Fiscal Policy and Asset Prices in a Dynamic Factor Model with Cointegrated Factors

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Abstract

This paper investigates the effects of fiscal policy on asset prices using structural dynamic factor model (SDFM) with cointegrated factors. Much of the focus in the literature were on monetary policy and asset prices, with little attention to fiscal policy. In this paper I estimated the impulse response functions (IRFs) of stock price and house to government spending shocks using a quarterly dataset with 207 macroeconomic and financial variables obtained from St. Louis FRED website. Government spending shock was identified by combining "named factor normalization" and "unit effect normalization" and applying Cholesky decomposition. The results of the IRFs shows that both stock price and house price responded positively to government spending shock and the effects were persistent and not temporal as suggested in the literature. Results from forecast error variance decomposition shows that government spending shock explained high percentage of the forecast error variance in real GDP, consumption, and fixed investment. This paper highlighted the importance of allowing cointegration among factors within the SDFM framework and the role played by using larger datasets in resolving the limited information problems inherent in SVAR analysis. The results implies that fiscal policy leads to a boom in housing and stock markets.

1 Introduction

The question on how asset prices respond to fiscal policy is very important to financial institutions and policy makers. Specifically, how stock prices and housing prices respond to government spending shock. There exist extensive literature on the effect of monetary policy on asset prices, but less emphasis is placed on how fiscal policy actions impact asset prices (house prices and and stock prices). This paper tries to answer the following questions; how do asset prices respond to government spending shocks? What is the economic significance of the variation in asset prices that is attributed to changes in government spending? Afonso and Sousa (2011) tried to tackle this question by estimating a Structural Vector Autoregression (SVAR) by employing recursive identification scheme. They found that government spending shocks had a negative on stock prices but this effect is negligible. For house prices, the effect of government spending was large and persistent and peaks after 8 to 10 quarters. Also, Agnello and Sousa (2013) found negative response of both stock prices and house prices and the effects on housing shows strong persistence for US in a panel VAR framework. It is pointed out in the literature that small-scale Vector Autoregressive (VARs) models often results in slow and insignificant responses (Beckworth, Moon, and Toles (2012); Galí and Gambetti (2015); and Calza, Monacelli, and Stracca (2013). Bernanke and Kuttner (2005) and Nakamura Steinsson, 2018) showed that incorporating large information set in a dynamic factor model leads to estimating significant effects as compared to a benchmark VAR.

The motivation for using Structural Dynamic Factor Model (SDFM) over SVAR is that large datasets spans the space of structural shocks better than SVAR. According to Stock and Watson (2016), the space of factor innovations may not be well approximated by the innovations of SVARs. This suggests that identifying shocks in SVAR could fail due to measurement errors but succeed in SDFM due to large information set. Also, including many variables in a SDFM has a benefit of generating internally consistent SIRFs for many variables. That is, in a SVAR framework, IRFs are estimated for the limited number of variables in the model but in SDFM, IRFs can be computed for other variables of interest. In addition, small scale SVARs potentially suffer from the omission of several variables that can be important for the transmission of fiscal shocks. Another drawback of SVAR is that it imposes invertibility, but it is possible that the structural moving average process of the model may not be invertible, implying that the VAR innovations will not span the space of the structural shocks. This is the "non-fundamentalness" problem discussed in the literature. If it happens that the true IRFs are non-invertible, then the VAR innovations may not recover the true SIRF. A reason for the non-invertibility of the structural moving average is that the number variables in the VAR is less than the number of shocks (Stock and Watson, 2016).

In this paper, I estimate the impulse response functions (IRFs) of asset prices specifically house prices and stock prices to government spending shocks in the DFM framework and accounting for cointegration among the factors. The result shows that stock prices and house prices respond positively to a government spending shock. The result implies that government spending does not depress both stock and housing markets as suggested by Afonso and Sousa (2011) & Agnello and Sousa (2013), who found negative response of both stock and housing prices to a positive fiscal policy shock. My results also reveal that government spending shock does not have a permanent effect on the variables in the model as the IRFs do not show persistence. The problem of persistent IRFs arise from accumulation of IRFs from VAR estimates using differenced factors. I overcome this problem by using non-stationary factors and accounting for cointegration, hence my IRFs are not accumulated. As highlighted in the literature (see Ramey (2011), Leeper et al., (2013), Ellahie and Ricco (2017)., low-dimensional SVAR suffers from limited information problem which could lead to misleading results as the VAR innovations may not recover the true IRFs. To confirm this, I replicated the results of Afonso and Sousa (2011) SVAR model with my data as a comparison to the SDFM of my paper, which is presented in Figure 4 of this paper. The results shows that both stock price and house prices responded negatively to fiscal policy shock as oppose to my results of positive response. This strengthens the argument in the literature on the limitation of low-dimension VAR's ability to recover the true IRFs as oppose to DFM.

