IDF	1.44	-51.18	65.06	32.89	20.72	-6.02	83.77	36.86	27.17

Note: 1. Entries of the first column are the lists of forecasting models used; the second column is the relative MSE of each model with regard to the AR model; the third column is the MSE-F test statistic; columns four to six are the simulated critical values of MSE-F test at the 1% , 5% and 10% significance level respectively; the seventh column is the ENC-F test statistic and columns eight to ten are the simulated critical values of ENC-F test at the 1% , 5% and 10% significance level respectively.

2. *, **, and *** indicate significant at the 10%, 5% and 1% level respectively.

specific models, my structural RIDF-AR-LAG model still consistently performs better than Stock and Watson's non-structural DI-AR-LAG model. I also notice the "rule of thumb" in forecasting literature (the simple AR model is the best) breaks for the CPI inflation totally. My *structural dynamic factor forecasting* models and Stock and Watson's *dynamic factor forecasting* models perform much better than the univariate AR model at all the forecasting horizons.

3.5 Conclusion

In this chapter, I use the method of structural factor analysis to forecast some key macroeconomic variables in a data rich environment. Using the larger and more updated data set containing 308 series from January 1972 until December 2003, I simulate an out-of –sample real time forecasting exercise using the proposed *structural dynamic factor forecasting* model and its variations for some key macroeconomic variables. I use several structural factors to summarize the information from a large set of candidate explanatory variables. Compared to Stock and Watson (2002)'s models, the models proposed in this chapter can further allow me to select the factors structurally for each variable to be forecasted. I find the obvious advantages of the *structural dynamic factor forecasting* models compared to alternatives that include the univariate autoregression (AR) model, the vector autoregression (VAR) model and Stock and Watson's non-structural factor models, especially when forecasting real variables, e.g., industrial production and real personal income.

CHAPTER IV

A DUAL MEASURE OF CORRELATION BETWEEN THE SOLOW RESIDUAL AND OUTPUT GROWTH

4.1 Introduction

The real-business-cycle (RBC) literature, exemplified by the work of Kydland and Prescott (1982) and its subsequent extensions, interprets the bulk of aggregate fluctuations observed in the postwar U.S. economy as a result of exogenous technology shocks. According to the RBC theory, prices are assumed to be fully flexible even in the short run. Nominal variables do not influence the real fluctuations of output and employment. The RBC theory singles out the real shocks, technology shocks, as the main source of aggregate fluctuations. For example, Kydland and Prescott (1991) treat the real technology shocks as the only driving force behind cyclical fluctuations.

To demonstrate the role of technology shocks in generating business cycles, Kydland and Prescott compute the primal Solow residual–the percentage change in output minus the percentage change in input, where different inputs are weighted by their factor shares. The primal Solow residual measures the portion of output growth that cannot be explained by growth in capital or labor. Kydland and Prescott interpret the primal Solow residual as a measure of the rate of technological progress, i.e., the growth rate of total factor productivity or technology shocks. By using this approach, the so-called quantity-based primal growth accounting approach, the authors argue that "technology shocks account for 70 percent of business cycle fluctuations." Using a slightly different version of the model, Prescott (1986) attributed 75 percent of output fluctuations to productivity shocks.

But the use of the primal Solow residual remains a controversial issue. The critics, e.g., Summers (1986) and Mankiw (1989), argue that the use of the primal Solow residual can be problematic, and can lead to excessively volatile productivity shocks. There are several measurement problems that can make the primal Solow residual a poor measure of productivity at cyclical frequencies. First, Summers and Mankiw emphasize the importance of labor hoarding, the phenomenon in which firms may continue to employ workers they do not need during recession. This means that labor input is overestimated in recession, and productivity as measured by the primal Solow residual falls even if there is no technology regress. As a result, the primal Solow residual is more cyclical than the available productivity technology. Second, people also question the standard assumption used in calculating the primal Solow residual in the real-business-cycle literature: the capital service is proportional to the capital stock. Burnside, Eichenbaum and Rebelo (1996) correct for variations in capital utilization by employing industrial electrical use as a proxy for capital services. They find that the values of the relative variance and the correlation between output growth and technology shocks are much smaller than those suggested in RBC studies. Finally, the measures of the primal Solow residual in RBC literature are based on aggregate national accounts data. As is well known, the task of computing reliable national statistics is an extremely difficult one, and even under the best circumstances such statistics are plagued with errors.

Motivated by the criticism of the measures of technology shocks used in the RBC literature, this chapter uses a price-based dual approach to measure the Solow residual. The dual Solow residual is measured as the share-weighted average of real factor prices. Any technology shock will cause corresponding changes in real factor prices. In a normal circumstance, a positive technology shock will increase productivities of factors, and increase their marginal product. If all firms in the economy are competitive and profit maximizing, then real factors' prices are equal to their marginal product. Therefore, any changes in real factors' prices should reflect technology shocks. Moreover, rather than using the aggregate quantity data employed in the primal approach, the use of dual Solow residuals allows for us to utilize more accurate and easily accessed price-based data. Therefore, the dual approach avoids many of the problems of the primal approach mentioned above and measures the technology shock more accurately. Hsieh (2002) finds that, compared with the primal Solow residual, the dual Solow residual can better explain industry revolution in East Asia. In this chapter, we re-examine the role of technology shocks in RBC using the dual Solow residual approach, and compare it with the primal approach.

The rest of the chapter is organized as follows. Section 4.2 details the dual growth accounting methodology used in this paper. Section 4.3 reports a simulation study that examines the effects of measurement errors in capital/labor on the primal and dual approaches. Section 4.4 measures technology shocks by using both the conventional primal approach and the dual approach by using U.S. aggregate data and by employing U.S. manufacturing sector data. Section 4.5 compares the results obtained from the primal and the dual approaches. Section 4.6 concludes the paper.

4.2 The Dual Growth Accounting Approach

In this section, by using the basic national account identity, we employ the dual growth accounting approach which states that national output is equal to the payments to the factors of production, i.e., capital and labor:

$$Y = rK + wL \tag{4.1}$$

where Y is aggregate output, K is input of capital, L is input of labor, r is the real rental price of capital and w is the real wage of labor. Differentiating both sides of equation (4.1) with respect to time, we obtain

$$\dot{Y} = \dot{r}K + r\dot{K} + \dot{w}L + w\dot{L} \tag{4.2}$$

where we use a dot over a variable denoting the time differential, i.e., $\dot{Y} = \dfrac{dY}{dt}$, etc.

Dividing Y on both sides, we have

$$\frac{\dot{Y}}{Y} = \frac{rK}{Y}\left(\frac{\dot{r}}{r} + \frac{\dot{K}}{K}\right) + \frac{wL}{Y}\left(\frac{\dot{L}}{L} + \frac{\dot{w}}{w}\right). \tag{4.3}$$

Eq. (4.3) can be rewritten as

$$\hat{Y} = s_K\left(\hat{r} + \hat{K}\right) + s_L\left(\hat{L} + \hat{w}\right) \tag{4.4}$$

where $s_K \equiv rK/Y$ and $s_L \equiv wL/Y$ are the factor income shares of capital and labor, respectively, and a circumflex over a variable denotes the percentage change or the growth rate, i.e., $\hat{Y} = \frac{\dot{Y}}{Y}$, etc. By rearranging the terms, we get:

$$\hat{Y} - s_K \hat{K} - s_L \hat{L} = s_K \hat{r} + s_L \hat{w} \tag{4.5}$$

Note that the primal measure of the Solow residual is given at the left-hand-side of the (4.5), i.e.,

$$SR_{\mathrm{Pr}imal} = \hat{Y} - s_K \hat{K} - s_L \hat{L}\,. \tag{4.6}$$

The dual estimate of the Solow residual is given at the right-hand-side of (4.5), i.e.,

$$SR_{Dual} = s_K \hat{r} + s_L \hat{w}\,. \tag{4.7}$$

See Barro (1999) for a more detailed discussion regarding the primal and dual approaches on growth accounting. When there is more than one type of capital or labor, we can calculate the aggregate growth rate of the rental price or wage as a weighted average of the growth rates of different types of capital or labor, in this case,

$$\hat{r} = \sum_{i=1}^{n} s_{Ki} \hat{r}_i \tag{4.8}$$

where s_{Ki} is the share of payment to type i capital, and $\hat{r}_i$ is the growth rate of the rental price of type i capital, n is the number of different types of capitals. Similarly,

$$\hat{w} = \sum_{j=1}^{m} s_{Lj} \hat{w}_j \tag{4.9}$$

where s_{Lj} is the share of payment to type j workers and $\hat{w}_j$ is the growth rate of wages of type j workers, m is the type of workers.

Hence, the primal and dual measures of the Solow residual should be theoretically identical given the national account identity, provided that production functions are constant returns to scale. Empirically, however, both measures may suffer measurement problems and discrepancy between these two could exist. According to our earlier discussions, both capital K and labor L are likely measured with error. As a consequence, both the primal Solow residual and the dual Solow residual will be measured with errors. In (4.6), all four variables ($\hat{K}$, s_K, $\hat{L}$ and s_L) that are used to calculate the primal Solow residual are measured with errors. In (4.7), since the two variables (s_K and s_L) are measured with errors, the dual Solow residual will also be measured with errors even with accurately measured interest rates and wages. To understand the effects of the measurement errors at levels of capital and labor on both primal and dual Solow residuals, we conduct a simulation study which is reported in the next section.

4.3 Monte Carlo Results

In this section, we conduct a simple Monte Carlo simulation experiment to examine the measurement error effect on using both the primal and the dual approaches to estimate the Solow residual. We will focus on the case that capital is measured with errors. The case of measurement error in labor is quite similar and is therefore not reported here. We will show that the measurement error affects the accuracy of the primal Solow residual substantially, while it has little effects on the dual Solow residual.

