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

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1 Introduction

The behavior of asset markets and its prices is an important factor influencing the decision-making of financial institutions, homeowners, consumers, businesses, and policy-makers. 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 stock prices). While monetary policy dominates academic and policy discussions on asset prices, fiscal policy has become crucial now that monetary policy reached a zero-interest rate lower bound and is ineffective in stimulating demand as seen in the recent recession (Feldstein, 2009). The theoretical understanding of stock markets' reaction to fiscal policies has been set out in a series of papers (Shah, 1964; Tobin, 1969; Blanchard, 1981; and Charpe et al., 2011). In these studies, fiscal policy affects stock markets through its effects on the level of economic activity. These effects can be positive, negative, or null depending on the assumption on the effects of fiscal policies on the level of economic activity (Keynesian, Classical, or Ricardian; see Barnheim, 1989). This provides the premise for empirical investigation. In addition, fiscal policy can also affect housing markets through taxes on housing capital gains and the imputed rental housing value, and value added taxes (VAT) on purchases of new houses. The tax deductibility of mortgage payments and housing rents can affect housing prices via their effects on households' disposable income and the demand of houses.

This paper specifically investigates how stock prices and housing prices respond to a government spending shock by answering the following question:. How do asset prices respond to government spending shocks? What is the economic significance of the variation in asset prices that are attributed to changes in government spending? Afonso and Sousa (2011) try to tackle this question by estimating a Structural Vector Autoregression (SVAR) by employing a recursive identification scheme. They find that government spending shocks have a negative effect on stock price,s but this effect is negligible. For house prices, the effect of government spending is large and persistent and peaks after 8 to 10 quarters. Agnello and Sousa (2013) also find a negative response on both stock prices and house prices and the effects are strongly persistent for the United States housing market in a panel VAR framework. The literature highlights that small-scale Vector Autoregressive (VARs) models often result 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 and Steinsson (2018) show that incorporating a large information set in a dynamic factor model leads to an estimation of significant effects as compared to a benchmark VAR.

The motivation for using a Structural Dynamic Factor Model (SDFM) over SVAR is that large datasets span the space of structural shocks better than SVAR. According to Stock and Watson (2016), the space of factor innovation may not be well approximated by the innovations of SVARs. This suggests that identifying shocks in a SVAR could fail due to measurement errors, but will succeed in SDFM due to its large information set. Also, including many variables in a SDFM has the benefit of generating internally consistent structural impulse response function (SIRFs) for many variables. That is, in a SVAR framework, impulse response functions (IRFs) are estimated for the limited number of variables in the model. However, 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 a SVAR is that it imposes invertibility. However, since it is possible that the structural moving average process of the model may not be invertible, 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 of 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 on house prices and stock prices to government spending shocks in the DFM framework and account for cointegration among the factors. The results show that stock prices and house prices respond positively to a government spending shock. The result implies that government spending does not depress the stock and housing markets as suggested by Afonso and Sousa (2011) and Agnello and Sousa (2013), who find a negative response of both the stock prices and housing prices to a positive fiscal policy shock. My results also reveal that a 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 an accumulation of IRFs from VAR estimates using differenced factors. I overcome this problem by using non-stationary factors and account for cointegration; hence, my IRFs are not accumulated. As highlighted in the literature [see Ramey (2011), Leeper et al., (2013), and Ellahie and Ricco (2017), a low-dimensional SVAR suffers from a limited information problem that may lead to misleading results as the VAR innovations may not recover the true IRFs. To confirm this issue, I replicate the results of Afonso and Sousa (2011)'s SVAR model with my data as a comparison to the SDFM in this paper, which is presented in Figure 4. The results show that both stock price and house prices responded negatively to a fiscal policy shock as opposed to my results showing a positive response. This strengthens the argument in the literature on the limitation of the low-dimension VAR's ability to recover the true IRFs as oppose to a 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 accounting for cointegration. This paper demonstrates the relevance of accounting for cointegration among the common factors when estimating the IRFs of a fiscal policy shock. The results show a more intuitive effect of a government spending shock on asset prices in a dynamic factor model framework. My contribution is two-folds. First, this is the first paper to use a 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 a large aspect of the economy, 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 a small-scale VAR, which sometimes yields counter-intuitive responses (see Jarocinski and Karadi, 2018) resulting from an information problem known as "nonfundamentalness" in the literature. Nonfundamentalness results from the failure of the empirical model to identify policy shocks that capture all relevant variables. Second, I estimate unrestricted VAR in levels to account for cointegration. Ignoring cointegration and specifying a VAR mdel 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

