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

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July 10, 2023

**Abstract**

This paper investigates the effects of fiscal policy on asset prices using structural dynamic factor model (SDFM) with cointegrated factors. In this paper I estimated the impulse response functions (IRFs) of stock price and house price to fiscal policy shocks using 207 quarterly variables about the U.S economy. I identify fiscal shock using narrative approach. specifically I use military spending (war dates) as a fiscal policy variable. The results of the IRFs shows that both stock price and house price responded positively to fiscal shock and the effects were persistent. The results implies that fiscal policy leads to a boom in housing and stock markets. This paper highlighted that data-rich models are important role in obtaining true IRFs as they provide more accurate representation of economic concepts.

**JEL Codes**: E2, C32, E62.

**Keywords**: Fiscal policy, Military spending, asset prices, dynamic factor model, cointegration, impulse response, factor normalization.

This paper has benefited greatly from extensive comments from Prof. Elena Pesavento. I also thank Prof. Juan Rubio and Prof. Kaiji Chen for his comments in shaping this paper. I acknowledge and appreciate the tremendous feedback from my colleagues, and participants of the 2023 ASSA-AEA Annual meetings and the Atlantic Economic Conference for their useful comments and suggestions.

# 1 Introduction

The behavior of asset prices is an important factor influencing the decision-making of financial institutions and policymakers. There exists 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, more emphasis has been placed on fiscal policy since the zero lower-bound period. The theoretical understanding of stock markets' reaction to fiscal policies has been set out in a series of papers ( Shah, 1964; Blanchard, 1981; and Charpe et al., 2011), in which 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 output (Keynesian, Classical, or Ricardian; see Barnheim, 1989). This provides the premise for empirical investigation. Furthermore, the housing markets can be influenced by fiscal policy through various channels, including the taxation of housing capital gains and the imputed rental value, as well as value-added taxes (VAT) imposed on the acquisition of new houses. Also, the demand for houses and housing prices can be affected by the tax deductibility of mortgage payments and housing rents, as these factors influence households' disposable income.

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 prices 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 motivation for using a Structural Dynamic Factor Model (SDFM) over SVAR is that large datasets span the space of structural shocks better than SVAR. The literature highlights that small-scale VAR 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. 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. Moreover, small-scale SVARs may face the drawback of excluding several macroeconomic variables that are significant in the propagation 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 fiscal policy shocks. I identify fiscal policy shocks using narrative approach within the Dynamic Factor Model (DFM) framework. The results show that stock prices and house prices respond positively to a expansionary fiscal policy shock. The result implies that fiscal policy 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 fiscal policy 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 allowing the factors to be non-stationary and possibly cointegrated.

The contribution of this paper is combining two important econometric methods (cointegration and dynamic factor models) to estimate the response of asset prices (stock prices and house prices) to fiscal policy shocks by applying narrative identification method. Also, this paper demonstrates the relevance of data-rich models when estimating the IRFs of a fiscal policy shock. 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 ("data-rich"), few factors can capture the dynamics in the economy, and their residuals are explained by idiosyncratic components (Stock and Watson, 2016). In addition, I estimate unrestricted VAR in levels to account for cointegration. Ignoring cointegration and specifying a VAR model 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)]. The paper is organized as follows. In Section 2, I provide literature review on theoretical relationship between fiscal policy and asset prices, and some empirical application of the dynamic factor models. Section 3 describes the model specification. Results and robustness checks are provided in Section 4, and Section 5 concludes

## 2 Literature Review

Different economic theories propose varying relationships between fiscal policy and the stock market. In the Keynesian perspective, an increase in government spending can cause a rise in disposable income, providing individuals with more opportunities to invest in the capital market. Consequently, the demand for stocks increases, resulting in higher stock prices. This implies a positive effect of government spending on stock prices. Furthermore, heightened fiscal measures boost consumer confidence and consumption levels, leading to increased sales and earnings for companies, thereby driving stock prices higher. Conversely, the Ricardian view suggests that fiscal policy has no impact on stock prices. According to this view, government attempts to stimulate economic growth through debt-financed spending are ineffective because individuals anticipate higher future tax collections to repay the debt. Such anticipation reduces consumption and investment, counteracting the positive effect of government spending and causing a decline in stock purchases, consequently exerting downward pressure on stock prices. Classical economic theory supports the notion that fiscal spending has a contractionary effect on stock prices. When the government finances its budget deficit by borrowing from the private sector, it competes for domestic funds, driving up real interest rates. As a result, loanable funds become more expensive, discouraging investment, and leading to a decrease in stock prices. Previous research has empirically examined the impact of fiscal policy shocks on asset prices. For example, Afonso and Sousa (2011) investigated the effect of fiscal policy on asset prices using a SVAR model. Analyzing quarterly data from 1971 to 2007 in Germany, Italy, the UK, and the U.S., they found that government spending shocks resulted in declines in both housing and stock prices. Similarly, Agnello and Sousa (2013) studied how asset markets responded to fiscal policy using a panel VAR of ten industrialized countries. Their findings indicated that positive fiscal shocks led to negative responses in stock prices and house prices.