Thus, the simulation results support our early argument that the dual approach provides a more accurate measure of the Solow residual.

We use the superscript 'star' to denote the true value. We assume that interest rate *r*, wage rate *w,* labor *L* and output *Y* are all measured accurately, while capital *K* is measured with errors. That is, $r = r^*$, $w = w^*$, $L = L^*$ and $Y = Y^*$, but $K \neq K^*$. Therefore, *Y* is generated by:

$$Y = rK^* + wL. \tag{4.10}$$

From equation (10) it is straightforward to show that:

$$SR^*_{\Pr imal} = SR^*_{Dual} \;, \tag{4.11}$$

where

$$SR^*_{\Pr imal} = \hat{Y} - s_K^* \hat{K}^* - s_L L \tag{4.12}$$

$$SR^*_{Dual} = s_K^* \hat{r} + s_L \hat{w} \tag{4.13}$$

with $s_K^* = \dfrac{rK^*}{Y}$ and $s_L = \dfrac{wL}{Y}$.

Let *K* denote the observed capital, we assume that *K* is measured with errors as follows:

$$K = K^* + \varepsilon_K , \tag{4.14}$$

where ε_K is the measurement error for capital. Now, the observed primal and dual Solow residuals are:

$$SR_{\Pr imal} = \hat{Y} - s_K \hat{K} - s_L \hat{L} \tag{4.15}$$

$$SR_{Dual} = s_K \hat{r} + s_L \hat{w} \tag{4.16}$$

where $s_K = \frac{rK}{Y}$ and $s_L = \frac{wL}{Y}$. Note that s_K is also measured with errors, because it depends on *K*. Therefore, both the primal and the dual Solow residuals are measured with errors. We will examine which one is affected more by the measurement error below via simulations. Our simulations include the following steps:

Step 1:

Generate the true data: *r, w,* K^* and *L*. In this exercise, we choose *r*, *w*, K^* and *L* from the real observed data. In particular, *r, w* and K^* are the weighted averages of the real rental prices, wage and capital stock that are used in section 4.4, and L^* is the observed total number of employee in the real data. Of course, one can generate these variables using other data generating processes, and the conclusion of our simulation results will not change. After we obtain *r, w,* K^* and *L,* we use equation (4.10) to generate *Y.*

Step 2:

Calculate the true Solow residuals based on the two measures in equation (4.11). By construction, they are identical, i.e., $SR^*_{\Pr imal} = SR^*_{Dual} = SR^*$.

Step 3:

Generate the observed capital (with errors). The error term ε_K is generated as follows:

$$\varepsilon_K = \beta(\alpha\hat{Y} + v_K), \tag{4.17}$$

where $\hat{Y}$ is the growth rate of output, v_K is an independent and identically distributed normal random variable with mean zero, and the standard error of v_K is the same as the sample standard error of $\hat{Y}$. We choose α =1, -1, 0, so that ε_K can be positively, negatively, or uncorrelated with $\hat{Y}$. We choose β such that $\sigma_{\varepsilon}^2 / \sigma_{K^*}^2$ = 5%, 10%, 20%, where σ_{ε}^2 and $\sigma_{K^*}^2$ are the sample variances of ε_K and K^*, respectively. Thus, we allow for the noise/signal ratio in capital measurement to vary from 5% to 20%.

Next, we calculate the observed Solow residuals SR_{Primal} and SR_{Dual} using (4.15) and (4.16) (both contain measurement errors). We then compute the correlation coefficients between the primal Solow residual (given in (4.15)) and the true Solow residual (given in (4.11)), and the correlation coefficient between the dual Solow residual of (4.16) and the true Solow residual of (4.11). The number of Monte Carlo simulations is 1000. We report the mean and standard error of the correlation coefficients. The results are given in Table 4.1.

From Table 4.1, we observe clearly that when capital is measured with errors, the observed dual Solow residual remains an accurate estimate of the true Solow residual as the correlation coefficients between the two are very close to one (at least 0.943) in all cases. In contrast, the primal Solow residual is much less accurate, with correlation coefficients ranging from 0.298 to 0.922. As the variance of the measurement error increases, the accuracy of the primal Solow residual deteriorates rapidly, while the dual Solow residual remains a good estimate of the true Solow residual even when the variance of the measurement error is 20% of the variation of the capital. The simulation standard errors of the dual approach are much smaller than those of using the primal approach, which reinforces the finding that the dual approach gives more accurate estimation of the true Solow residual. We have also done simulations that labor is measured with errors. The results are quite similar to the ones reported in Table 4.1, which are not reported here to save space. Thus, our simulation results support our argument that the dual Solow residual provides a more accurate estimate for the true Solow residual than the primal approach when capital (and/or labor) is measured with errors.

Table 4.1
Monte Carlo Simulation Results

	α	Mean of Corr(SR_{Dual}, SR^*)	Std Dev. of Corr(SR_{Dual}, SR^*)	Mean of Corr($SR_{Primall}$, SR^*)	Std Dev. of Corr(SR_{Primal}, SR^*)
$\sigma_\varepsilon^2/\sigma_{K^*}^2$ =5%	1	0.994	0.002	0.794	0.041
	0	0.996	0.002	0.867	0.038
	-1	0.988	0.003	0.922	0.028
$\sigma_\varepsilon^2/\sigma_{K^*}^2$ =10%	1	0.988	0.004	0.592	0.085
	0	0.992	0.004	0.776	0.063
	-1	0.974	0.007	0.869	0.045
$\sigma_\varepsilon^2/\sigma_{K^*}^2$ = 20%	1	0.978	0.007	0.298	0.148
	0	0.984	0.007	0.650	0.099
	-1	0.943	0.016	0.786	0.066

4.4 Measuring Technology Shocks

4.4.1 Aggregate Data

In this section, we measure technology shocks by using the dual approach as well as the conventional primal approach used in the RBC studies. Our study is based on U.S. annual data from the period 1964 to 2001. All the growth rates are approximated by the first differences of the logarithms of the data. We discuss the data collection process below.

4.4.1.1 The dual Solow residual

The dual estimate of the Solow residual is calculated as a weighted average of the growth rate of real rental prices of different types of capital goods and real wages of different types of workers, where the weights are the share of payment to each factor.

The growth rate of real wage

First, the average annual nominal wage is calculated from the product of the average weekly earning and the number of weeks in a year for the ten major private industries.[17] To compute the growth rate of real wage, we subtract the growth rate of the consumer price index from the growth rate of the nominal wage.

Next, we need to get the share of payment for each industry. It is computed as the product of the annual nominal wage and the number of workers in each industry divided by the sum of them over all the ten industries. The restriction of choosing the ten industries is due to data limitation. However, this will not affect the accuracy of our calculation, provided that the wages in other private industries and the government sector are relatively stable over time.

The growth rate of the real rental price

Turning to the rental price of capital, we calculate it based on the standard Hall-Jorgenson (1967) rental price formula: the real rental price is equal to the product of its

[17] These ten industries are (from the goods-producing sector) natural resources and mining; construction; and manufacturing; and (from the service-providing sector) trade, transportation and utilities; information;

relative price and the real interest rate plus the depreciation rate, i.e.,

$$R_j / p = \frac{p_j^k}{p}\left(i - \pi + \delta_j\right) \tag{4.18}$$

where p_j^k / p is the relative price of type j capital, i is the nominal interest rate, π is the inflation rate and δ_j is the depreciation of type j capital. The capital goods are divided into five categories: residential buildings, nonresidential buildings, other construction, transportation equipment and machinery equipment.

As a robust check, we use three different approaches to calculate the relative price of capital. In the first approach, we compute it as the ratio of the investment goods deflator of each capital good over the GDP deflator. For residential buildings, we use the deflator of residential structures; for nonresidential buildings, we use the deflator of nonresidential structures; and for the other three categories, we adopt the same deflator for nonresidential equipment and software. The choice of investment goods deflators is limited because they are only available in three broad categories (nonresidential structure; nonresidential equipment and software; and residential structure). The second approach is similar to the first approach except that we the GDP deflator by CPI. For the last approach, we calculate the relative prices of all five types of capital as the ratio of the single CPI index over the GDP deflator.

Next, for the depreciation rates, we adopt the estimates from Hulten and Wykoff (1981). Specifically, the depreciation rates are 1.3 percent for residential buildings, 2.9

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financial activities; professional and business services; education and health services; leisure and hospitality; and other services.

percent for nonresidential buildings, 2.1 percent for other constructions, 18.2 percent for transportation equipment and 13.8 percent for machinery equipment.

Turning to the real interest rate, we calculate it by subtracting the inflation rate–the growth rate of the CPI–from the federal funds rate.[18]

We also need the share of payments to each type of capital. We compute this as the product of the nominal rental price of capital and the estimated capital stock divided by the total payments to capital. However, since our estimated capital stock data is in units of currency (billions of dollars) already, we can obtain it directly as the ratio of the stock of each capital over the total capital stock.

Because there is no direct data source for the stock of capital, we calculate it by applying the standard perpetual inventory method, which states that the stock of capital comes from accumulations of gross physical investment along with depreciation of existing stocks, i.e.,

$$K_j(t+1) = K_j(t) + I_j(t) - \delta_j \bullet K_j(t) \tag{4.19}$$

where $K_j(t)$ is the stock of type *j* physical capital at time t, $I_j(t)$ is the flow of gross investment during period t, and δ is the constant depreciation rate. To do that, first of all, we need to estimate the initial stock of capital. As in Young (1995), we initialize the capital stock series by assuming that the growth rate of investment in the first five years is representative of the growth of investment prior to the beginning of the series, i.e., the

[18] We also use 3-month Treasury bill rate instead of the federal funds rate. The results are almost the same.

initial stock of capital is equal to the ratio of first investment data over the sum of its average growth rate in the first five years and its depreciation rate.

$$K_j(0) = \frac{I_j(0)}{g_j + \delta_j} \tag{4.20}$$

where $K_j(0)$ is the estimated initial capital stock of asset j, $I_j(0)$ is the first year's investment data for asset j, δ_j is the depreciation rate for asset j and g_j is the average growth rate of investment in asset j in the first five years of the investment series. Given a positive depreciation rate and a relatively long investment series, and also given that we are not interested in the analysis of early period data, the estimated stock of capital is insensitive to the initial estimate of capital stock. In our study, we are only interested in the data after 1964, but the published investment series goes back to 1946; therefore, we have eighteen years' investment data to construct our capital stock series.