The relationship between fiscal policy and the stock market varies according to different economic theories. In the Keynesian theory, a rise in government expenditure could lead to an increase in the level of disposable income, meaning individuals have greater opportunity to invest in the capital market, thus pushing up demand for stocks. This raises the prices of stocks in the market, suggesting an indirect relationship between government expenditure and stock prices. Also, increased fiscal measures stimulate higher levels of consumer confidence and consumption, resulting in firms experiencing a corresponding increase in sales and earnings, which translates to a rise in stock prices. However, according to the Ricardian view, stock prices are unaffected by fiscal policy because they have no impact on the aggregate demand as it assumes that borrowings from the private sector will be offset by the private savings of rational households. It is argued that the government's attempt to boost economic growth through debt-financed government spending (as in most cases around the world) will not be effective as individuals expect a higher tax collection in the future to repay the debt. This behavior offsets the increase in the government spending component of the aggregate demand due to a reduction in consumption and investment, thereby translating to a lower level of stock purchases, placing downward pressure on stock prices. Furthermore, classical economic theory also supports a contractionary effect of fiscal spending on stock prices. This occurs when the government finances its budget deficit by borrowing from the private sector, increasing competition for the domestic pool of funds. This places an upper pressure on real interest rates, resulting in loanable funds becoming more expensive. This can discourage the investment component of the aggregate demand, causing a decline in stock prices.

A closely-related paper on fiscal policy with factors is by Laumer (2020), who estimated the IRFs of consumption to a government spending shock using a Factor-Augmented VAR (FAVAR) model with stationary factors. The author estimated a model within Bayesian framework and follows a sign restriction identification method, with the assumption that signs alone are enough to identify structural parameters. The literature documents some shortcomings in using sign-restriction identification in structural inference. First, sign restriction identification suffers from issues of masquerading shocks, a situation in which some elements of the identified sets of the VARs induce 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). Second, 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) ignore cointegration among the factors and estimated IRFs using difference data, but differencing the data throws away useful macroeconomic information.

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

Alessi and Kerssenfischer (2019) investigate how asset prices respond to monetary policy shocks in the U.S. and the Euro Area using a dynamic factor model. Their results show that asset prices respond in a stronger and quicker fashion in comparison to a benchmark VAR model. They employ DFM because it significantly enlarges the information set compared to a standard VAR and adopt the nonstationary DFM framework by Barigozzi, Lippi, and Luciani (2016 a, b). The authors compare the response of a stock and house prices applying a small-scale VAR and DFM. Although, the authors use the same instrument to identify monetary policy shocks, the results from using both the VAR model and DFM are different in the U.S. and Euro Area. The results from the DFM show that asset prices respond strongly to a monetary policy shock, but the results from small-scale VAR produces counter-intuitive responses. They conclude that DFM should be adopted in empirical applications aimed at identifying monetary policy shocks because it captures a amount of large information that is important in the decision-making of central banks.

Afonso and Sousa (2011) investigate the effect of fiscal policy on asset prices in a SVAR model. Using quarterly data from 1971 to 2007, the authors adopt recursive identification and examine the response of asset markets to a fiscal policy shock using data from Germany, Italy, the UK and the U.S. They find that government spending shocks causes a fall in both 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 show that stock prices and house prices respond negatively to a positive fiscal shock.