The main contribution of this paper is combining two important econometric methods (cointegration and dynamic factor models) to estimate the response of asset prices (stock price and house price) to government spending shocks using non-stationary factors and account for cointegration. This paper demonstrate the relevance of accounting for cointegration among the common factors when estimating IRFs of a fiscal policy shock. The results show a more intuitive effect of government spending shock on asset prices in a dynamic factor model framework. My contribution is in two folds. First, this is the first paper using Structural Dynamic Factor Model (SDFM) to estimate the effect of fiscal policy on asset prices. In the Dynamic factor model (DFM), the information set can be expanded to cover large aspect of the economy and few factors can capture the dynamics in the economy, and their residuals are explained by idiosyncratic components (Stock and Watson, 2016). The DFM overcomes the problem of small-scale VAR which sometimes yields counter-intuitive responses (see Jarocinski Karadi, 2018) resulting from information problem known as "nonfundamentalness" in the literature. The "nonfundamentalness" result from the failure of the empirical model in identifying policy shocks that capture all relevant variables. Secondly, I estimated unrestricted VAR in levels to account for cointegration. Ignoring cointegrating and specifying VAR with differenced series leads to loss of long run information that is valuable to macroeconomists. Failure to account for non-stationarity and cointegration in the factors may lead to invalid results (see Barigozzi, Lippi and Luciani, 2021).

2 Literature Review

A closely related paper on fiscal policy with factors is by Laumer (2020) who estimated IRFs of consumption to government spending shock using the Factor-Augmented VAR (FAVAR) model with stationary factors. The author estimated the model within Bayesian framework and followed sign restriction identification method, with the assumption that signs alone are enough to identify structural parameters. The literature documented some short-comings of using sign-restriction identification in structural inference. First, sign restriction identification suffer from issues of masquerading shocks, a situation where some elements of the identified sets of the VARs induces the identified shock vectors that are different from the true disturbances. Similarly, there is a possibility that some elements of the identified set can also induce IRFs of the variable of interest to the shock of interest with the wrong sign (Wolf, 2017). Secondly, there is the issue of uninformative priors and sensitivity of inference using Bayesian prior distributions (Stock and Watson, 2016; Moon and Schorfheide , 2012). Laumer (2020) ignored cointegration among the factors and estimated IRFs using difference data. But differencing the data throws away useful macroeconomic information.

Barigozzi et al., (2021) used dynamic factor model with cointegrated factors to estimate the effect oil price shocks on the US economy. They used non-stationary factors because most macroeconomic variables are non-stationary and differencing them leads to loss of long run information, which is relevant to policymakers. So, instead of modelling the DFM on differenced factors, they specified a VECM on the factors in addition to specifying an unrestricted VAR for the factors. With numerical exercise, the authors found that the performance of the VECM and the unrestricted VAR are similar. In an empirical application of the effect of oil price shocks on US economy, they found a temporal effect on oil price on US economy. The authors also investigated the effect on news shock on US economy and found that the economy first experiences a boom followed by a recession, a result that overturned the findings of Stock and Watson (2014)

Alessi and Kerssenfischer (2019) investigated how asset prices respond to monetary policy shocks in US and Euro Area using a dynamic factor model. Their results show that asset prices respond stronger and quicker in comparison to a benchmark VAR model. They employed DFM because it significantly enlarges the information set compared to standard VAR. They followed the nonstationary DFM framework by Barigozzi, Lippi, and Luciani (2016 a, b). The authors compared the response of a stock and house prices applying small-scale VAR and DFM. Though, the authors used same instrument to identify monetary policy shocks, the results from using both the VAR model and DFM are different in both regions. The results from the DFM shows that asset prices responded strongly to monetary policy shock but results from small-scale VAR produces counterintuitive responses. They concluded that DFM should be adopted in empirical applications aimed at identifying monetary policy shocks because it captures large information that is important in the decision making of central banks.

Afonso and Sousa (2011) investigated the effect of fiscal policy on asset prices in a SVAR model. Using quarterly data from 1971 to 2007, the authors adopted recursive identification and examined the response of asset markets to fiscal policy shock using data from Germany, Italy, U.K and U.S. They found that government spending shocks causes a fall in housing prices and stock prices. Similarly, Agnello and Sousa (2013) examine how asset markets respond to fiscal policy using a panel VAR of ten industrialized countries.Their result showed stock prices and house prices responded negatively to positive fiscal shock.

3 Model Specification

To estimate the model, I will use a Dynamic Factor Model (DFM) following Stock and Watson (2016) and Barogozzi et al.(2020). In the DFM, each variable in the dataset of dimension N, are decomposed into common component and idiosyncratic components. The model starts with an $N \times 1$ vector of variables specified as follows:

$$\mathbf{X_t} = \mathbf{\Lambda F_t} + \xi_\mathbf{t}, \tag{1}$$

$$\mathbf{A}(L)\mathbf{F_t} = \mathbf{K}\eta_\mathbf{t}, \qquad \mathbf{A}(L) = \mathbf{I} - \mathbf{A_1}L - ... - \mathbf{A_p}L^p, \tag{2}$$

$$\eta_\mathbf{t} = \mathbf{H}\epsilon_\mathbf{t}, \tag{3}$$

$\xi_\mathbf{t} \sim N(0, \Psi)$ and $\eta_\mathbf{t} \sim N(0, \mathbf{\Sigma}_\eta)$

where $\mathbf{X_t} = (x_{1t}, \ldots, x_{Nt})'$ is an $N \times 1$ vector of observable variables, $\mathbf{F_t} = (f_{1t}, \ldots, f_{rt})'$ is an $r \times 1$ vector of unobservable factors, $\mathbf{\Lambda} = (\lambda_1', \ldots, \lambda_N')'$, is the $N \times r$ matrix of factor loadings, $\xi_\mathbf{t} = (\xi_{1t}, \ldots, \xi_{Nt})'$ is the $N \times 1$ vector of idiosyncratic components, $\mathbf{A}(L)$ is an $r \times r$ conformable lag polynomial, $\eta_\mathbf{t} = (\eta_{1t}, \ldots, \eta_{qt})'$ is the $q \times 1$ vector of uncorrelated innovation to the common factors, $\mathbf{K}$ has a dimension of $r \times q$. It is assumed that the structural shocks ϵ_t are uncorrelated

$$E\epsilon_t\epsilon_t' = \mathbf{\Sigma}_\epsilon = \begin{pmatrix} \sigma^2_{\epsilon_1} & & 0 \\ & \ddots & \\ 0 & & \sigma^2_{\epsilon_q} \end{pmatrix}$$