The factor shares in output

In the United States, capital and labor shares of output have been approximately constant over time. There are many studies regarding estimating the factor shares and most of the results are quite close. Here we adopt the estimates from Dougherty (1991) by using 0.41 as the value of the share of capital in output and 0.59 as the share of labor in output, implying a constant return to scale production function. We use the same numbers for the factor shares in the primal approach.

4.4.1.2 The primal Solow residual

For the primal approach, we follow the usual practice used in the RBC literature: measuring technology shocks using the growth rate of real GDP minus the product of the share of each factor, i.e., capital and labor, and their growth rate.[19]

The growth rate of real capital input

Ideally, we would like to use the flow of services of physical capital as a measure of capital input. However, this type of data is usually not available. Instead, we follow the usual practice in the RBC studies by assuming that the flow of service is proportional to the stock. There are five categories of capital goods used in the dual approach. We employ the same five categories in the primal approach in each category of capital goods, we calculate the nominal stock of capital using the standard perpetual-inventory approach based on the investment data and the depreciation rates. The growth rate of real capital stock is the weighted average of five types of capital stock, with the weight being determined by the share of payments to each type of capital. For each type of capital, the growth rate of real capital stock is constructed from the growth rate of nominal capital stock less the growth rate of the GDP deflator.

The growth rate of labor input

We use the full-time and part-time employee data as the input of labor. We also

[19] The growth rate of real GDP is constructed from the growth rate of nominal GDP less the growth rate of the GDP deflator.

use the total hours worked by full- and part-time employees as the alternative measurement of labor following the usual practice in the RBC literature

4.4.2 Manufacturing Sector

To check our results for robustness, in this section, we also compute the dual Solow residual and the primal Solow residual for the U.S. manufacturing sector. Choosing this sector allows us to compare our results with Burside, Eichembaum and Rebelo (1996), who present capital utilization corrected measures of technology shocks for the manufacturing sector using the primal method. The calculation process used in the manufacturing sector is the same as the one used in the aggregate data. But since we only have one sector to consider here, we do not need to use the weighted averages to calculate the growth rate of real wages, real rental prices and capital as the aggregate case.

4.5 Empirical Results

Table 4.2 reports the summary statistics of our measured dual and primal Solow residuals. We calculate the dual Solow residuals using three different approaches (three different measures of relative prices of capital goods). First we observe that the average values of dual Solow residuals are all negative, which is somewhat unexpected. Figure 4.2 plots the dual Solow residual (using the first dual method, dual 1 as in Table 4.2). A closer examination of Figure 4.2 shows that the negative mean value is mainly due to the severe downturns in 1974 and 1980. The middle 1970s' oil shock and the later 1970s' oil shock together with the Federal Reserve's interest rate hike (in an attempt to control inflation) caused tremendous downturns in real wage and real rental price growth. For data after 1980 (1981 to 2002), the mean of the dual Solow residual is a positive value of 0.0003. Even though the means of the dual approach over the whole sample period are negative, statistically, they are not significantly different from zero due to their relatively large standard deviations. In contrast to the dual estimates, the calculated primal Solow residuals (shown in the last two columns of Table 4.2) have positive average values over the sample period, but as in the case of dual Solow residuals, they are not significantly

Table 4.2
Aggregate Data: Summary Statistics of the Solow Residuals

	Dual (1)	Dual (2)	Dual (3)	Primal (1)	Primal (2)
Mean	-0.0008	-0.0008	-0.0008	0.0056	0.0082
Median	0.0003	0.0003	0.0003	0.0055	0.0070
Maximum	0.0297	0.0297	0.0297	0.0318	0.0334
Minimum	-0.0321	-0.0321	-0.0321	-0.0204	-0.0192
Std. Dev.	0.0113	0.0113	0.0113	0.0135	0.0124
Skewness	-0.3850	-0.3860	-0.3850	-0.1090	0.0454
Kurtosis	4.5490	4.5490	4.5490	2.1280	2.3150
Relative Volatility	0.2850	0.2850	0.2850	0.4100	0.3450

Note: Dual (1): real rental price of each capital goods= the ratio of the investment goods deflator of each capital good over the GDP deflator; Dual (2): real rental price of each capital goods= the ratio of the investment goods deflator of each capital good over the CPI; Dual (3): real rental price of each capital goods= the ratio of the single CPI index over the GDP deflator; Primal (1): Labor =weighted average of number of workers in 10 industries; Primal (2): Labor = total hours worked.

different from zero. Therefore, we do not observe statistically significant discrepancies between the two methods as far as the sample mean is concerned. The last row of Table 4.2 gives the relative volatility of the technology shocks over GDP fluctuation, which is computed as the ratio of the variance of Solow residuals over the variance of GDP growth. We find a significant difference in the relative volatility by using the two different approaches. The point estimates of the relative volatilities reduce by about 31 percent and 17 percent, respectively, from 0.41 and 0.35 (using the two primal estimates) to about 0.29 (using the dual estimates).

Next, we study the results in Table 4.3 from the least square regressions. We regress the growth rate of real GDP on a constant and the estimated Solow residual. The Solow residual is estimated in five different ways—two using the primal approach, and the other three using the dual approach. The coefficients of the primal Solow residuals are almost one, with relatively high R-squares of 0.56 and 0.45, respectively, implying that the correlation between the growth of real output and technology shocks is around 0.7 (the square root of R-square in the least square regression). This is consistent with earlier findings in the RBC studies. The success of replicating the primal estimate by using our collected data set can be seen clearly in Figure 4.1, where the growth rate of GDP is plotted against the primal Solow residual.[20] Our result is almost identical to that presented in Mankiw's macroeconomics textbook.[21] We observe from Figure 4.1 that the growth of output closely follows the primal Solow residual. According to Prescott's interpretation, this shows that technology shocks are an important source of economics fluctuation. Turning to the results of using the dual approach, we find the coefficients of the dual Solow residuals are all positive and significantly different from zero, and that this is not only consistent among the three dual estimates but also in the primal ones. We

[20] The figures are almost identical using the two primal Solow residual estimates. The primal Solow residual plotted in Figure 1 is calculated by using the employment data as labor input.
[21] See Mankiw's *Macroeconomics* (5th edition), page 506, for a comparison.

also notice that the technology shocks have a much smaller explanatory power when measured by the dual approach. The R-squares are down by about 42 percent and 28 percent, corresponding to the two primal estimates. The correlations between the growth of output and technology shocks measured by the dual Solow residuals are only around 0.57, much smaller than the ones (around 0.7) measured by the primal Solow residuals. As shown in Figure 4.2, output growth and technology shocks do show some co-movement most of the time, but not as strong a relationship as the one displayed in Figure 4.1 in which the primal approach is used.

Table 4.3
Aggregate Data: Results from Least Squares Regressions

	Dual (1)	Dual (2)	Dual (3)	Primal (1)	Primal (2)
Coefficient	1.0510	1.0510	1.0510	1.1670	1.1580
Standard Error	0.2560	0.2560	0.2560	0.1730	0.2160
T-statistic	4.1050	4.1060	4.1040	6.7440	5.3640
Prob.	0.0002	0.0002	0.0002	0.0000	0.0000
R-squared	0.3250	0.3250	0.3250	0.5580	0.4510
Correlation	0.5710	0.5700	0.5700	0.7470	0.6720

Note: In each regression, the growth rate of real GDP is the dependent variable and the constant and the Solow residual are explanatory variables.

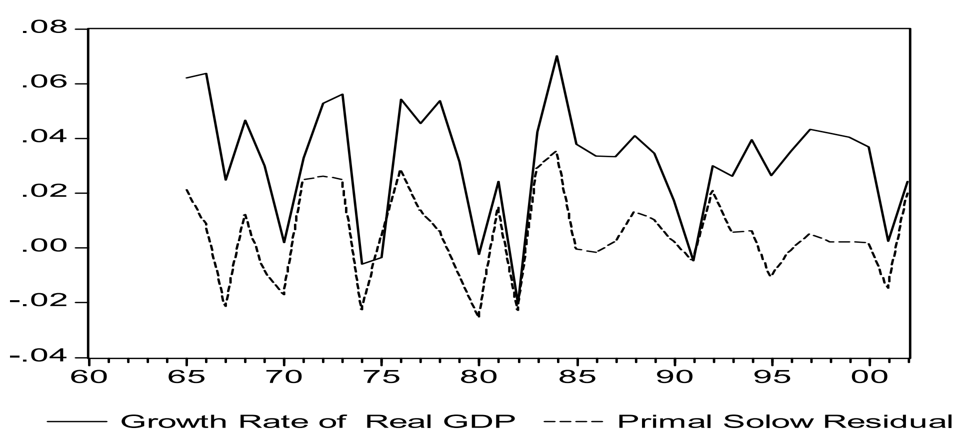

Figure 4.1. Aggregate Data:Growth Rate of Real GDP versus the Primal Solow Residual