3 Model Specification

To estimate the model, I use a Dynamic Factor Model (DFM) following Stock and Watson (2016) and Barogozzi et al.(2021). In the DFM, each variable in the dataset of dimension N are decomposed into a common component and idiosyncratic components. The model starts with an $N \times 1$ vector of variables specified as follows:

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

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

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

$\xi_{\mathbf{t}} \sim N(0, \Psi)$ 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, and $\eta_{\mathbf{t}} = (\eta_{1t}, \ldots, \eta_{rt})'$ is the $r \times 1$ vector of uncorrelated innovation to the common factors. 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 $r \times r$ dimension structural impact matrix, which is invertible, and is used to identify the structural shocks from the factor innovations. The model specified in Equation (1)-(3) represents the static form of the DFM, which depends on the r number of static factors, $\mathbf{F_t}$, and dynamic shocks.

3.1 Estimation

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

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

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 is denoted by $\mathbf{\Lambda A}(\mathbf{L})^{-1}\mathbf{H}$. One advantage of a Structural DFM (SDFM) is that more variables can be included in the model and the number of variables can be greater than the number of shocks when estimating the IRFs. For the case where the focus is on the first shock only, the SIRF will be given as $\mathbf{\Lambda}(\mathbf{AL})^{-1}\mathbf{H}_1$, where $\mathbf{H_1}$ is the first column of matrix $\mathbf{H}$ (Stock and Watson, 2016). I follow 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 an unrestricted VAR in levels.

3.2 Factor Normalization and Estimation

Since Equation (1) is not identified, a 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 $\mathbf{F}$, is defined as a sequence of such that $\mathbf{F} = \{F_1, F_2, \cdots F_T\}$ and $\mathbf{\Sigma_F}$ 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

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

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,the 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). Therefore, the first factor is assigned to the first variable so that the common component of $\mathbf{X_{1t}}$ is $\mathbf{F_{1t}}$. I thereby order government spending first so that the normalization corresponds to the innovation in the first factor. The first factor represents the government spending factor and the innovation in the first factor become 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 G_t is ordered first in X_t followed by the remaining variables in the model so that the first factor corresponds to the government spending factor labelled F_t^G.

3.3 Estimating the Number of Factors and Dynamic Shocks

There are several methods to determine the number of factors that needs to be included in the model. The method can be determined by a combination of prior knowledge, information criteria, or by using scree plots. When using scree plots, the number of factors is selected using the marginal contribution of the next consecutive factor. Theoretically, information criteria can also be used to determine the number of factors. I use the information criteria developed 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 ($\hat{\Lambda}$ and $\hat{F}$), $g(N,T)$ 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 the Estimation of IRFs

To estimate IRFs in the presence of cointegrated vectors, I estimate 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) show that IRFs from a vector error correction model (VECM) are similar to those obtained from specifying an unrestricted VAR in levels using recursive identification. The simulation results in Barigozzi et. al. (2021) also show 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 follow Barigozzi et al.(2021) to estimate an unrestricted VAR in levels using Equation (2). The choice of estimating an unrestricted VAR in levels is also motivated by Gospodinov, Herrera, and Pesavento (2013).

A unit effect normalization is then applied in addition to the named factor normalization to link the innovation in the first factor to the structural shock in order to allow us to identify the government spending factor. The matrix $\mathbf{H}$ is identified by imposing $r(r-1)/2$ 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 the Cholesky identification, government spending is ordered first, which assumes that the government spending shock is the only shock that has contemporaneous effect 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 $\mathbf{H}$. Since we want to identify only the 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 Equation (6), which gives us the named factor normalization on $\mathbf{\Lambda}$. The estimated IRF of shock j on variable i at time k defined as

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

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 $\widehat{\mathbf{A}}_k^{\text{VAR}}$ is the VAR estimate of $\mathbf{A}(L)$.