Also, $\eta_\mathbf{t}$ and $\xi_\mathbf{t}$ are uncorrelated at all leads and lags. The factors and idiosyncratic component can be serially correlated. $\mathbf{H}$ is a $q \times q$ dimension structural impact matrix which is invertible, and used in identifying the structural shocks from the factor innovations. The model specified in equation (1)- (3) represents the static form of the DFM which depends on r number of static factors, $\mathbf{F_t}$ and q dynamic shocks. I assumed the following as in Stock and Watson (2016).

Assumption on common factors and shocks

(a) $\epsilon_{\mathbf{t}} = (\epsilon_{1t} \cdots \epsilon_{qt})'$ is a vector of white noise with q-dimensions i.e., $\mathrm{E}[\epsilon_{\mathbf{t}}] = \mathbf{0}_q, \mathrm{E}[\epsilon_{\mathbf{t}}\epsilon_{\mathbf{t}}'] = \mathbf{I}_q$, and $\epsilon_{\mathbf{t}}$ and $\epsilon_{\mathbf{t-k}}$ are independent for any $k \neq 0$.

(b) The rank, $rk\left(\mathrm{E}\left[\mathbf{F_t F_t}'\right]\right) = r$

Assumption on the factor loadings: For the factor loadings, $N^{-1}\Lambda'\Lambda \rightarrow \mathbf{I}_r$ as $N \rightarrow \infty$. This prevents the r factors from being redundant.

Assumption on the idiosyncratic components: The idiosyncratic components are allowed to be either $I(0)$ or $I(1)$.

3.1 Estimation

This paper aimed at estimating the Structural IRF (SIRF) which can be obtained by substituting (3) into (2) and the resulting expression is substituted into (1) to obtain,

$$\mathbf{X_t} = \mathbf{\Lambda A}(\mathrm{L})^{\mathbf{-1}}\mathbf{KH}\epsilon_{\mathbf{t}} + \xi_{\mathbf{t}} \tag{4}$$

Here, one can assess the dynamic response on all variables in the model from a unit change in $\epsilon_{\mathbf{t}}$, which represents the SIRF and denoted by $\mathbf{\Lambda A}(\mathbf{L})^{-1}\mathbf{KH}$. One advantage of Structural DFM (SDFM) is that more variables can be included in the model and the number of variabless can be greater than the number of shocks when estimating the IRFs. For the case where the focus is on the first shock only, then the SIRF will be given as $\mathbf{\Lambda}(\mathbf{AL})^{-1}\mathbf{KH}_1$, where $\mathbf{H_1}$ is the first column of matrix $\mathbf{H}$ (Stock and Watson, 2016). I followed the procedure in Barigozzi et al., (2021) in a non-stationary DFM framework in estimating the factor loadings, the common factors and the IRFs by specifying unrestricted VAR in levels.

3.2 Factor Normalization and Estimation

Since equation (1) is not identified, normalization restriction has to be imposed on the factor loading before estimating the factors. The normalization on the factor loading is specified as $N^{-1}\Lambda'\Lambda = I_r$ and the covariance of $\mathbf{F}$ defined as a sequence of such that $\mathbf{F} = \{F_1, F_2, \cdots F_T\}$, $\mathbf{\Sigma_F}$ is diagonal. In general, the factors are estimated using the principal components (PC) estimation by minimizing the equation below:

$$\min_{\mathbf{F},\mathbf{\Lambda}} V_r(\mathbf{\Lambda}, \mathbf{F}),$$

where

$$V_r(\mathbf{\Lambda}, \mathbf{F}) = \frac{1}{NT} \sum_{t=1}^{T} (\mathbf{X_t} - \mathbf{\Lambda F_t})' (\mathbf{X_t} - \mathbf{\Lambda F_t})$$

However, to achieve the goal of this paper, I estimate the factor loadings using PC in addition to the "named factor" normalization restriction by Stock and Watson (2016) where I can associate a factor with a specific variable, in this case government spending variable. In the named factor normalization restriction, the factors are estimated by constraining the first loading to be equal to the identity matrix. The named factor normalization is specified as:

$$\mathbf{\Lambda^{NF}} = \begin{bmatrix} I \\ \\ \Lambda^{NF}_{r+1:n} \end{bmatrix},$$

This normalization is applied in structural DFM (SDFM) where the variables are ordered such that the first variables becomes the naming variables (Stock and Watson, 2016). This way, the first factor is assigned to the first variable so that the common component of $\mathbf{X_{1t}}$ is $\mathbf{F_{1t}}$. So, I ordered government spending first so that the normalization corresponds to the innovation in the first factor. This implies that the first factor represents government spending factor and the innovation in the first factor becomes innovations in the government spending factor. The ordering of the variables in $\mathbf{X_t}$ is specified below:

$$
\begin{pmatrix} G_t \\ X_{2:n,t} \end{pmatrix} = \begin{pmatrix} I \\ \Lambda_{2:n} \end{pmatrix} \begin{pmatrix} F_t^G \\ F_{2:r,t} \end{pmatrix} + \begin{pmatrix} \xi_{1t} \\ \xi_{2:n,t} \end{pmatrix}
$$

Here, government spending, $\mathbf{G_t}$ is ordered first in X_t followed by the remaining variables in the model so that the first factor correspond to government spending factor labelled $\mathbf{F_t^G}$.