Within the frame work of dynamic factor model, Laumer (2020), the author 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). In addition, Laumer (2020) ignores possible cointegration among the factors and estimated IRFs using difference data, which may throw away useful macroeconomic information.

Also, 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 transitory effect of oil price on US economic activity (GDP, Consumption and Investment). That is, the effect of oil price shock dies off after 5 years. 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).

In addition, 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 stock prices and house prices using a small-scale VAR and a DFM. The authors identify monetary policy shock using monetary policy instrument. Specifically, the authors used the German Bobl future as instrument in the euro area, with a time span of 10 minutes prior to the press release to 20 minutes after the press release. For US, the authors use the change in the 3-month-ahead federal funds future 10 minutes prior to 20 minutes after FOMC announcements. Although the authors use a similar instrument to identify monetary policy shocks, the results from 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 large amount of information that is important in the decision-making of central banks.

## 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:

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

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

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

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

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 $\epsilon_t$ 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 $\mathbf{\Lambda A}(\mathbf{L})^{-1}\mathbf{H}_1$, 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 $\mathbf{N^{-1}\Lambda'\Lambda} = \mathbf{I_r}$ 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:

$$\min_{\mathbf{F},\mathbf{\Lambda}} V_r(\mathbf{\Lambda}, \mathbf{F}), \tag{5}$$

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 principal component 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 "military dates" factor. In the named factor normalization restriction, the factors are estimated by constraining the first loading to be equal to $\Lambda_1$. The named factor normalization is specified as:

$$\mathbf{\Lambda^{NF}} = \begin{bmatrix} \mathbf{\Lambda_1} \\ \mathbf{\Lambda^{NF}_{r+1:n}} \end{bmatrix}. \tag{6}$$

where $\mathbf{\Lambda_1} = (1 \quad 0 \ldots 0)$

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 military dates variable first so that the normalization corresponds to the innovation in the first factor. The first factor represents the military dates factor and the innovation in the first factor become innovations in the military dates factor.

The ordering of the variables in $\mathbf{X_t}$ is specified below:

$$\begin{pmatrix} M_t \\ \mathbf{X_{2:n,t}} \end{pmatrix} = \begin{pmatrix} \Lambda_1 \\ \mathbf{\Lambda_{2:n}} \end{pmatrix} \begin{pmatrix} F_t^M \\ \mathbf{F_{2:r,t}} \end{pmatrix} + \begin{pmatrix} \xi_{1t} \\ \xi_{2:n,t} \end{pmatrix}. \tag{7}$$

Here, the military dates variable, $M_t$ is ordered first in $\mathbf{X_t}$ followed by the remaining variables in the model so that the first factor corresponds to the "military dates" factor labelled $F_t^M$. Additional restrictions (see Section 3.5) allows us to use the named factor normalization to identify fiscal policy shock.

## 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.

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

where $V_r(\hat{\mathbf{\Lambda}}, \hat{\mathbf{F}})$ is the objective function of the principal components evaluated at ($\hat{\mathbf{\Lambda}}$ and $\hat{\mathbf{F}}$), $g(N,T)$ 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 Estimation of Impulse Response Functions

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 $\phi_{ijk}$ 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). This is also motivated by Gospodinov, Herrera, and Pesavento (2013).

### 3.5 Identification of Government Spending Shocks

The main challenge in the fiscal policy literature is the identification of fiscal policy shock. It is important for the fiscal policy variable to be exogenous to measure the effect of unanticipated shock. I follow Ramey and Shapiro (1998)'s narrative identification approach by identifying fiscal policy shock using military spending corresponding to the major military build-ups. Because military buildups occurs unexpectedly, they are able to capture the unanticipated movements in government spending, and are likely to be exogenous (Ramey, 2011). The military dates variable takes a value of unity in 1950:3, 1965:1, 1980:1, and 2001:3, and zeroes elsewhere, representing the four episodes of military buildups. Hence, the military dates variable is used as a measure of fiscal policy in the model. To estimate equation (1), the "military dates" variable is ordered first before the other variables in $\mathbf{X_t}$ as specified in Equation (7). The unobserved factors are then estimated by minimizing Equation (5) and applying the named factor normalization in Equation (6).