3.5 Summary of Steps

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

2. Using $\hat{\mathbf{F}}_{\mathbf{t}}$, an unrestricted VAR model in Equation (2) is employed 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 the information criteria by Bai and Ng (2002).

3. The VAR residuals $\hat{\eta}_t$ are then used to estimate $\mathbf{H}$ following the identification restrictions in

Equation (6), where **H** has a lower triangular structure. This is done using the Cholesky decomposition with **H** having a value of 1 as elements on its diagonal.

4 Data

The dataset consist of 207 quarterly observations representing the U.S. economy. The time series variables range 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 the Stock and Watson (2016) dataset, which has 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. My dataset therefore spans the period 1985Q1-2021Q4. The start date for my sample is 1985 because of the "great moderation" where the U.S. economy experienced a structural break. Structural breaks can lead to overestimation of the number of factors and may also cause an inconsistent estimation of the factor loadings [Stock and Watson (2016); Breitung and Eickmeier (2011)]. The S&P 500 is the index used in measuring stock price, and government spending is a measure of fiscal policy. All $I(1)$ variables are not transformed, however for $I(2)$ variables, first differences were taken.

5 Results

In this section, I present the results of the model. It includes a test on the number of estimated factors, the IRFs of government spending shock, variance decomposition, and a 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 follow Bai & Ng (2002)'s information criteria and select the number of factors r to be 7.

Table 1: Determining the Number of Factors

r	Bai & Ng-IC$_p$
1	−0.179
2	−0.213
3	−0.246
4	−0.273
5	−0.268
6	−0.240
7	**−0.284**
8	−0.228
9	−0.215
10	−0.180

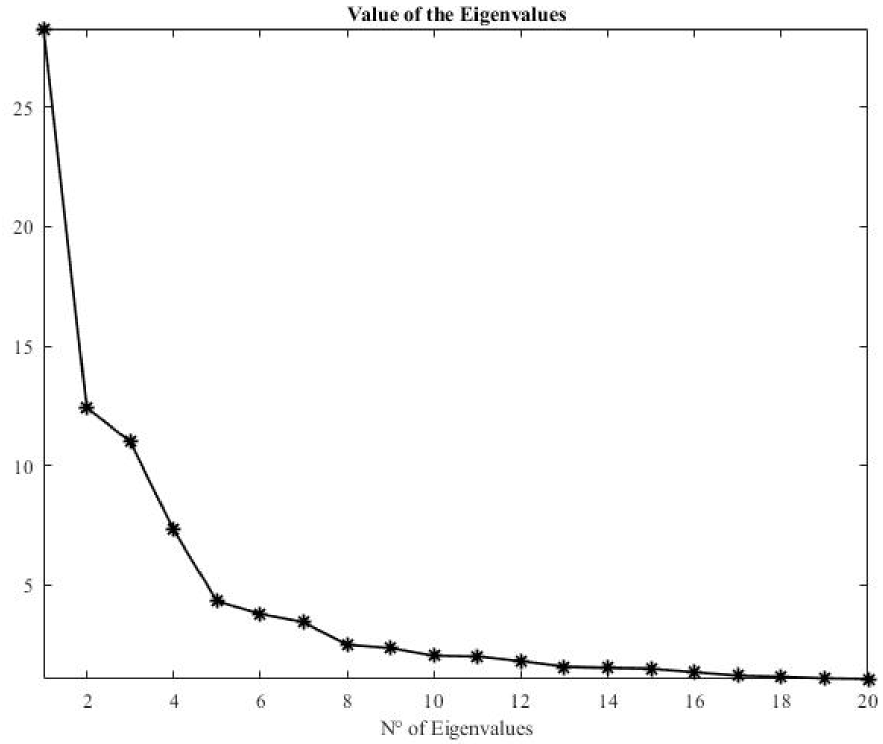


Figure 1: Scree Plot of the Number of Factors

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 results for 1,2, 4, and 7 common factors. According to Table 2, the first factor explains all the variation in government spending because it is the government spending factor. It also explains a good amount of variation in the consumption, including real GDP as well as employment. Also, all factors explain large variations in important macroeconomic indicators, which indicates that the model captures important movements in the business cycle.