3.3 Estimating the number of factors and dynamic shocks

There exist several methods to determine the number of factors to that needs to be included in the model. This can be a combination of prior knowledge, information criteria or using scree plots. Using scree plots, the number of factors is selected using the marginal contribution of the next consecutive factor. Also, Theoretically, information criteria can also be used to determine the number of factors. I use information criteria developed by by Bai and Ng (2002). In Bai and Ng (2002), the optimal number of factors is determined by minimizing the equation below.

$$
IC_p(r) = \ln V_r(\hat{\Lambda}, \hat{F}) + rg(N, T),
$$

where $V_r(\hat{\Lambda}, \hat{F})$ is the objective function of the principal components evaluated at $(\hat{\Lambda}, \hat{F})$, $g(N, T)$ represents the penalty factor. Specifically, I used IC_{p1}, where the penalty function $g(N, T)$, is explicitly written as $\frac{N+T}{NT} \ln \frac{NT}{N+T}$.

3.4 Identification of Shocks and Estimation of IRFs

To estimate IRFs in the presence of cointegrated vectors, I estimated a an unrestricted VAR model. According to Sims, Stock, and Watson (1990), an unrestricted VAR model can consistently estimate the parameters of a cointegrated VAR for non-stationary factors. Also, Barigozzi et al., (2021) showed that IRFs from a vector error correction model(VECM) is similar to those obtained from specifying unrestricted VAR in levels using recursive identification. The simulation results in Barigozzi et. al., (2021) also showed that the estimator for the IRFs for unrestricted VAR, $\widehat{\phi}_{ijk}^{\text{VAR}}$ converges faster to the true value ϕ_{ijk} than the IRF estimator for VECM, $\widehat{\phi}_{ijk}^{\text{VECM}}$. In this paper, I followed Barigozzi et al.,(2021) to estimate an unrestricted VAR in levels using equation (2). The choice of estimating unrestricted VAR in levels is also motivated by the paper by Gospodinov, Herrera, and Pesavento (2013).

Next, the normalization restriction is imposed on the factor loadings $\mathbf{\Lambda}$ and $\mathbf{K}$. The number of dynamic factors q is set to be equal to the number of static factors ($r = q$), hence the dimension of matrix $\mathbf{K}$ in equation (2) is $q \times q$. Therefore, the dimension of $\eta_{\mathbf{t}}$ is 7, and matrix $\mathbf{K}$ is normalized to be identity matrix. A unit effect normalization is applied in addition to the named factor normalization to link the innovation in the first factor to the structural shock. The matrix $\mathbf{H}$ is identified by imposing $q(q-1)/2$ restrictions making $\mathbf{H}$ a lower triangular matrix. Since the focus is on identifying just one shock, equation (3) is rewritten as

$$\eta_{\mathbf{t}} = \mathbf{H} \begin{pmatrix} \epsilon_{1t} \\ \widetilde{\eta}_{\bullet t} \end{pmatrix} = \begin{bmatrix} H_1 & H_{\bullet} \end{bmatrix} \begin{pmatrix} \epsilon_{1t} \\ \widetilde{\eta}_{\bullet t} \end{pmatrix} \tag{5}$$

with H_1 representing the first column of H and $H_{\bullet}$ representing the remaining columns. In line with Cholesky identification, government spending is ordered first, which assumes that government spending shock is the only shock that had contemporaneous effects on government spending. This also implies that government spending is unaffected on impact by any other shock in the model.

Therefore equation (5) becomes

$$
\begin{pmatrix} \eta_t^{G_t} \\ \\ \eta_{\bullet t} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \\ H_{12} & H_{\bullet t} \end{pmatrix} \begin{pmatrix} \epsilon_t^{g_t} \\ \\ \widetilde{\eta}_{\bullet t} \end{pmatrix} \tag{6}
$$

where the unit effect normalization is imposed on the coefficients on the diagonal of $\mathbf{H}$. Because we want to identify only government spending shock $\eta_t^{G_t}$, the identification of other shocks are irrelevant and the ordering of the remaining variables can be arbitrary. Therefore, the Structural DFM is identified using economic restrictions on $\mathbf{H}$ in (6), the named factor normalization on $\mathbf{\Lambda}$, and setting $\mathbf{K}$ to identity matrix. The estimated IRF of shock j on variable i at time k defined as :

$$
\widehat{\phi}_{ij,k}^{\mathrm{VAR}} = \widehat{\lambda}_i' \left[\widehat{\mathbf{A}_k}^{\mathrm{VAR}} \right]^{-1} \widehat{\mathbf{K}} \widehat{\mathbf{h}}_j, \tag{7}
$$

where $\widehat{\lambda}_i'$ represents the i-th row of $\widehat{\mathbf{\Lambda}}$, $\widehat{\mathbf{h}}_j$ is the j-th column of $\widehat{\mathbf{H}}$ and $\widehat{\mathbf{A}}_k^{\mathrm{VAR}}$ is the VAR estimate of $\mathbf{A}(L)$.

3.5 Summary of steps

1. The variables are ordered by placing government spending first, and the seven unobserved static factors are then estimated by principal component least-squares minimization.