I then proceed to estimate an unrestricted VAR model in Equation (2) using $\hat{\mathbf{F}}_{\mathbf{t}}$, to obtain the estimates of the residuals $\widehat{\eta}$ and the lag polynomials $\widehat{\mathbf{A}}(\mathbf{L})$. The VAR residuals $\hat{\eta}_t$ are then used to estimate $\mathbf{H}$ following the identification restrictions in Equation (11), where $\mathbf{H}$ has a block triangular structure. Equations (4) is the unidentified IRFs, which represents the effect of structural shocks on observable variables, re-written as:

$$\Lambda \mathbf{A}(\mathbf{L})^{-\mathbf{1}}\mathbf{H}\epsilon_{\mathbf{t}} = \mathbf{\Omega}(\mathbf{L})\mathbf{H}\epsilon_{\mathbf{t}} \tag{8}$$

where $\mathbf{\Omega}(\mathbf{L})$ represents $\mathbf{\Lambda A}(\mathbf{L})^{-\mathbf{1}}$ with $\mathbf{\Omega}(\mathbf{L})\mathbf{H}$ capturing the impact of structural shocks, $\epsilon_{\mathbf{t}}$ on observable variables in $\mathbf{X_t}$. The goal here is to identify the matrix $\mathbf{H}$, which links the reduced-form shocks $\eta_{\mathbf{t}}$ to the structural shocks $\epsilon_{\mathbf{t}}$ in Equation (3). In the literature, $\mathbf{H}$ is usually identified by imposing zero restrictions on the contemporaneous effect of structural shocks on observable variables. Specifically within the VAR framework, to achieve identification, the covariance matrix of the reduced-form shocks is decomposed into a lower triangular matrix (Cholesky Decomposition).

In this paper, to identify the $\mathbf{H}$ matrix, Equation (3) is rewritten as follows:

$$\eta_{\mathbf{t}} = \mathbf{H}\epsilon_{\mathbf{t}} = [\mathbf{H_1} \dots \mathbf{H_q}] \begin{pmatrix} \epsilon_t^m \\ \vdots \\ \epsilon_t^q \end{pmatrix} \tag{9}$$

where $\mathbf{H_1}$ is the first column of $\mathbf{H}$, and $\epsilon_t^m$ is the first structural shock, that is the military dates shock. With fiscal policy shock, $(\epsilon_t^m)$ being the shock of interest, we only need to identify $\mathbf{H_1}$.
From Equation (9), we have,

$$\eta_{\mathbf{t}} = \begin{bmatrix} \mathbf{H_1} & \mathbf{H_\bullet} \end{bmatrix} \begin{pmatrix} \epsilon_t^m \\ \widetilde{\epsilon}_{\bullet t} \end{pmatrix} = \begin{pmatrix} H_{11} & H_{1\bullet} \\ H_{\bullet 1} & H_{\bullet\bullet} \end{pmatrix} \begin{pmatrix} \epsilon_t^m \\ \tilde{\epsilon}_{\bullet t} \end{pmatrix} \tag{10}$$

with $\mathbf{H_1}$ representing the column of interest and $\mathbf{H_\bullet}$ representing the remaining columns which are irrelevant in identifying $\mathbf{H_1}$ (see Kerssenfischer (2019); Stock and Watson (2016); Barigozzi et al., (2021)). In the DFM framework, I identify matrix $\mathbf{H}$ by imposing zero restriction identification. This partially identifies the first column $\mathbf{H_1}$ without the need to identify the other columns $\mathbf{H_\bullet}$. In economic terms, this identification implies that military dates shock is not contemporaneously affected by other shocks in the model and matrix $\mathbf{H}$ has a block triangular structure [see Stock and Watson (2016), Barigozzi et al., (2021) and Alessi and Kerssenfischer (2019)].
After identifying matrix $\mathbf{H}$, the unit effect normalization is imposed on $\mathbf{H}$. This implies that a unit increase in $\epsilon_t^m$ induces a contemporaneous unit increase in a specific variables of interest in $\mathbf{X_t}$ (see Stock and Watson, 2016). Specifically, the unit effect normalization sets $\mathbf{H_{jj}} = 1$ where a unit increase in $\epsilon_t^m$ increases $\eta_t$ by one unit, which in turn increases $\mathbf{X_t}$ by one unit. Applying unit effect normalization to Equation (10), we have:

$$\begin{pmatrix} \eta_t^m \\ \eta_{\bullet t} \end{pmatrix} = \begin{pmatrix} 1 & \mathbf{0} \\ \mathbf{H_{1\bullet}} & \mathbf{H_{\bullet\bullet}} \end{pmatrix} \begin{pmatrix} \epsilon_t^m \\ \widetilde{\eta}_{\bullet t} \end{pmatrix}, \tag{11}$$

where the unit effect normalization is imposed on the coefficients on the diagonal of $\mathbf{H}$. Now that matrix $\mathbf{H}$ is identified, and unit effect normalization is imposed, the IRFs of shock $j$ on variable $i$ at time $k$ can be computed as:

$$\widehat{\phi}_{ij,k}^{\text{VAR}} = \widehat{\lambda}_i' \left[\widehat{\mathbf{A}_k}^{\text{VAR}}\right]^{-1} \widehat{\mathbf{h}}_j, \tag{12}$$

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 $\mathbf{A}(L)$.

# 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. I extend the Stock and Watson (2016) dataset to cover the period up to 2021Q4. My dataset therefore spans the period 1947Q1-2021Q4. The "military date" variable is the measure of fiscal policy, and takes a value of unity in 1950:3, 1965:1, 1980:1, and 2001:3, and zeroes elsewhere. The S&P 500 is the index used in measuring stock price. 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 fiscal policy 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. 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** | $\mathbf{-0.284}$ |
| 8 | $-0.228$ |
| 9 | $-0.215$ |
| 10 | $-0.180$ |

Notes: This table shows number of factors and their respective information criteria. The Bai & Ng information criteria selects 7 as the optimal number of factors to be included in the model.