Table 2: Importance of Common Factors for Selected Variables

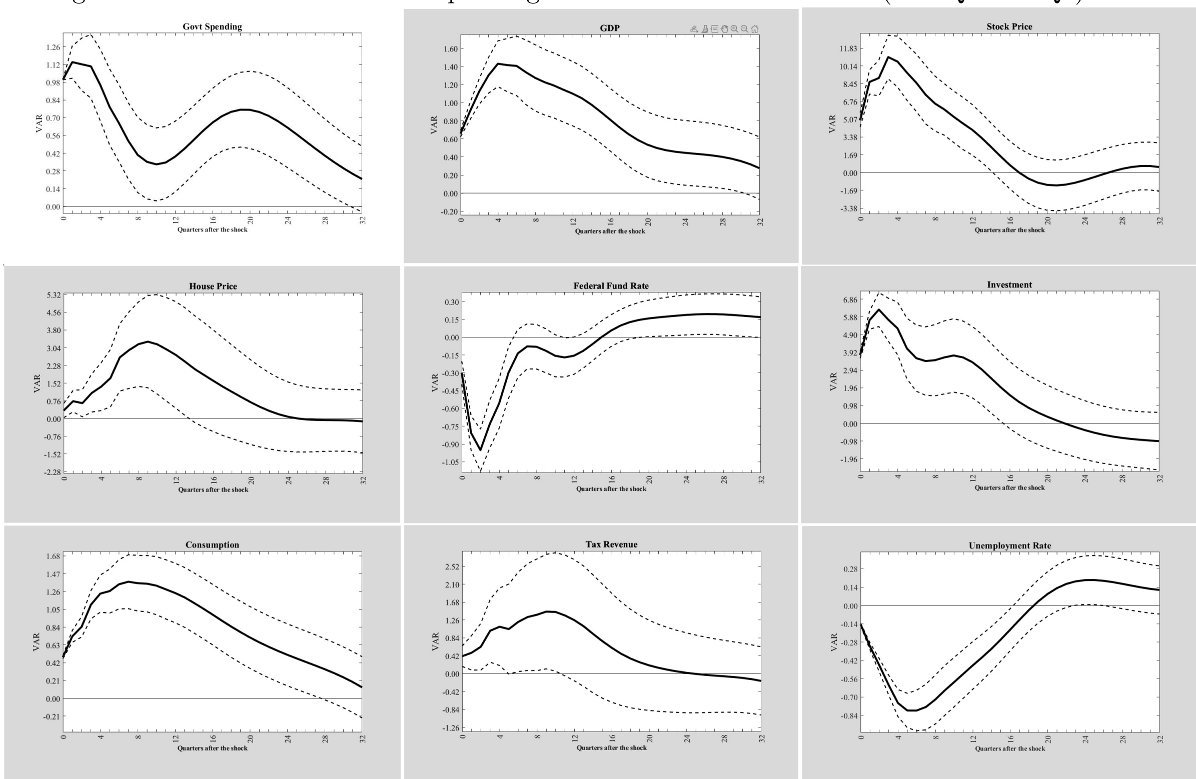
R^2 of Number of Factors

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
House Price	0.17	0.19	0.46	0.54
GDP Deflator	0.25	0.08	0.11	0.15

5.2 Impulse Response of Government Spending Shock

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

Figure 2: IRFs of a Government Spending Shock on Selected Variables (1985Q1-2021Q4).