2. Using $\hat{\mathbf{F}}_{\mathbf{t}}$, an unrestricted VAR model in equation (2) is estimated with $\mathbf{K} = \mathbf{I}$, to obtain the estimates of the residuals, $\widehat{\eta}$ and the lag polynomials $\widehat{\mathbf{A}}(\mathbf{L})$. The number of static factors r is obtained using information criteria by Bai and Ng (2002), and the number of factor innovations, q is set to equal to the number of factors r.

3. The VAR residuals $\hat{\eta}_t$ are then used to estimate $\mathbf{H}$ following the identification restrictions in (6) where $\mathbf{H}$ has a lower triangular structure. This is done using the Cholesky decomposition with $\mathbf{H}$ having 1 as elements on its diagonal.

4 Data

The dataset consist of 207 quarterly observations representing the US economy. The time series variables ranges from real activity variables, prices, productivity and earnings, interest rates and spreads, money and credit, asset variables, and variables representing international activity. This is an extension of Stock and Watson (2016) dataset, which had a full sample from 1959Q1-2014Q4 and a sub-sample from 1985Q1-2014Q4. I extend the Stock and Watson (2016) dataset to cover the period up to 2021Q4. So my dataset spans the period 1985Q1-2021Q4. I choose the start date for my sample to be 1985 because of the "great moderation" where US economy experienced a structural break. Structural breaks can lead to over-estimation of the number of factors and may also cause inconsistent estimation of the factor loadings (Stock and Watson (2016); Breitung and Eickmeier, 2011). S&P 500 is the index used in measuring Stock price, government spending is a measure of fiscal policy. All $I(1)$ variables were not transformed, but for $I(2)$ variables, first differences were taken.

5 Results

In this section I present the results of the model. It includes test on the number of estimated factors, IRFs of government spending shock, variance decomposition and robustness check.

5.1 Number of factors

To determine the number of factors in a DFM, I combine information criteria and the scree plot. The decision point for the scree plot is the ”elbow” of the plot. However, using the scree plot gives arbitrary results, hence I followed Bai & Ng (2002)'s information criteria and selects the number of factors r to be 7.

Table 1: Determining the number of factors

q	Bai & Ng-IC$_p$
1	-0.179
2	-0.213
3	-0.246
4	-0.273
5	-0.268
6	-0.240
7	$\mathbf{-0.284}$
8	-0.228
9	-0.215
10	-0.180

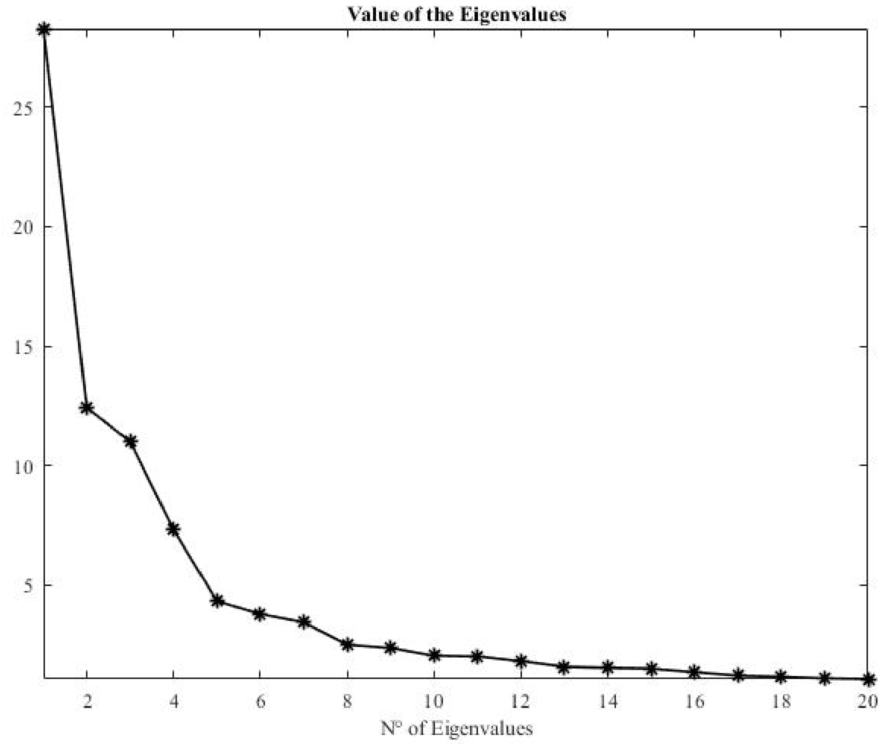


Figure 1: Scree plot of the number of factors

Table 2 presents the contribution of the common factors in some selected variables. The contribution of the factors are the R^2 values of the common factors. I present result for 1,2, 4, and 7 common factors. According to Table 2, the first factor explained all the variation in government spending because the first factor is the government spending factor. It also explains a good amount of variation in the consumption, real GDP as well as employment. Also, all factors explain large variations in important macroeconomic indicators. This indicates that the factors captures important movements in the variables.