Table 2: Importance of Common Factors for Selected Variables

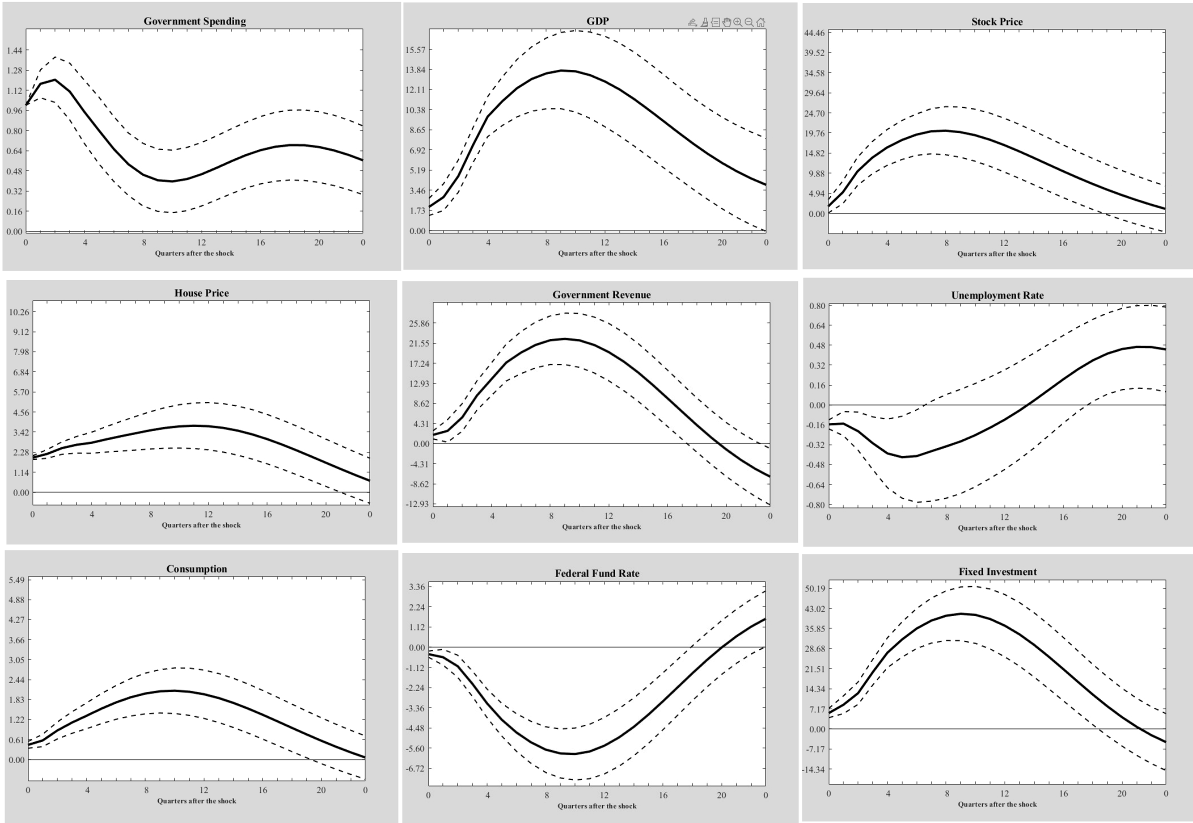
$R^2$ of Number of Factors

| Series | Factor 1 | Factor 2 | Factor 4 | Factor 7 |
|---|---|---|---|---|
| Real GDP | 0.36 | 0.70 | 0.75 | 0.80 |
| Consumption | 0.20 | 0.55 | 0.60 | 0.58 |
| Investment | 0.32 | 0.40 | 0.5 | 0.51 |
| Government Spending | 0.85 | 0.72 | 0.81 | 0.84 |
| Tax Revenue | 0.38 | 0.42 | 0.40 | 0.56 |
| Unemployment Rate | 0.27 | 0.61 | 0.73 | 0.65 |
| Employment Nonfarm | 0.21 | 0.85 | 0.86 | 0.82 |
| Fed Funds | 0.05 | 0.21 | 0.33 | 0.48 |
| S&P 500 | 0.09 | 0.30 | 0.47 | 0.68 |
| House Price | 0.12 | 0.19 | 0.46 | 0.54 |
| GDP Deflator | 0.28 | 0.18 | 0.13 | 0.17 |

Notes: Table 2 displays the contribution of selected factors in explaining variations in some variables in the model. The contribution of the factors are measured by their $R^2$ values.

In Table 2, the contribution of the factors are the $R^2$ values. I present results for 1,2, 4, and 7 common factors. According to Table 2, the first factor (military date factor) explained 85% of the variation in government spending. It also explains 20% of the variation in the consumption, 36% in real GDP and 21% in employment. Also, all other factors explain large variations in important macroeconomic indicators, which indicates that the model captures important movements in the business cycle.

Figure 1: IRFs of a Fiscal Policy (Military Dates) Shock on Selected Variables




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

## 5.2 Impulse Response of Fiscal Policy Shock

The results in Figure 1 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 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 that fiscal policy shock increases 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 1. My result is different from those found in Agnello and Sousa (2013), where positive fiscal shock had a negative impact on both stock and housing prices. Also, Afonso and Sousa (2011) found 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 results shows 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 fiscal policy shock, which supports the Keynesian view. This findings 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) found 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 fiscal policy shock.

## 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 fiscal policy shock. Table 3 displays the contribution of the fiscal policy 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 |