The results show that both the stock price and house price respond positively to a government spending shock. Interest rate (federal fund rate) responds negatively to a government spending shock, causing investment to rise. This result is in line with Keynesian theory showing how expansionary fiscal policy (government spending) leads to an increase in economic activity, which in turn increases demand for financial assets (stocks) resulting in a rise in stock price. Individuals have a greater opportunity to invest in the capital market, pushing up the demand for stocks, which raises the prices of stocks in the market. Another transmission channel is when government spending causes an increase in money supply in circulation, which lowers interest rates. Lower interest rates increase demand for stocks, thereby raising the prices of stocks. This is depicted in the results of the impulse response function in Figure 2. My result is different from those find in Agnello and Sousa (2013), who find that a positive fiscal shock has a negative impact on both stock and housing prices. Also, Afonso and Sousa (2011) find a negative response of stock and house price to shocks in government spending for the U.S. using a Panel VAR for 10 industrialised countries. My findings are in line with the Keynesian economic prediction, which shows that an increase in government spending causes a rise in the demand for financial assets. This implies that an expansionary fiscal policy shock does not depress the stock and housing markets as purported by Afonso and Sousa (2011) and Agnello and Sousa (2013).

From the results above, output and consumption respond positively to a government spending shock, which supports the Keynesian view on the effect of an increase in government spending. This finding is also in line with the results of Fisher and Peters (2010), Zeev and Pappa(2017), and Gali et.al (2007); however it contradicts Mountford and Uhlig (2009); who uses SVAR with sign restriction identification. I also compare my results to Laumer (2020) in a stationary DFM case. Even though Laumer (2020) finds a positive effect of a government spending shock on real GDP, consumption, tax receipts and GDP deflator, the IRFs show persistent behavior, a phenomenon that is attributed to stationary data. Since I specify a VAR in levels for non-stationary factors, I overcome the problem of obtaining generic long-run effects of a government spending shock on the levels of the variables. This points to the importance of accounting for cointegration among the common factors. Unemployment on the other hand shows a negative impact to government spending shock; because an increase in government spending increases economic activity through high employment, unemployment therefore 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 a 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, a government spending shock explains a substantial fraction (75%) of the one-step ahead forecast error of government spending. Also, government spending shocks explain 70% of GDP's forecast error variation, 35% of consumption, and 56% of fixed investment. In addition, the government spending shocks explain 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.