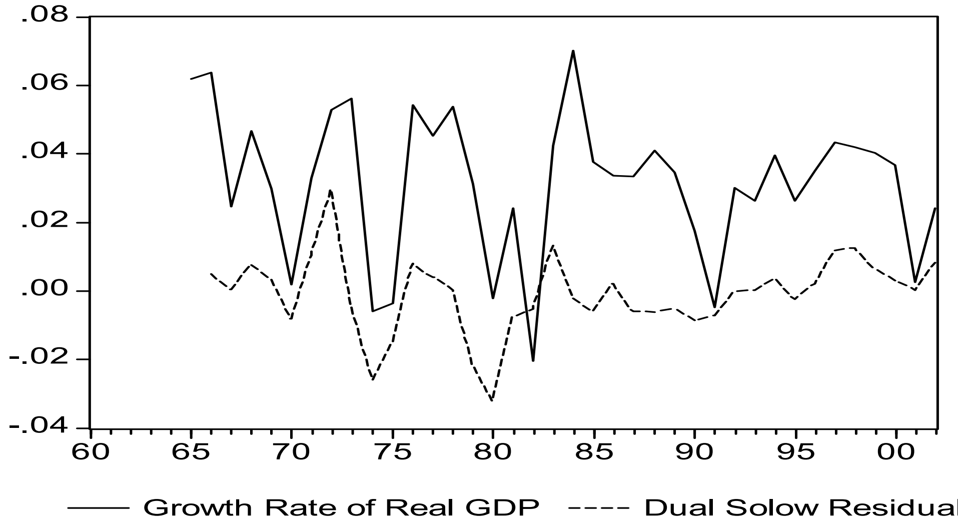

Figure 4.2. Aggregate Data: Growth Rate of Real GDP versus the Dual Solow Residual

For a robustness check, we also calculate the dual Solow residual and primal Solow residual for the manufacturing sector. In Table 4.4, we report the summary statistics. We see that both the primal and dual Solow residuals have a negative but insignificant average value in the manufacturing sector. However, we find that the relative volatility, as the ratio of the variance of the manufacturing sector's output and the variance of the Solow residual, drops dramatically by using the dual approach. It is reduced by about 60 percent. This is also a very significant decline in the correlation between the growth rate of output and the Solow residual. As shown in Table 4.5, the correlation drops to 0.12 when the technology shocks are measured using the dual approach, which is in sharp contrast with the very high correlation obtained by using the conventional primal approach. The difference is quite abvious as showed in Figure 4.3 and Figure 4.4. The estimation result from the manufacturing sector is consistent not only with our aggregate estimates, but is also in close agreement with the finding of Burside, Eichembaum and Rebelo (1996) who used electricity use as a proxy of capital stock.

Table 4.4
Manufacturing Sector: Summary Statistics of the Solow Residuals

	Dual	Primal
Mean	-0.007	-0.035
Median	-0.008	-0.018
Maximum	0.095	0.067
Minimum	-0.091	-0.161
Std. Dev.	0.039	0.061
Skewness	0.219	-0.430
Kurtosis	3.180	2.463
Relative Volatility	0.543	1.322

Note: In this table, the pointed estimate of dual Solow residual in 1981 is calculated by replacing the nominal interest rate and inflation rate by the average values from 1979–1981 to cancel out the extreme polity effect (contractionary monetary polity to fight against inflation) on the real rental price. And the primal Solow residual is up to 1992 because of the availability of the investment series.

Table 4.5
Manufacturing Sector: Results from Least Squares Regressions

	Dual	Primal
Coefficient	0.127	0.825
Standard Error	0.215	0.078
T-statistic	0.588	10.510
Prob.	0.560	0.000
R-squared	0.012	0.786
Correlation	0.110	0.887

Note: In each regression, the growth rate of real GDP is the dependent variable and the constant and the Solow residual are explanatory variables.

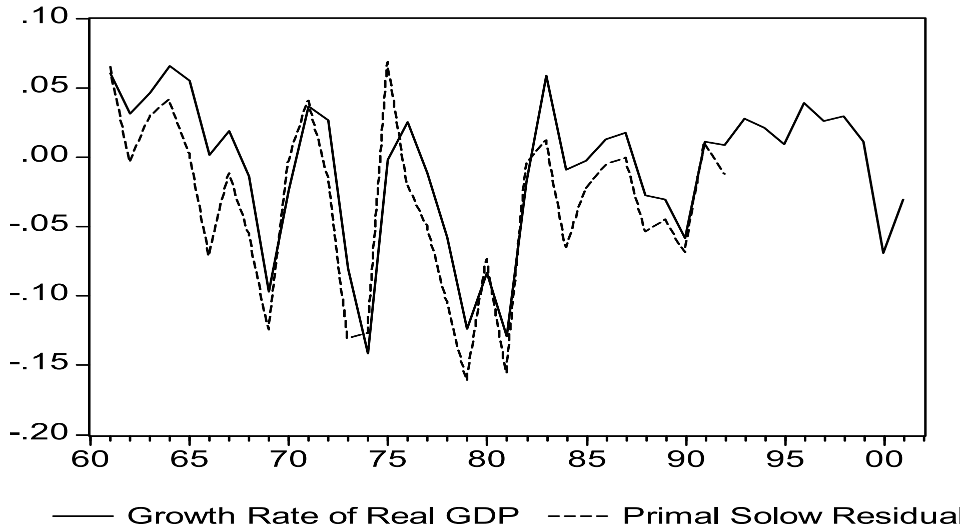

Figure 4.3. Manufacturing Sector: Growth Rate of Real GDP versus the Primal Solow Residual

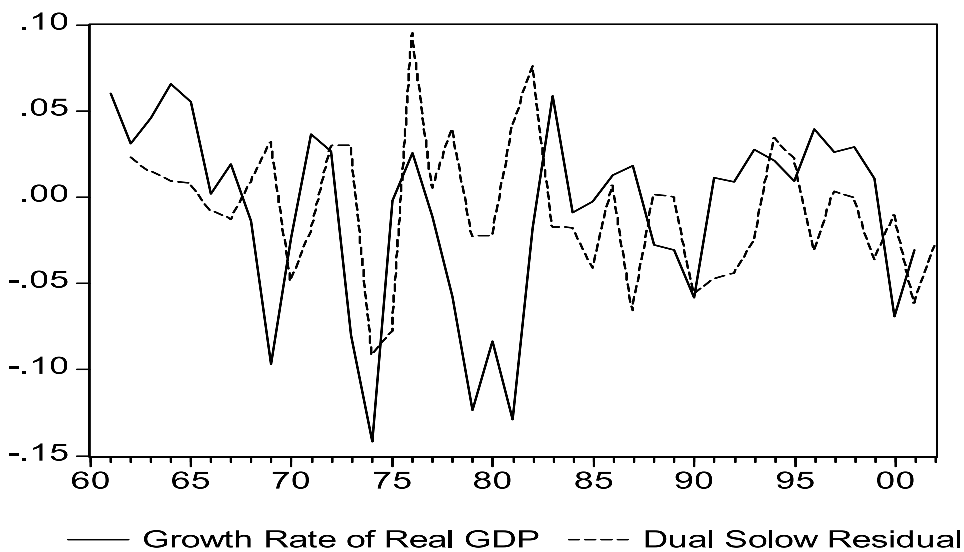

Figure 4.4. Manufacturing Sector: Growth Rate of Real GDP versus the Dual Solow Residual

4.6 Conclusion

In this chapter, we measure U.S. technology shocks by implementing a dual approach based on price data, which we argue is more reliable than aggregate quantity data. By doing so, we find that the relative volatility and the correlation between output fluctuation and technology shocks are significantly smaller than those found in the previous RBC studies. For the aggregate data, if we use employment data as labor to calculate the primal Solow residual, the relative volatility and the correlation between output fluctuation and technology shocks is reduced by about 30 percent by using the dual approach. When total working hours is used as labor to calculate the primal Solow residual, the relative volatility and the correlation between output fluctuation and technology shocks go down by 17 percent and 15 percent, respectively. Our results are in line with the assertion that the role of technology shocks in generating business cycles may have been exaggerated in the RBC literature. We want to emphasize that our results are not in conflict with Prescott's famous claim that economic fluctuations are optimal responses to uncertainty in the rate of technological change. Rather, our findings suggest that the dual Solow residual may provide more accurate measurement of technology shocks, and that one may need to look sources other than technology shock fluctuations for a complete understanding of the business cycle phenomena.

CHAPTER V

SUMMARY AND CONCLUSIONS

In chapter II, I use the method of structural factor analysis to evaluate the effects of monetary policy and forecast some key macroeconomic variables in a data rich environment. This allows me to employ the information from a very large data set, and at the same time I can still interpret the underlying factors estimated by *principal components* structurally. To evaluate the effects of monetary policy, I propose two structural factor models. One is the *structural factor augmented vector autoregressive* (SFAVAR) model, where shocks to the federal funds rate are treated as innovations to monetary policy as much of the previous literature and the other is the *structural factor vector autoregressive* (SFVAR) model, where an underlying monetary factor is used to represent monetary policy. Compared to the traditional VAR models, both models contain more information from hundreds of data series which can be and are actually monitored by the Center Bank. Also, the factors used are structurally meaningful, a feature that adds to the understanding the "black box" of the monetary transmission mechanism. Under reasonable identification schemes, both models generate qualitatively reasonable impulse response functions. Especially, using the SFVAR model, both the "price puzzle" and the "liquidity puzzle" are eliminated. This model also has the flexibility to allow us to generate the impulse response function for any variable of interest.

In chapter III, I employ the method of structural factor analysis to forecast some key macroeconomic variables. Using a large data set containing 308 series from January 1972 until December 2003, I simulate an out-of –sample real time forecasting exercise using the proposed *structural dynamic factor forecasting* model and its variations for some key macroeconomic variables. I use several structural factors to summarize the information from a large set of candidate explanatory variables. Compared to Stock and Watson (2002)'s models, the models proposed in this chapter can further allow me to select the factors structurally for each variable to be forecasted. I find the obvious advantages of the *structural dynamic factor forecasting* models compared to alternatives that include the univariate autoregression (AR) model, the vector autoregression (VAR) model and Stock and Watson's non-structural factor models, especially when forecasting real variables, e.g., industrial production and real personal income.

