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Government spending news and stock price index

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Abstract

In this paper, we investigate the effects of US federal spending news on the S&P 500 stock price index. Unlike previous studies, we model news based on actual spending bills signed by the US President and focus on a period of important spending changes in US history (January 2000 - December 2022). Using a Mixed Frequency Time-Varying Parameters Factor Augmented Vector Autoregressive (MF-TVP-FAVAR) model, we find a negative impact of spending news shock on the S&P 500 index. We ascertain the robustness of our result using the Nasdaq and Dow Jones stock price indices as well as estimates from a Bayesian VAR model.

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1 Introduction

Macroeconomic policy, including fiscal and monetary policy news, is considered a major source of stock market volatility (Baker et al., 2019). A vast literature investigates the effects of monetary policy shocks on stock market volatility (Fama and French, 1989; Gertler and Gilchrist, 1993; Jensen and Johnson, 1995; Thorbecke, 1997; Patelis, 1997; Conover et al., 1999; Bjørnland and Leitemo, 2009; Laopodis, 2010). Relatively fewer studies focus on the stock market's response to fiscal policy (Darrat, 1988; Jansen et al., 2008; Agnello et al., 2013; Afonso and Sousa, 2011, 2012; Van Aarle et al., 2003). Indeed, fiscal policy news involving tax or government spending changes alters the anticipated profits and real interest rates, leading investors to modify their asset holdings.(Blanchard, 1981; Stoian and Iorgulescu, 2020).

Fiscal policy effects on stock prices are ambiguous and depend on whether the changes in expected real interest rates dominate those in expected profits as evidenced by Structural Vector Autoregressive (SVAR) models. Darrat (1988) uses a multiple regression analysis on Canada between the first quarter of 1960 to fourth quarter of 1984, detecting significantly large declines in current stock prices following increases in the fiscal deficit. Ardagna (2009) uses a panel data model on OECD countries between 1960 and 2002, estimating an increase in stock market prices after reductions in government expenditure. Afonso and Sousa (2011) use an SVAR model on quarterly data for four countries (U.S., U.K., Germany, and Italy) from 1970 to 2007 and consider the revenue and expenditure components of the fiscal deficit separately, finding that government expenditure shocks have a negative effect on stock prices, while government revenue shocks have a small, positive effect. These mixed results and the sparse empirical literature jointly suggest the need for further investigations on the topic using alternate approaches.

In this study, we use an MF-TVP-FAVAR (mixed-frequency time-varying parameters factor-augmented vector autoregressive) model to examine the sensitivity of stock prices to federal spending news. We track all Congress spending bills signed by the president between 2000 and 2020, with the date of a bill's first approval in either chamber (House or Senate) marking the shock's onset. We calculate the accompanying stock price deviations from the average using the BIAS index proposed by Ren et al. (2020a) to construct the spending news on the stock price index. We focus on the S&P 500 index which includes 500 large US companies, offering a more comprehensive view of the market than other prominent indices that either span fewer companies (Dow Jones) or focus on a specific industry (Nasdaq). We employ these other indices to verify our results.

Our work contributes to the literature in important ways. First, instead of relying on media or newspaper coverage of fiscal policy, we focus on the actual Congress spending bills. This avoids possible biases in media coverage due to: news outlets' profit maximization considerations (Tetlock, 2007; Engelberg and Parsons, 2011; Carlin et al., 2014) or; journalists' interpretation of the policy (Baker et al., 2019, 2022; Manela and Moreira, 2017) or; the quality of news writing (Shiller, 2017). Second, we measure the actual change in the stock price index using BIAS whereas the literature mainly considers moving average change in stock prices (Laopodis, 2010). Finally, our MF-TVP-FAVAR model allows us to control for the direct factors instead of proxies like the industrial production index as a measure of output and also adjusts for structural breaks in the data from policy changes over time.

The rest of the paper is structured as follows: Section 2 describes the model and estimation strategy; Section 3 presents the data and empirical results and; Section 4 concludes.