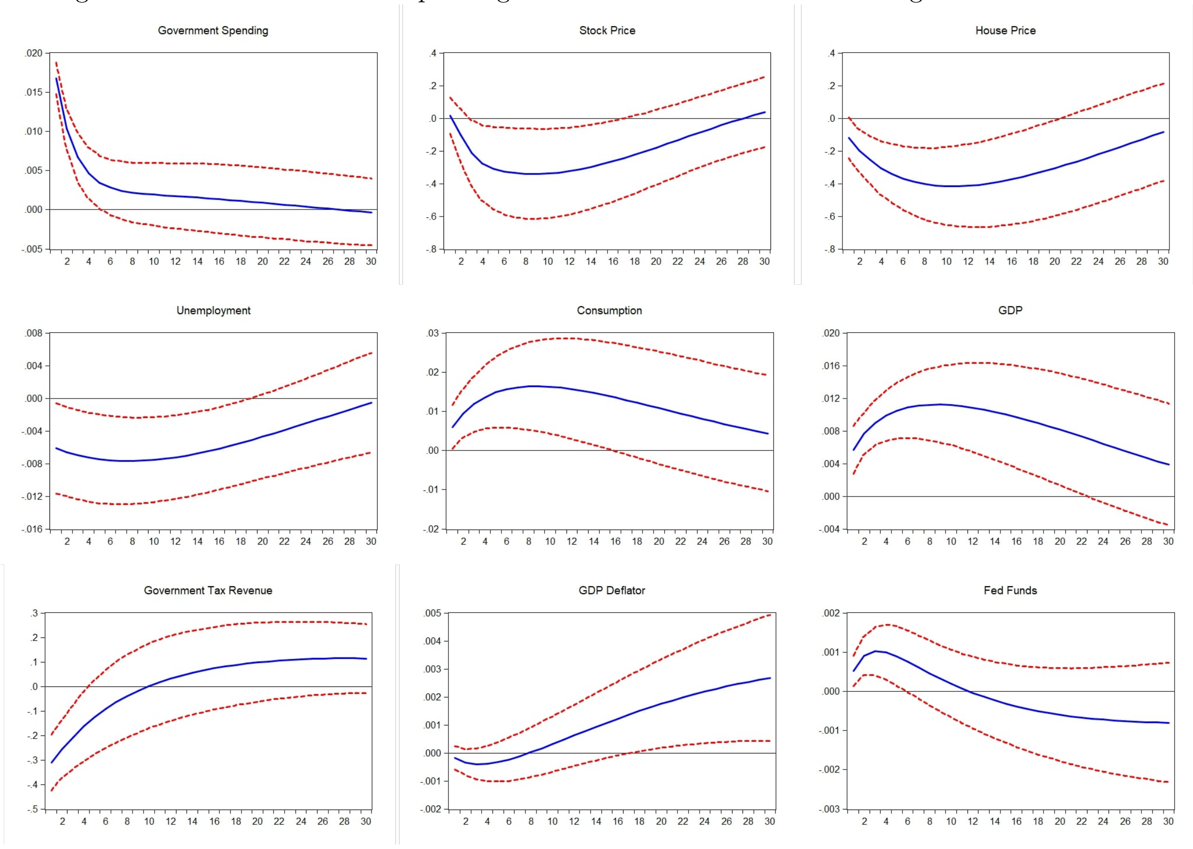
5.4 Robustness Check using Full Sample Data (1959Q1-2021Q4)

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, which shows the sub-sample (1985Q1-2021Q4) result. Stock price and house price both respond positively to a government spending shock. Consumption and output also show a positive response to government spending shock. Even though the initial impact on output is small, it begins to rise and peaks after 8 quarters. Unemployment responds negatively to a government spending shock as expected. These results show that the effect of a government spending shock produces similar results compared to estimates from the sub-sample. Therefore, using the sub-sample data does not change the response of variables considered in the model to a government spending shock. The full-sample results reinforce my main results.

5.5 Impulse Response Function using a SVAR Model (Comparison)

In this section, I present the replication of Afonso and Sousa (2011)'s SVAR model for comparison purposes and the result is present in Figure 4. I follow their identification strategy and the ordering of variables in their SVAR model. The result from the IRFs indicate that stock prices and house prices respond negatively to a government spending shock as stated in Afonso and Sousa (2011). This result is different from the results I obtain using the structural DFM (SDFM). Using SDFM, I find a positive response of stock price and house prices to government spending shocks. The difference in the results between SVAR and SDFM is attributed to the 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 the estimation of distorted IRFs. As noted in the literature, Bernanke and Kuttner (2005) and Nakamura and

Figure 3: IRF of Government Spending Shocks on Selected Variables using SVAR Model



Steinsson, 2018) show that incorporating a large information set in a dynamic factor model leads to estimating significant effects as compared to a benchmark VAR.

6 Conclusion

This paper investigates the response of asset prices (stock price and house price) to a government spending shock within the framework of a dynamic factor model with cointegrated factors. The number of factors and shocks are selected using the Bai and Ng (2002) information criteria 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, which implies that government spending does not depress both stock and housing markets as suggested by Agnello and Sousa (2013). The transmission channel of my results is that an increase in government spending causes an increase in money supply in circulation, which lowers the interest rates. Lower interest rates increase the demand for stocks, thereby raising the price of stocks. House prices also increase due to increase in consumer spending resulting from an increase in aggregate demand. Output also responds positively to a government spending shock, which is in line with the Keynesian prediction. Unemployment responds negatively to a government spending shock, which 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 loss 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 the IRFs of a fiscal policy shock.

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