In chapter IV, we measure U.S. technology shocks by implementing a dual approach based on price data, which we argue is more reliable than aggregate quantity data. By doing so, we find that the relative volatility and the correlation between output fluctuation and technology shocks are significantly smaller than those found in the previous RBC studies. For the aggregate data, if we use employment data as labor to calculate the primal Solow residual, the relative volatility and the correlation between output fluctuation and technology shocks is reduced by about 30 percent by using the dual approach. When total working hours is used as labor to calculate the primal Solow residual, the relative volatility and the correlation between output fluctuation and technology shocks go down by 17 percent and 15 percent, respectively. Our results are in line with the assertion that the role of technology shocks in generating business cycles may have been exaggerated in the RBC literature. We want to emphasize that our results are not in conflict with Prescott's famous claim that economic fluctuations are optimal responses to uncertainty in the rate of technological change. Rather, our findings suggest that the dual Solow residual may provide more accurate measurement of technology shocks, and that one may need to look sources other than technology shock fluctuations for a complete understanding of the business cycle phenomena.

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APPENDIX A

DATA DESCRIPTION FOR CHAPTERS II AND III

1. Real Activity Series			
	Mnemonic	Description	T
1	IP	Industrial Production Index (SA, 1997=100)	5
2	IP51	Industrial Production: Consumer Goods (SA, 1997=100)	5
3	IP511	Industrial Production: Durable Consumer Goods (SA, 1997=100)	5
4	IP5111	Industrial Production: Automotive Products (SA, 1997=100)	5
5	IP51121	Industrial Production: Computers, Video and Audio Equipment (SA, 1997=100)	5
6	IP51122	Industrial Production: Appliances, Furniture, and Carpeting (SA, 1997=100)	5
7	IP51123	Industrial Production: Miscellaneous Durable Goods (SA, 1997=100)	5
8	IP512	Industrial Production: Nondurable Consumer Goods (SA, 1997=100)	5
9	IP5121	Industrial Production: Nondurable Nonenergy Consumer Goods (SA, 1997=100)	5
10	IP51211	Industrial Production: Foods and Tobacco (SA, 1997=100)	5
11	IP51212	Industrial Production: Clothing (SA, 1997=100)	5
12	IP51213	Industrial Production: Chemical Products (SA, 1997=100)	5
13	IP51214	Industrial Production: Paper Products (SA, 1997=100)	5
14	IP5122	Industrial Production: Consumer Energy Products (SA, 1997=100)	5
15	IP521	Industrial Production: Business Equipment (SA, 1997=100)	5
16	IP5211	Industrial Production: Transit Equipment (SA, 1997=100)	5
17	IP5212	Industrial Production: Information Processing and Related Eqpt (SA, 1997=100)	5
18	IP5213	Industrial Production: Industrial and Other Equipment (SA, 1997=100)	5
19	IP523	Industrial Production: Defense and Space Equipment (SA, 1997=100)	5
20	IP53	Industrial Production: Materials (SA, 1997=100)	5

21	IP531	Industrial Production: Durable Goods Materials (SA, 1997=100)	5
22	IP5311	Industrial Production: Durable Consumer Parts (SA, 1997=100)	5
23	IP5312	Industrial Production: Durable Equipment Parts (SA, 1997=100)	5
24	IP5313	Industrial Production: Other Durable Materials (SA, 1997=100)	5
25	IP531T2	Industrial Production: Nonenergy Materials (SA, 1997=100)	5
26	IP532	Industrial Production: Nondurable Goods Materials (SA, 1997=100)	5
27	IP5321	Industrial Production: Textile Materials (SA, 1997=100)	5
28	IP5322	Industrial Production: Paper Materials (SA, 1997=100)	5
29	IP5323	Industrial Production: Chemical Materials (SA, 1997=100)	5
30	IP533	Industrial Production: Energy Materials (SA, 1997=100)	5
31	IP5331	Industrial Production: Primary Energy Materials (SA, 1997=100)	5
32	IP5332	Industrial Production: Converted Fuel (SA, 1997=100)	5
33	IP5381	IP: Nonenergy Material Inputs to Finished Processors (SA, 1997=100)	5
34	IP5382	IP: Nonenergy Material Inputs to Semifinished & Primary Processors (SA, 97=100)	5
35	IP54	Industrial Production: Nonindustrial Supplies (SA, 1997=100)	5
36	IP541	Industrial Production: Construction Supplies (SA, 1997=100)	5
37	IP542	Industrial Production: Business Supplies (SA, 1997=100)	5
38	IP5422	Industrial Production: Commercial Energy Products (SA, 1997=100)	5
39	IPB0	Industrial Production: Mining (SA, 1997=100)	5
40	IPB31	Industrial Production: Oil and Gas Well Drilling (SA, 1997=100)	5
41	IPFP	Industrial Production: Final Products (SA, 1997=100)	5
42	IPMFG	Industrial Production: Manufacturing [SIC] (SA, 1997=100)	5
43	IPNG	Industrial Production: Energy (SA, 1997=100)	5
44	IPNNG	Industrial Production: Nonenergy, Total (SA, 1997=100)	5
45	IPP	Industrial Production (SA, %Change)	1
46	CU561	Capacity Utilization: Crude Stage of Processing (SA, Percent of Capacity)	1
47	CU562	Capacity Util: Primary/Semifinished Stage of Processing (SA, % of Capacity)	1
48	CU564	Capacity Utilization: Finished Stage of Processing (SA, Percent of Capacity)	1
49	CUB0	Capacity Utilization: Mining (SA, Percent of Capacity)	1
50	CUE1T2	Capacity Utilization: Food, Beverage, & Tobacco Products (SA, % of Capacity)	1
51	CUE3T4	Capacity Utilization: Textile and Product Mills (SA, Percent of Capacity)	1

52	CUE5T6	Capacity Utilization: Apparel and Leather (SA, Percent of Capacity)	1
53	CUF1	Capacity Utilization: Wood Products (SA, % of Capacity)	1
54	CUF2	Capacity Utilization: Paper (SA, Percent of Capacity)	1
55	CUF3	Capacity Util: Printing & Related Support Activities (SA, Percent of Capacity)	1
56	CUF4	Capacity Utilization: Petroleum and Coal Products (SA, Percent of Capacity)	1
57	CUF5	Capacity Utilization: Chemicals (SA, Percent of Capacity)	1
58	CUF6	Capacity Utilization: Plastics and Rubber Products (SA, Percent of Capacity)	1
59	CUF7	Capacity Utilization: Nonmetallic Mineral Products (SA, Percent of Capacity)	1
60	CUG1	Capacity Utilization: Primary Metal (SA, Percent of Capacity)	1
61	CUG2	Capacity Utilization: Fabricated Metal Product (SA, Percent of Capacity)	1
62	CUG3	Capacity Utilization: Machinery (SA, Percent of Capacity)	1
63	CUG4	Capacity Utilization: Computer and Electronic Products (SA, % of Capacity)	1
64	CUG41	Capacity Utilization: Computer and Peripheral Equipment (SA, % of Capacity)	1
65	CUG42	Capacity Utilization: Communications Equipment (SA, Percent of Capacity)	1
66	CUG441	Capacity Utilization: Semiconductors and Related Equipment (SA, % of Capacity)	1
67	CUG5	Capacity Utilization: Elec Eqpt, Appliances & Components (SA, % of Capacity)	1
68	CUG61T3	Capacity Utilization: Motor Vehicles and Parts (SA, Percent of Capacity)	1
69	CUG64T9	Capacity Utilization: Aerospace & Misc Transportation (SA, Percent of Capacity)	1
70	CUG7	Capacity Utilization: Furniture and Related Products (SA, Percent of Capacity)	1
71	CUG9	Capacity Utilization: Miscellaneous Durable Goods (SA, Percent of Capacity)	1
72	CUHT	Capacity Utilization: Hi-Tech Industries (SA, Percent of Capacity)	1
73	CUMDG	Capacity Utilization: Durable Goods Mfg [NAICS] (SA, Percent of Capacity)	1
74	CUMFG	Capacity Utilization: Manufacturing [SIC] (SA, Percent of Capacity)	1
75	CUMFN	Capacity Utilization: Manufacturing [NAICS] (SA, Percent of Capacity)	1
76	CUMFO	Capacity Utilization: Other Manufacturing [Non-NAICS] (SA, Percent of	1