Table 2: Importance of Common Factors for Selected Variables

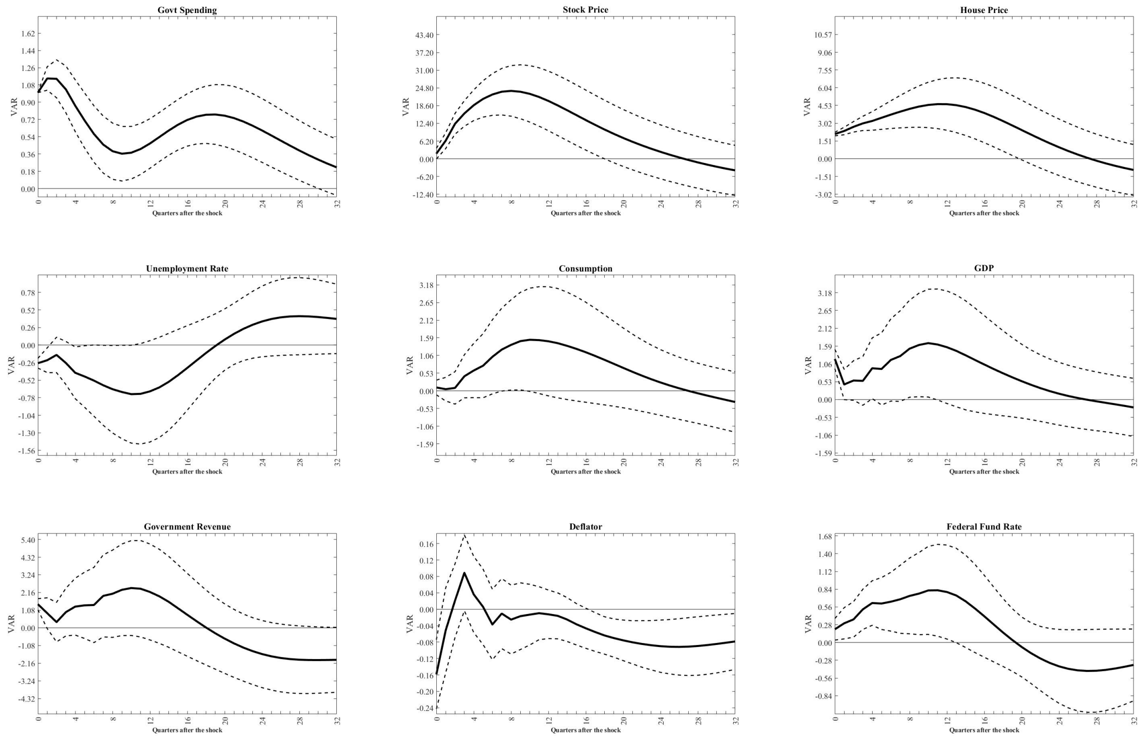
R^2 of Number of factors

Series	Factor 1	Factor 2	Factor 4	Factor 7
Real GDP	0.68	0.71	0.76	0.81
Consumption	0.52	0.57	0.61	0.68
Investment	0.45	0.49	0.52	0.54
Government Spending	1.0	0.87	0.84	0.89
Tax Revenue	0.45	0.44	0.47	0.51
Unemployment Rate	0.70	0.78	0.83	0.85
Employment Nonfarm	0.73	0.85	0.86	0.82
Labor productivity	0.38	0.35	0.38	0.50
Housing starts	0.08	0.27	0.53	0.60
Fed Funds	0.02	0.21	0.33	0.48
S&P 500	0.06	0.30	0.47	0.68
Real House Price	0.17	0.19	0.46	0.54
GDP Deflator	0.25	0.08	0.11	0.15
House Price	0.10	0.13	0.17	0.19

5.2 Impulse Response of Government Spending Shock

The results of estimating the IRFs by specifying unrestricted VAR in levels are displayed in Figure 2. The thick black line is the IRF estimated with unrestricted VAR in levels, and 68% bootstrap confidence band is the dotted lines. The x-axis represents quarters after the shocks, the y-axis represents the percentage points.

Figure 2: IRFs of government spending shock on selected variables (1985Q1-2021Q4).



The result shows that both stock price and house price responded positively to government spending shock. This is in line with theory because expansionary fiscal policy (government spending) leads to increase in economic activity which increase demand for financial assets, causing a rise in stock price. My result is different from those found in Agnello and Sousa (2013), who found that a positive fiscal shock (government spending shock) had a negative impact on both stock and housing prices. Also, Afonso and Sousa (2011) found negative response of stock and house price to shocks in government spending for US using a Panel VAR for 10 industrialised countries. My findings are more in line with economic prediction as increase in government spending causes a rise in aggregate demand, which booms demand for financial assets, hence stock prices rise. The difference in my findings compared to Afonso and Sousa (2011) and Agnello and Sousa (2013) is attributed to narrow information set of SVAR model and measurement error, which produce distorted IRFs. The results also do not show persistence from the effect of government spending shock. Hence, government spending shock does not have a permanent effects on the variables. This is desirable because theoretically fiscal policy is not expected to have a permanent effect on the economy.

Output and Consumption responded positively to government spending shock, which supports the Keynesian view on the effect of an increase in government spending. This is in line with the result of Fisher and Peters(2010), Zeev & Pappa(2017), Gali et.al (2007) but contradicts Mountford and Uhlig (2009) who uses SVAR with sign restriction identification. Comparing my results to Laumer (2020) in a stationary DFM case, even though Laumer (2020) found positive effect of government spending shock on Real GDP, Consumption, Tax receipts and GDP Deflator, the IRFs show persistent behavior, a phenomenon which is attributed to stationary data. This problem arise from accumulation of IRFs from VAR estimates on differenced factors. Since I specify a VAR in levels for non-stationary factors, I overcome the problem of obtaining generic long run effects of government spending shock on the levels of the variables. This point to the importance of accounting for cointegration among the common factors and demonstrates that fiscal policy does not have a permanent effect on the real economy. Unemployment on the other hand shows a negative impact of government spending shock. This agrees with theory because increase in government spending increases economic activity through high employment, hence unemployment decreases.