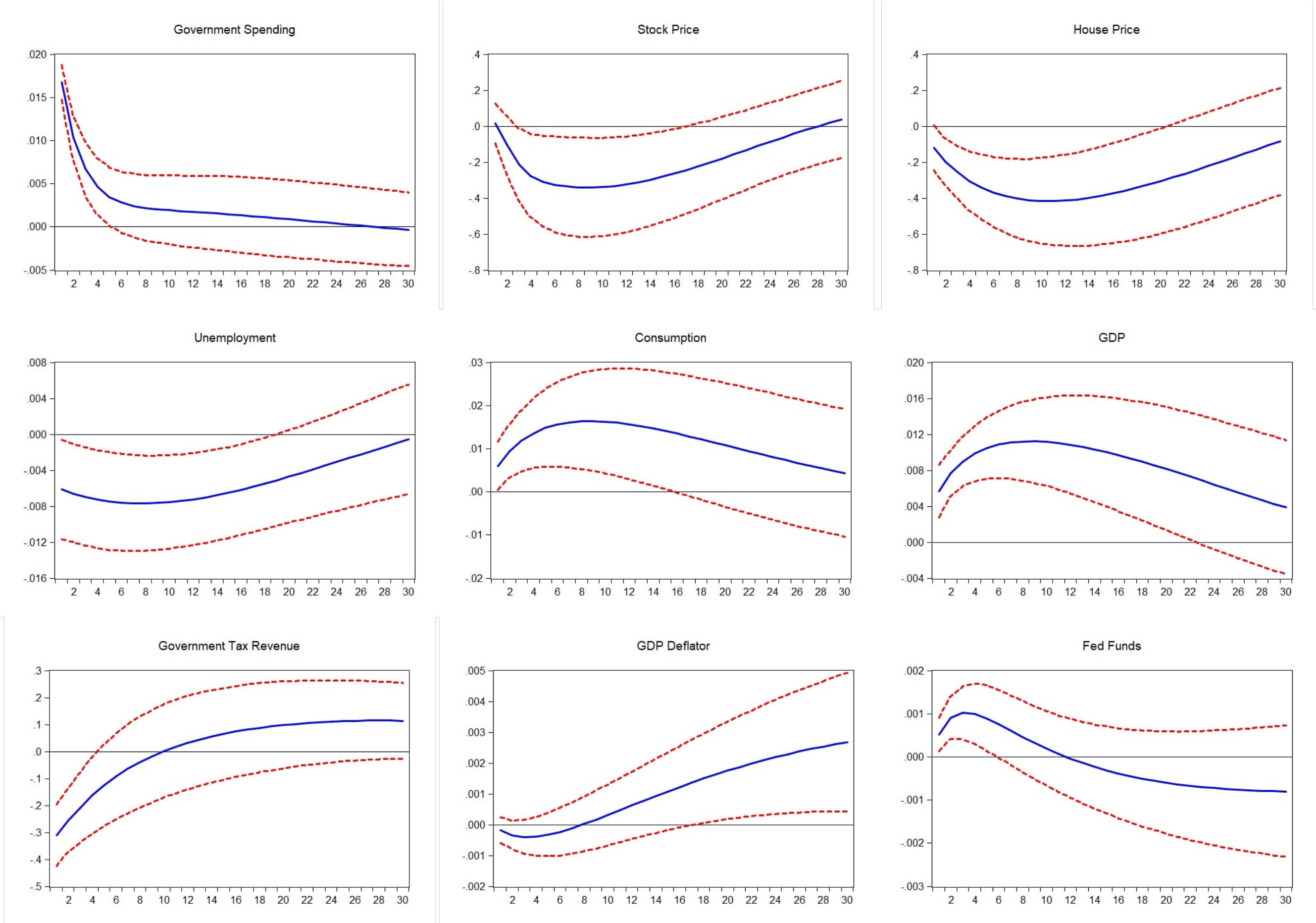
Notes: Table 3 displays the contribution of government spending shock in explaining variations in the forecast error variance of selected variables in the model.

Table 3 shows that 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 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 3. 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. As noted in the literature, Bernanke and Kuttner (2005) and Nakamura and 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. The DFM framework is able to incorporate large amounts of information set in the model which mitigates biases from mis-specification and insufficient information. De Nora (2021) compared VAR model to FAVAR model for a monetary policy study using narrative identification and found that data-rich FAVAR resolve the "price puzzle", where expansionary monetary policy leads to price fall (more in line with economic theory) than price increase usually found within the VAR framework with Cholesky Identification. As pointed out by De Nora (2021) if any relevant information in the model is erroneously omitted, it will be absorbed into the reduced-form residuals, which can produce bias and distorted IRFs. Also, using large datasets also resolves the invertibility problem inherent in VAR model (Stock and Watson, 2018). In addition, a large information set comprises rich information about the economy and provides a more accurate representation of economy. Also, IRFs can be observed for many variables of interest, which help in uncovering the transmission of the shock through the economy.

Figure 2: IRF of Government Spending Shocks on Selected Variables using SVAR Model




The blue line is the IRF estimated with the SVAR model, and the red dotted lines are the 68% confidence band.

The x-axis represents quarters after the shock, and the y-axis represents the percentage points

# 6 Conclusion

This paper investigates the response of asset prices (stock price and house price) to fiscal policy shock within the framework of a dynamic factor model with cointegrated factors. The number of factors are selected using the Bai and Ng (2002) information criteria. The result shows that a positive fiscal policy shock has a positive effect on stock prices and house prices, which implies that fiscal policy 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 fiscal policy 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 fiscal policy shock, which is in line with the Keynesian prediction. Also, this paper demonstrates the relevance of data-rich models when estimating the IRFs of a fiscal policy shock.

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