		Capacity)	
77	CUMFXHT	Capacity Utilization: Manufacturing Excl Hi-Tech (SA, Percent of Capacity)	1
78	CUMND	Capacity Utilization: Nondurable Goods Manufacturing (SA, Percent of Capacity)	1
79	CUT	Capacity Utilization: Industry (SA, Percent of Capacity)	1
80	CUUTL	Capacity Utilization: Electric and Gas Utilities (SA, Percent of Capacity)	1
81	CUXHT	Capacity Utilization: Industry Excl Hi-Tech Industries (SA, % of Capacity)	1
82	NMI	Mfrs' Inventories: All Manufacturing Industries (EOP, SA, Mil.$)	5
83	NMIDG	Manufacturers' Inventories: Durable Goods (EOP, SA, Mil.$)	5
84	NMING	Mfrs' Inventories: Nondurable Goods Industries (EOP, SA, Mil.$)	5
85	NMS	Mfrs' Shipments: All Manufacturing Industries (SA, Mil.$)	5
86	NMSDG	Manufacturers' Shipments: Durable Goods (SA, Mil.$)	5
87	NMSNG	Mfrs' Shipments: Nondurable Goods Industries (SA, Mil.$)	5
88	NRI	Retail Inventories: Total (EOP, SA, Mil.$)	5
89	NRII1	Retail Inventories: Motor Vehicle & Parts Dealers (EOP, SA, Mil.$)	5
90	NRIXM	Retail Inventories: Total Excl Motor Vehicle & Parts Dealers (EOP, SA, Mil.$)	5
91	NRR	Inv/Sales Ratios: Total Retail (SA)	2
92	NRRI1	Inv/Sales Ratios: Retail: Motor Vehicle & Parts Dealers (SA)	2
93	NRRXM	Inv/Sales Ratios: Total Retail Excl Motor Vehicle & Parts Dealers (SA)	2
94	NRS	Retail Sales: Total (SA, Mil.$)	5
95	NRSI1	Retail Sales: Motor Vehicle & Parts Dealers (SA, Mil.$)	5
96	NRSTXM	Retail Sales & Food Services Excl Motor Vehicles & Parts Dealers (SA, Mil.$)	5
97	NRSV2	Retail Sales: Food Services & Drinking Places (SA, Mil.$)	5
98	NRSXM	Retail Sales: Total Excl Motor Vehicle & Parts Dealers (SA, Mil.$)	5
99	CDBHM	Real Personal Consumption Expenditures: Durable Goods (SAAR, Bil.Chn.2000$)	5
100	CNBHM	Real Personal Consumption Expenditures: Nondurable Goods (SAAR, Bil.Chn.2000$)	5
101	CSBHM	Real Personal Consumption Expenditures: Services (SAAR, Bil.Chn.2000$)	5
102	YPMH	Real Personal Income (SAAR, Bil.Chn.2000$)	5
103	YPDHM	Real Disposable Personal Income (SAAR, Bil.Chn.2000$)	5
104	YPDPHM	Real Disposable Personal Income per Capita (SAAR, Chn.2000$)	5
105	HPT	New Pvt Housing Units Authorized by Building Permit (SAAR,	4

		Thous.Units)	
106	HSM	Manufacturers' Shipments of Mobile Homes (SAAR, Thous.Units)	4
107	HSM1	Mobile Home Shipments + Single Family Units Started (SAAR, Thous.Units)	4
108	HSMT	Mobile Home Shipments + Total Housing Units Started (SAAR, Thous.Units)	4
109	HST	Housing Starts (SAAR, Thous.Units)	4
110	HSTM	Housing Starts: Total Multifamily (SAAR, Thous.Units)	4
111	HSTMW	Housing Starts: Midwest (SAAR, Thous.Units)	4
112	HSTNE	Housing Starts: Northeast (SAAR, Thous.Units)	4
113	HSTS	Housing Starts: South (SAAR, Thous.Units)	4
114	HSTW	Housing Starts: West (SAAR, Thous.Units)	4
115	LACONSA	All Employees: Construction (SA, Thous)	5
116	LAGOODA	All Employees: Goods-producing Industries (SA, Thous)	5
117	LAGOVTA	All Employees: Government (SA, Thous)	5
118	LAINFOA	All Employees: Information Services (SA, Thous)	5
119	LALEIHA	All Employees: Leisure & Hospitality (SA, Thous)	5
120	LAMANUA	All Employees: Manufacturing (SA, Thous)	5
121	LANAGRA	All Employees: Total Nonfarm (SA, Thous)	5
122	LANDURA	All Employees: Nondurable Goods Manufacturing (SA, Thous)	5
123	LANTRMA	All Employees: Natural Resources and Mining (SA, Thous)	5
124	LAPBSVA	All Employees: Professional & Business Services (SA, Thous)	5
125	LAPRIVA	All Employees: Total Private Industries (SA, Thous)	5
126	LAPSRVA	All Employees: Private Service-providing Industries (SA, Thous)	5
127	LARTRDA	All Employees: Retail Trade (SA, Thous)	5
128	LASERPA	All Employees: Service-providing Industries (SA, Thous)	5
129	LASRVOA	All Employees: Other Services (SA, Thous)	5
130	LATTULA	All Employees: Trade, Transportation & Utilities (SA, Thous)	5
131	LAWTRDA	All Employees: Wholesale Trade (SA, Thous)	5
132	LET20	Civilian Employment: 20 yr + (SA, Thousands)	5
133	LEWFT	Civilians Employed: Full-time (SA, Thous)	5
134	LEWPT	Civilians Employed: Part-time (SA, Thous)	5
135	LHELP	Index of Help-Wanted Advertising in Newspapers (SA, 1987=100)	5
136	LHELPR	Ratio: Help-Wanted Advertising in Newspapers/Number Unemployed (SA)	4

137	LP	Civilian Participation Rate: 16 yr + (SA, %)	5
138	LPDURGA	Production Workers: Durable Goods Manufacturing (SA, Thous)	5
139	LPMANUA	Production Workers: Manufacturing (SA, Thous)	5
140	LPNDURA	Production Workers: Nondurable Manufacturing (SA, Thous)	5
141	LQ	Civilian Employment/Population Ratio: 16 yr + (SA, %)	5
142	LR	Civilian Unemployment Rate: 16 yr + (SA, %)	1
143	LRCONSA	Average Weekly Hours: Construction (SA, Hrs)	1
144	LRDURGA	Average Weekly Hours: Durable Goods Manufacturing (SA, Hrs)	1
145	LREDUHA	Average Weekly Hours: Education & Health Services (SA, Hrs)	1
146	LRF7A	Average Weekly Hours: Mfg: Nonmetallic Mineral Products (SA, Hrs)	1
147	LRFIREA	Average Weekly Hours: Financial Activities (SA, Hrs)	1
148	LRFT	Civilian Unemployment Rate: Full Time-Workers (SA, %)	1
149	LRGOODA	Average Weekly Hours: Goods-producing Industries (SA, Hrs)	1
150	LRINFOA	Average Weekly Hours: Information Services (SA, Hrs)	1
151	LRJL	Civilian Unemployment Rate: Job Losers (SA, %)	1
152	LRLEIHA	Average Weekly Hours: Leisure & Hospitality (SA, Hrs)	1
153	LRMANUA	Average Weekly Hours: Manufacturing (SA, Hrs)	1
154	LRNDURA	Average Weekly Hours: Nondurable Goods Manufacturing (SA, Hrs)	1
155	LRNE	Civilian Unemployment Rate: New Entrants (SA, %)	1
156	LRNTRMA	Average Weekly Hours: Natural Resources and Mining (SA, Hrs)	1
157	LRPBSVA	Average Weekly Hours: Professional & Business Services (SA, Hrs)	1
158	LRPRIVA	Average Weekly Hours: Total Private Industries (SA, Hrs)	1
159	LRPSRVA	Average Weekly Hours: Private Service-providing Industries (SA, Hrs)	1
160	LRPT	Civilian Unemployment Rate: Part-Time Workers (SA, %)	1
161	LRRE	Civilian Unemployment Rate: Reentrants (SA, %)	1
162	LRRTRDA	Average Weekly Hours: Retail Trade (SA, Hrs)	1
163	LRSRVOA	Average Weekly Hours: Other Services (SA, Hrs)	1
164	LRTRANA	Average Weekly Hours: Transportation & Warehousing (SA, Hrs)	1
165	LRTTULA	Average Weekly Hours: Trade, Transportation & Utilities (SA, Hrs)	1
166	LRUTILA	Average Weekly Hours: Utilities (SA, Hrs)	1
167	LRWTRDA	Average Weekly Hours: Wholesale Trade (SA, Hrs)	1
168	LTU	Unemployed, 16 Years & Over: 16 yr + (SA, Thous)	1
169	LU0	Civilians Unemployed for Less Than 5 Weeks (SA, Thous.)	1
170	LU15	Civilians Unemployed for 15-26 Weeks (SA, Thous.)	1

171	LU5	Civilians Unemployed for 5-14 Weeks (SA, Thous.)	1
172	LUT27	Civilians Unemployed for 27 Weeks and Over (SA, Thous.)	1

2. Inflation/Price Series

	Mnemonic	Description	T
173	PCU	CPI-U: All Items (SA, 1982-84=100)	5
174	PCUCC	CPI-U: Commodities (SA, 1982-84=100)	5
175	PCUCCD	CPI-U: Durables (SA, 1982-84=100)	5
176	PCUCCL	CPI-U: Commodities Less Food and Beverages (SA, 1982-84=100)	5
177	PCUCS	CPI-U: Services (SA, 1982-84=100)	5
178	PCUCSO	CPI-U: Other Services (SA, 1982-84=100)	5
179	PCUCST	CPI-U: Transportation Services (SA, 1982-84=100)	5
180	PCUFB	CPI-U: Food and Beverages (SA, 1982-84=100)	5
181	PCUFO	CPI-U: Food (SA, 1982-84=100)	5
182	PCUFON	CPI-U: Nonalcoholic Beverages (SA, 1982-84=100)	5
183	PCUH	CPI-U: Housing (SA, 1982-84=100)	5
184	PCUHF	CPI-U: Fuels and Utilities (SA, 1982-84=100)	5
185	PCUHFF	CPI-U: Fuels (SA, 1982-84=100)	5
186	PCUHFO	CPI-U: Fuel Oil and Other Fuels (SA, 1982-84=100)	5
187	PCUHH	CPI-U: Household Furnishings and Operation (SA, 1982-84=100)	5
188	PCUHS	CPI-U: Shelter (SA, 1982-84=100)	5
189	PCUM	CPI-U: Medical Care (SA, 1982-84=100)	5
190	PCUMC	CPI-U: Medical Care Commodities (SA, 1982-84=100)	5
191	PCUMS	CPI-U: Medical Care Services (SA, 1982-84=100)	5
192	PCUO	CPI-U: Other Goods and Services (SA, 1982-84=100)	5
193	PCUOES	CPI-U: Educational Books and Supplies (SA, 1982-84=100)	5
194	PCUP	CPI-U: All Items, 1982-84=100 (SA, %Change)	1
195	PCUSC	CPI-U: Commodities Less Food (SA, 1982-84=100)	5
196	PCUSCFE	CPI-U: Commodities Less Food & Energy Commodities (SA, 1982-84=100)	5
197	PCUSEC	CPI-U: Energy Commodities (SA, 1982-84=100)	5
198	PCUSLE	CPI-U: All Items Less Energy (SA, 1982-84=100)	5
199	PCUSLF	CPI-U: All Items Less Food (SA, 1982-84=100)	5
200	PCUSLFE	CPI-U: All Items Less Food and Energy (SA, 1982-84=100)	5
201	PCUSLM	CPI-U: All Items Less Medical Care (SA, 1982-84=100)	5