5.3 Variance Decomposition Analysis

The variance decomposition is used in determining the fraction of the a variable's forecast error that is attributed to government spending shock. Table 3 displays the contribution of the government spending shock to the variation of the forecast error of the selected variables.

Table 3: Forecast Error Variance Decomposition for Selected Variables

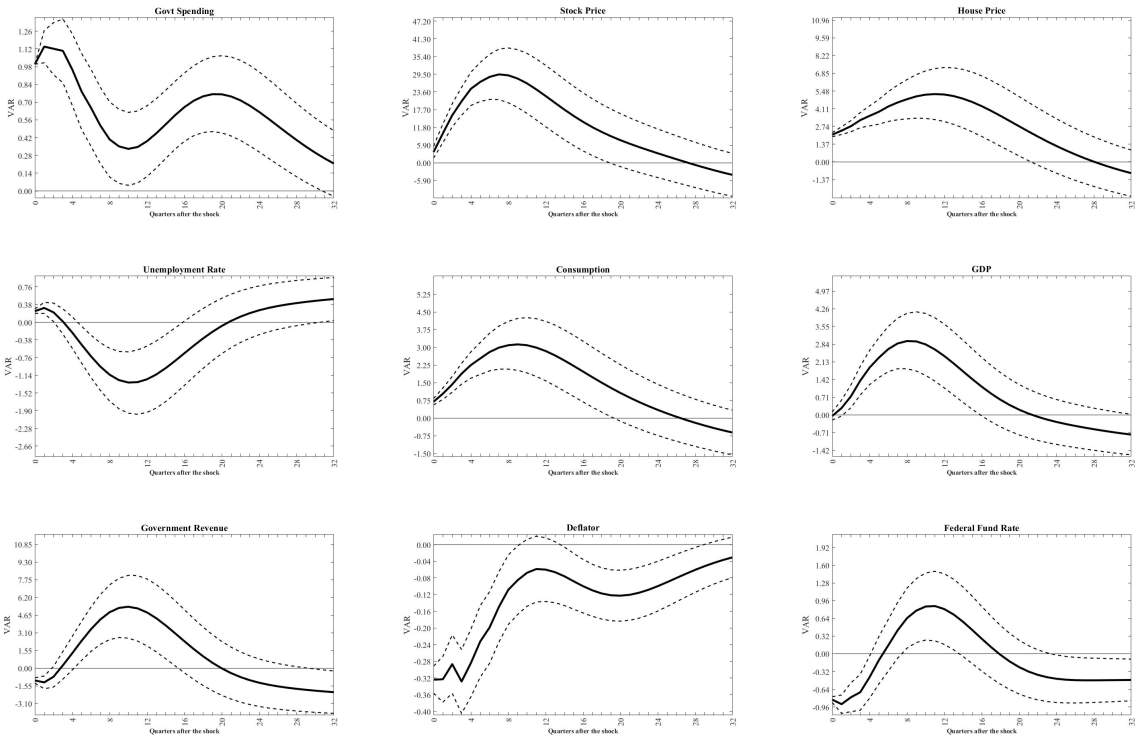
Variable	Contribution
GDP	0.70
Consumption	0.35
Investment	0.56
Employment	0.64
Unemployment rate	0.44
Government Spending	0.75
Tax Revenue	0.18
Fed funds rate	0.23
Hours Worked	0.62
GDP Deflator	0.30
S&P 500	0.32
House Price	0.10

In Table 3, government spending shock explained a substantial fraction (75%) of the one step ahead forecast error of government spending. Also, government spending shocks explained 70% of GDP's forecast error variation, 35% of consumption, and 56% of fixed investment. In addition,the government spending shocks explains small variation in the forecast error of house prices (10%). Finally, 32% of the variation in stock price's forecast error is explained by the government spending shock.

5.4 Robustness Check using full sample data (1959Q1-2021Q4)

To check the robustness of the model, I re-estimate the model using full data from 1959Q1 to 2021Q4 to determine the stability of the results in the sub-sample 1985Q1-2021Q4. The results of the IRFs for the full sample (1959Q1-2021Q4) presented in Figure 3 are very consistent with those in Figure 2, the sub-sample (1985Q1-2021Q4) result. Both stock price and house price respond positively to government spending shock. Consumption and output also show a positive response to government spending shock. Even though the initial impact on output was small, it begins to rise and peaked after 8 quarters. Unemployment responded negatively to government spending shock as expected. This results shows that the effect of government spending shock produces similar results compared to estimates from the sub-sample. So, using the sub-sample data does not change the response of variables considered in the model to government spending shock. Therefore, the full-sample results reinforces my main results.

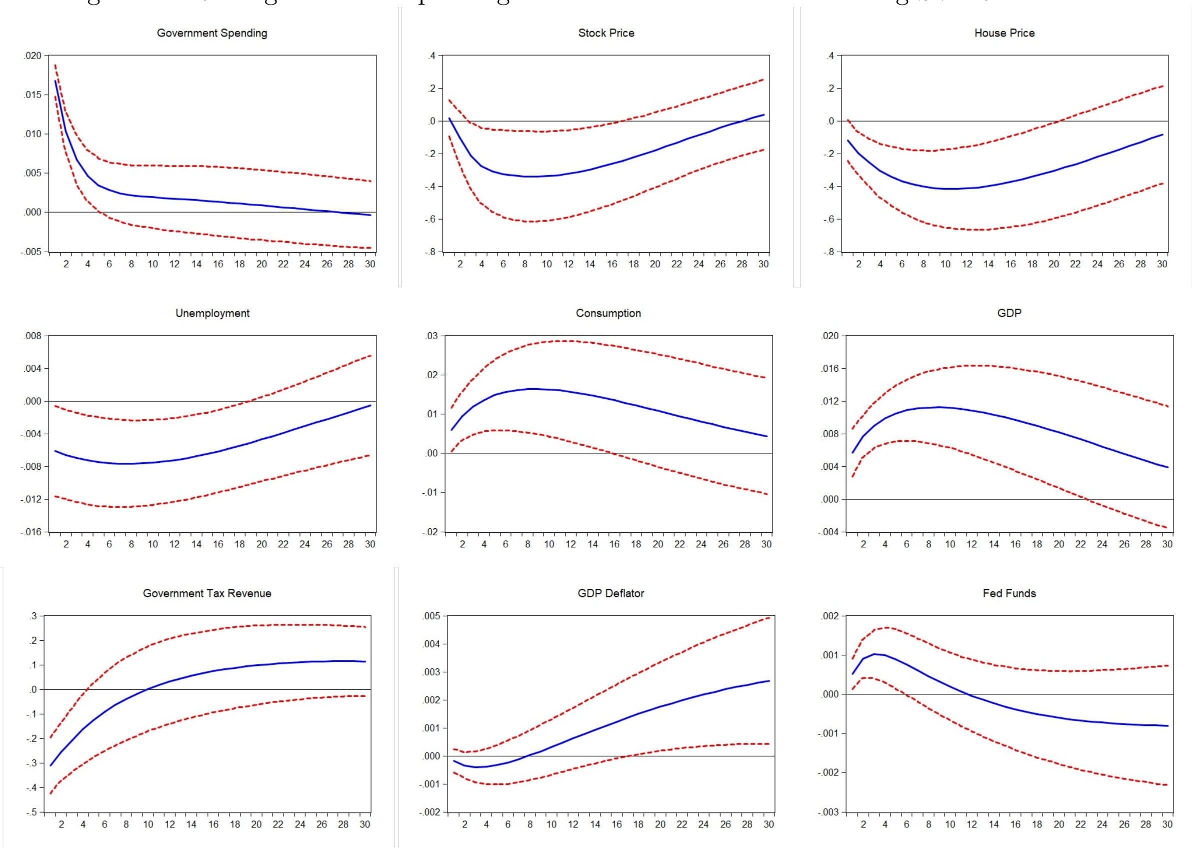
Figure 3: IRF of government spending shocks on selected variables using full sample (1959Q1-2021Q4)



5.5 Impulse Response Function using a SVAR Model (Comparison)

In this section, I presented the replication of Afonso and Sousa (2011) SVAR model for comparison purposes and the result is present in Figure 4. I followed their identification strategy and ordering of variables in their SVAR model. The result from the IRFs indicated that stock prices and house prices responded negatively to government spending shock as stated in Afonso and Sousa (2011). This result is different from the results I obtained using the structural DFM (SDFM). Using SDFM, I found positive response of stock price ad house prices to government spending shocks. The difference in the results of SVAR and SDFM could be attributed to limitation of small scale SVARs. Since small scale SVARs potentially suffer from limited information problem due to inclusion of few variables in the model, the VAR innovations may not span the space of the structural shocks, and therefore may not recover the true IRFs. This leads to estimation of distorted IRFs. As noted in the literature, Bernanke and Kuttner (2005) and Nakamura Steinsson, 2018) showed that incorporating large information set in a dynamic factor model leads to estimating significant effects as compared to a benchmark VAR.

Figure 4: IRF of government spending shocks on selected variables using SVAR Model



6 Conclusion

This paper investigates the response of asset prices (stock price and house price) to government spending shock within the framework of dynamic factor model with cointegrated factors. The number of factors and shocks were selected using information criteria by Bai and Ng (2002) and Amengual and Watson (2007) respectively. The result shows that a positive government spending shock has a positive effect on stock prices and house prices. The result implies that government spending does not depress both stock and housing markets as suggested by Agnello and Sousa (2013). My result is different from the findings of Afonso and Sousa (2011), who found negative response of both stock and housing prices to a positive fiscal policy shock using low-dimensional SVAR with 6 variables. My findings are more intuitive because a rise in government spending causes aggregate demand to increase, leading to demand for financial assets. This causes a rise in stock price. House prices also increase because of increase in consumer spending resulting from increase in aggregate demand, coming from positive government spending shock. My results also reveal that government spending shock does not have a permanent effect on the variables as the IRFs do not show persistence. Output also responded positively to government spending shock, which is in line with Keynesian prediction. Unemployment responded negatively to government spending shock, a result that is in line with theory.

The main contribution of this paper is combining two important econometric methods (cointegration and dynamic factor models) to estimate the response of asset prices (stock price and house price) to government spending shocks. I consider non-stationary factors and account for cointegration by estimating an unrestricted VAR in levels because differencing the series before estimation may lead to lost of factor structure and may not realistically represent the data. Therefore, this paper demonstrate the relevance of accounting for cointegration in the common factors in estimating IRFs of a fiscal policy shock. The results show a more intuitive effect of government spending shock on asset prices in a dynamic factor model framework.

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