202	PCUSLS	CPI-U: All Items Less Shelter (SA, 1982-84=100)	5
203	PCUSND	CPI-U: Nondurables (SA, 1982-84=100)	5
204	PCUSSLE	CPI-U: Services Less Energy Services (SA, 1982-84=100)	5
205	PCUT	CPI-U: Transportation (SA, 1982-84=100)	5
206	PCUTP	CPI-U: Private Transportation (SA, 1982-84=100)	5
207	PCUTPM	CPI-U: Motor Fuel (SA, 1982-84=100)	5
208	PCUTPMG	CPI-U: Gasoline (SA, 1982-84=100)	5
209	PCUTPR	CPI-U: Motor Vehicle Maintenance & Repair (SA, 1982-84=100)	5
210	PCUTPU	CPI-U: Used Cars and Trucks (SA, 1982-84=100)	5
211	PCUTPV	CPI-U: New Vehicles (SA, 1982-84=100)	5
212	SP1000	PPI: Crude Materials for Further Processing (SA, 1982=100)	5
213	SP1100	PPI: Crude Foodstuffs and Feedstuffs (SA, 1982=100)	5
214	SP1150	PPI: Crude Nonfood Materials for Further Processing (SA, 1982=100)	5
215	SP1400	PPI: Crude Materials less Agricultural Products (SA, 1982=100)	5
216	SP2000	PPI: Intermediate Materials, Supplies and Components (SA, 1982=100)	5
217	SP2700	PPI: Intermediate Materials less Foods and Feeds (SA, 1982=100)	5
218	SP2800	PPI: Intermediate Foods and Feeds (SA, 1982=100)	5
219	SP3000	PPI: Finished Goods (SA, 1982=100)	5
220	SP3100	PPI: Finished Consumer Goods (SA, 1982=100)	5
221	SP3110	PPI: Finished Consumer Foods (SA, 1982=100)	5
222	SP3120	PPI: Finished Consumer Nondurable Goods less Foods (SA, 1982=100)	5
223	SP3130	PPI: Finished Consumer Durable Goods (SA, 1982=100)	5
224	SP3200	PPI: Finished Goods: Capital Equipment (SA, 1982=100)	5
225	SP3300	PPI: Finished Consumer Goods ex Foods (SA, 1982=100)	5
226	SP3400	PPI: Finished Goods ex Foods (SA, 1982=100)	5
227	LECONSA	Avg Hourly Earnings: Construction (SA, $/Hr)	5
228	LEDURGA	Avg Hourly Earnings: Durable Goods Manufacturing (SA, $/Hr)	5
229	LEEDUHA	Avg Hourly Earnings: Education & Health Services (SA, $/Hr)	5
230	LEFIREA	Avg Hourly Earnings: Financial Activities (SA, $/Hr)	5
231	LEGOODA	Avg Hourly Earnings: Goods-producing Industries (SA, $/Hr)	5
232	LEINFOA	Avg Hourly Earnings: Information Services (SA, $/Hr)	5
233	LELEIHA	Avg Hourly Earnings: Leisure & Hospitality (SA, $/Hr)	5
234	LEMANUA	Avg Hourly Earnings: Manufacturing (SA, $/Hr)	5
235	LENDURA	Avg Hourly Earnings: Nondurable Goods Manufacturing (SA, $/Hr)	5

236	LENTRMA	Average Hourly Earnings: Natural Resources and Mining (SA, $/Hr)	5
237	LEPBSVA	Avg Hourly Earnings: Professional & Business Services (SA, $/Hr)	5
238	LEPRIVA	Average Hourly Earnings: Total Private Industries (SA, $/Hour)	5
239	LEPSRVA	Avg Hourly Earnings: Private Service-providing Industries (SA, $/Hr)	5
240	LERTRDA	Avg Hourly Earnings: Retail Trade (SA, $/Hr)	5
241	LESRVOA	Avg Hourly Earnings: Other Services (SA, $/Hr)	5
242	LETRANA	Avg Hourly Earnings: Transportation & Warehousing (SA, $/Hr)	5
243	LETTULA	Avg Hourly Earnings: Trade, Transportation & Utilities (SA, $/Hr)	5
244	LEUTILA	Avg Hourly Earnings: Utilities (SA, $/Hr)	5
245	LEWTRDA	Avg Hourly Earnings: Wholesale Trade (SA, $/Hr)	5
246	LKPRIVA	Average Weekly Earnings: Total Private Industries (SA, $/Week)	5
247	LVMANUA	Avg Hourly Earnings: Manufacturing Excluding Overtime (SA, $/Hr)	5
248	JCBM	PCE: Chain Price Index (SA, 2000=100)	5
249	JCDBM	PCE: Durable Goods: Chain Price Index (SA, 2000=100)	5
250	JCNBM	PCE: Nondurable Goods: Chain Price Index (SA, 2000=100)	5
251	JCSBM	PCE: Services: Chain Price Index (SA, 2000=100)	5
252	JCXFEBM	PCE less Food & Energy: Chain Price Index (SA, 2000=100)	5

3. Monetary Series			
	Mnemonic	Description	T
253	FAB	Bank Credit: All Commercial Banks (SA, Bil.$)	5
254	FABW	Loans & Leases in Bank Credit: All Commercial Banks (SA, Bil.$)	5
255	FABWC	C & I Loans in Bank Credit: All Commercial Banks (SA, Bil.$)	5
256	FABWO	Other Loans & Leases in Bank Credit: All Commercial Banks (SA, Bil.$)	5
257	FABWQ	Consumer Loans in Bank Credit: All Commercial Banks (SA, Bil.$)	5
258	FABWR	Real Estate Loans in Bank Credit: All Commercial Banks (SA, Bil.$)	5
259	FABWY	Security Loans in Bank Credit: All Commercial Banks (SA, Bil.$)	5
260	FABY	Securities in Bank Credit: All Commercial Banks (SA, Bil.$)	5
261	FABYG	US Government Securities in Bank Credit: All Commercial Banks (SA, Bil$)	5
262	FABYO	Other Securities in Bank Credit: All Commercial Banks (SA, Bil.$)	5

263	FARAM	Adjusted Monetary Base (SA, Mil.$)	5
264	FARAN	Adjusted Nonborrowed Reserves of Depository Institutions (SA, Mil.$)	5
265	FARANP	Adjusted Nonborrowed Reserves Plus Extended Credit (SA, Mil.$)	5
266	FARAR	Adjusted Required Reserves of Depository Institutions (SA, Mil.$)	5
267	FARAT	Adjusted Reserves of Depository Institutions (SA, Mil.$)	5
268	FARMSR	Adj Monetary Base inc Deposits to Satisfy Clearing Bal Contracts (SA, Bil.$)	5
269	FCTR	Consumer Credit (EOP, SAAR, %Chg)	1
270	FM1	Money Stock: M1 (SA, Bil.$)	5
271	FM2	Money Stock: M2 (SA, Bil.$)	5
272	FM3	Money Stock: M3 (SA, Bil.$)	5
273	FMC	Money Stock: Currency (SA, Bil.$)	5
274	FMD	Money Stock: Demand Deposits (SA, Bil.$)	5
275	FMMSC	Money Stock: Savings Deposits At Commercial Banks incl MMDAs (SA, Bil.$)	5
276	FMMSI	Money Stock: Savings Deposits At Thrift Instns incl MMDAs (SA, Bil.$)	5
277	FMMST	Money Stock: Savings Deposits, including MMDAs (SA, Bil.$)	5
278	FMN2	Money Stock: Nontransactions Components in M2 (SA, Bil.$)	5
279	FMN3	Money Stock: Nontransactions Components in M3 Only (SA, Bil.$)	5
280	FMSLC	Money Stock: Large Time Deposits at Commercial Banks (SA, Bil.$)	5
281	FMSTC	Money Stock: Small Time Deposits at Commercial Banks (SA, Bil.$)	5
282	FMSTI	Money Stock: Small Time Deposits at Thrift Institutions (SA, Bil.$)	5
283	FMSTT	Money Stock: Small-Denomination Time Deposits (SA, Bil.$)	5
284	FMT	Money Stock: Travelers Checks (SA, Bil.$)	5
285	FON	Nonrevolving Consumer Credit Outstanding (EOP, SA, Bil.$)	5
286	FOT	Consumer Credit Outstanding (EOP, SA, Bil.$)	5
287	F10FED	Interest Rate Spread: 10-Year Treasury Bond Less Fed Funds Rate (%)	1
288	FAAA	Moody's Seasoned Aaa Corporate Bond Yield (% p.a.)	1
289	FBAA	Moody's Seasoned Baa Corporate Bond Yield (% p.a.)	1
290	FCDS1	1-Month Certificates of Deposit, Secondary Market (% p.a.)	1
291	FCDS3	3-Month Certificates of Deposit, Secondary Market (% p.a.)	1
292	FCDS6	6-Month Certificates of Deposit, Secondary Market (% p.a.)	1
293	FCM1	1-Year Treasury Bill Yield at Constant Maturity (% p.a.)	1
294	FCM10	10-Year Treasury Note Yield at Constant Maturity (% p.a.)	1

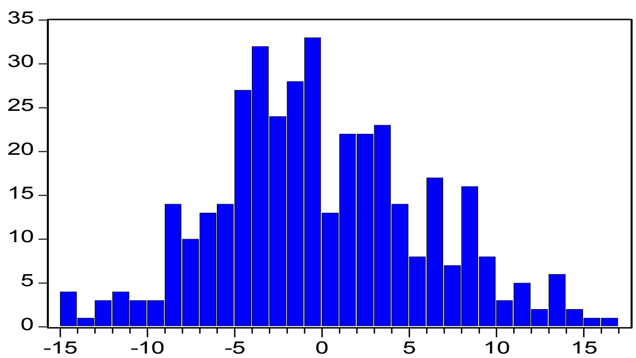
295	FCM20	20-Year Treasury Bond Yield at Constant Maturity (% p.a.)	1
296	FCM3	3-Year Treasury Note Yield at Constant Maturity (% p.a.)	1
297	FCM5	5-Year Treasury Note Yield at Constant Maturity (% p.a.)	1
298	FCM7	7-Year Treasury Note Yield at Constant Maturity (% p.a.)	1
299	FCP3	3-Month Nonfinancial Commercial Paper (% per annum)	1
300	FFED	Federal fundss [effective] Rate (% p.a.)	1
301	FFINC	Auto Finance Company Interest Rates: New Car Loans (NSA, %)	1
302	FFIUC	Auto Finance Company Interest Rates: Used Car Loans (NSA, %)	1
303	FFP1	1-Month Financial Commercial Paper (% per annum)	1
304	FFP3	3-Month Financial Commercial Paper (% per annum)	1
305	FTB3	3-Month Treasury Bills (% p.a.)	1
306	FTB6	6-Month Treasury Bills (% p.a.)	1
307	FTBS3	3-Month Treasury Bills, Secondary Market (% p.a.)	1
308	FTBS6	6-Month Treasury Bills, Secondary Market (% p.a.)	1

Notes: 1. All series are originally taken from Haver USECON database. The time span is from 1972:01 to 2003:12.

2. T is the transformation code: 1=no transformation,2=first difference, 4=logarithm, 5=first difference of logarithm.

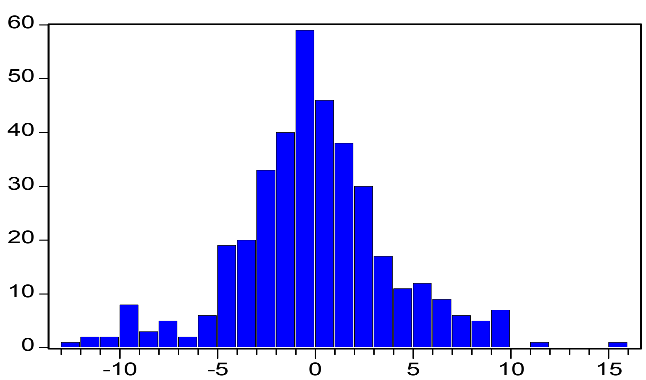
APPENDIX B

DESCRIPTIVE STATISTICS OF THE STRUCTURAL RESIDUAL FACTORS FOR CHAPTER II



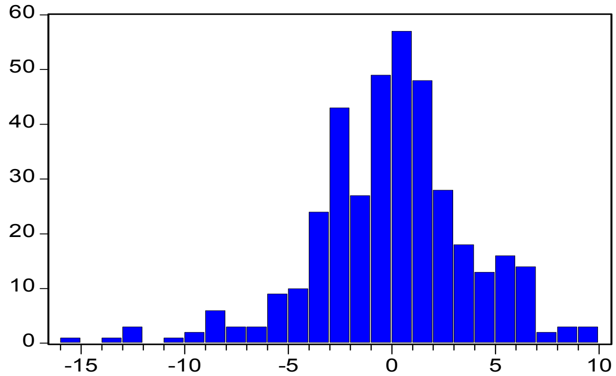
Series: Real Activity Residual Factor
Sample 1972M01 2003M12
Observations 383

Mean	-3.12e-09
Median	-0.613359
Maximum	16.88598
Minimum	-14.62523
Std. Dev.	5.968445
Skewness	0.222014
Kurtosis	2.846220
Jarque-Bera	3.523754
Probability	0.171722



Series:Inflation/Price Residual Factor
Sample 1972M01 2003M12
Observations 383

Mean	-5.28e-09
Median	-0.116982
Maximum	15.57874
Minimum	-12.90277
Std. Dev.	4.014228
Skewness	0.010678
Kurtosis	4.171974
Jarque-Bera	21.92641
Probability	0.000017

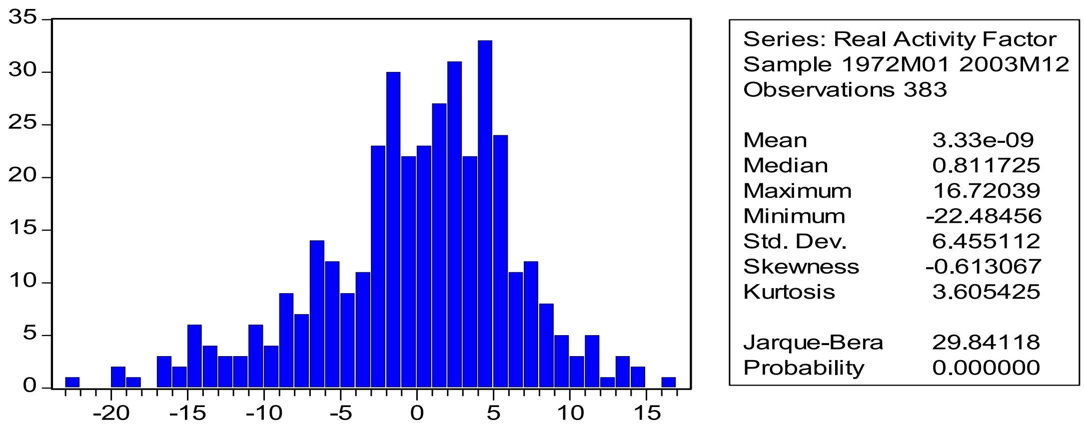


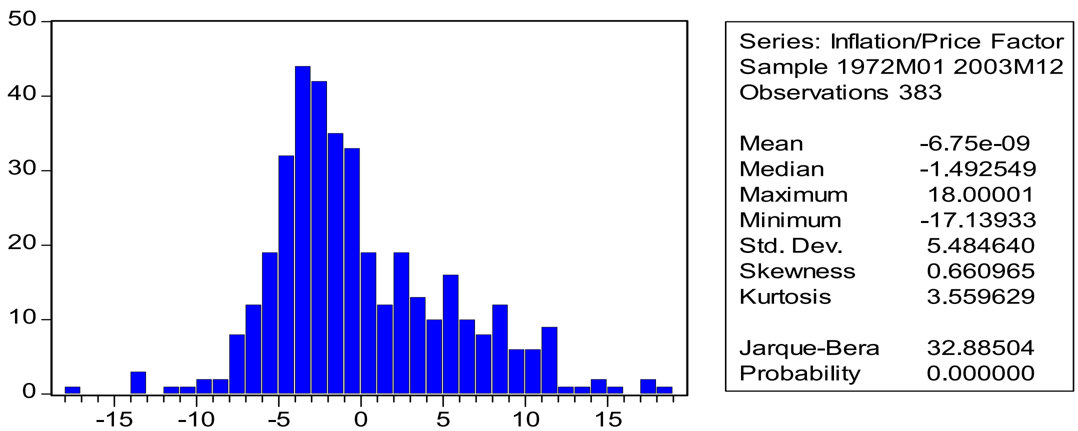
Series: Monetary Policy Residual Factor	
Sample 1972M01 2003M12	
Observations 383	
Mean	3.29e-09
Median	0.290460
Maximum	9.421894
Minimum	-15.83402
Std. Dev.	3.763450
Skewness	-0.525747
Kurtosis	4.571846
Jarque-Bera	57.22139
Probability	0.000000

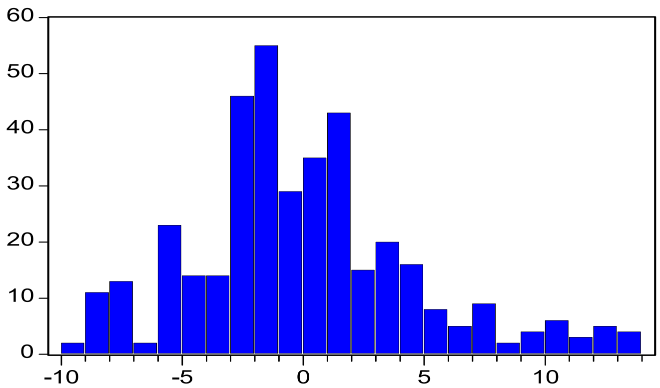
Note: The real activity residual factor is estimated from the residual vector of all the other 171 real activity related variables regressed on industrial production; the inflation/price residual factor is estimated from the residual vector of all the other 79 price related variables regressed on consumer price index and the monetary policy residual factor is estimated from the residual vector of all the other 55 money or interest rates related variables regressed on the federal funds rate. All these three structural residual factors estimated using the principal component method are then used to augment the three-variable traditional VAR (industrial production , CPI and the federal funds rate) in my SFAVAR model.

APPENDIX C

DESCRIPTIVE STATISTICS OF THE STRUCTURAL FACTORS FOR CHAPTER II







Series: Monetary Policy Factor	
Sample 1972M01 2003M12	
Observations 384	
Mean	2.47e-09
Median	-0.643255
Maximum	13.83952
Minimum	-9.384861
Std. Dev.	4.600871
Skewness	0.645967
Kurtosis	3.629321
Jarque-Bera	33.04226
Probability	0.000000

Note: These three factors are the factors used in my SFVAR model. The real activity factor is estimated from the vector of all the 172 real activity related variables; the inflation/price factor is estimated from the vector of all the 80 price related variables and the monetary policy factor is estimated from the residual vector of all the 56 money or interest rates related variables.

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