2 Model

We use the model developed by Yemba et al. (2023). The model enables combining multiple time series observed at different frequencies such as quarterly GDP with monthly inflation. All series are observable at monthly frequency after the transformation. The state space representation of MF-TVP-FAVAR(p) can be written as

$$X_t = \Gamma_t^F F_t + \Gamma_t^Z Z_t + v_t, v_t \sim i.i.d.N(0, R_t) \tag{1}$$

$$\begin{pmatrix} F_t \\ Z_t \end{pmatrix} = C_t + \sum_{j=1}^{p} B_{t,j} \begin{pmatrix} F_{t-j} \\ Z_{t-j} \end{pmatrix} + e_t, e_t \sim i.i.d.N(0, Q_t), \tag{2}$$

where the informational time series $X_t = \begin{pmatrix} F_t \\ Z_t \end{pmatrix}$ are related to the unobservable factors F_t and the observable factors, Z_t. Γ_t^F are factor loadings and Γ_t^Z are regression coefficients. F_t contains the latent factors that influence our variables of interest but cannot enter the normal vector Z_t of VAR model. C_t is the intercept, and $(B_{t,1}, ..., B_{p,t})$ are VAR coefficients. v_t and e_t are zero-mean Gaussian disturbances with time-varying covariances R_t and Q_t, respectively. p represents the order of the model. (1) and (2) are transition equations. We adopt the common identifying assumption in the factor literature that R_t is diagonal, thus ensuring that v_t is a vector of idiosyncratic shocks and F_t contains information common to all latent variables. We assume that the US economy is driven by fundamental unobserved factors that can be categorized into activity, prices, and interest rate factors. These factors capture the fluctuations in key macroeconomic variables such as output, price, and stock price index.

Following the literature (Banerjee et al., 2008; Breitung and Eickmeier, 2011; Bates et al., 2013; Koop and Korobilis, 2014) we allow all parameters to take different values at each time t and introduce structural breaks in factor loadings. These are important assumptions because we believe there is a temporal variation or breaks in the loadings and covariances of factor models which use both the stock prices and macroeconomic data.

Similar to Koop and Korobilis (2014) our model employs a multivariate system to estimate the impulse response functions using all latent factors and macroeconomic variables. Unlike Koop and Korobilis (2014), we do not differentiate between macroeconomic and financial variables. Our latent factors consist of macroeconomic variables from economic activities, prices, stock price indices, and interest rates. Thus, the final estimated factors reflect information associated with federal spending news.

To complete our MF-TVP-FAVAR model, we define the measurement equations

$$Y_t = M_t^y \Lambda^y Z_t, \tag{3}$$

$$H_t = M_t^h \Lambda^h F_t, \tag{4}$$

$$\Gamma_t = \Gamma_{t-1} + u_t, u_t \sim i.i.d.N(0, W_t) \tag{5}$$

$$\beta_t = \beta_{t-1} + \eta_t, \eta_t \sim i.i.d.N(0, V_t) \tag{6}$$

where Λ^y and Λ^h are aggregation matrices based on the weighting scheme underlying latent variables quoted at monthly frequency; M_t^y and M_t^h are deterministic selection matrices that yield a time-varying observation vector by selecting rows corresponding to the monthly variables (see Mariano and Murasawa (2003), Schorfheide and Song (2015), and Ankargren et al. (2020)). See Appendix 1 for the details of transforming quarterly data to monthly.

Additionally, the model assumes that u_t and η_t are uncorrelated over time and with each other. This assumption is at the core of the definition of the small-scale dynamic factor model as in Stock and Watson (2009) and implies that the model separates out common correlation underlying the observed variables from individual variations in each series. In vector form, we define $F_t = \left(F_{mt}^{'}, F_{qt}^{'}\right)^{'}$, $\Gamma_t = \left((\Gamma_t^F)^{'}, (\Gamma_t^Y)^{'}\right)$, and VAR coefficients $\beta_t = \left(C_t^{'}, \text{vec}(\beta_{t,1})^{'}, ..., \text{vec}(\beta_{t,p})^{'}\right)^{'}$. For simplicity, we assume that the vectors of loadings Γ_t and VAR coefficients β_t evolve as multivariate Random Walks (RW).

The $n \times 1$ vector Z_t of macroeconomic variables enter the regular Z_t of a VAR model. Z_t consists of $n_m \times 1$ vector Z_{mt} containing the variables that are observed at monthly frequency and $n_q \times 1$ vector Z_{qt} containing the variables that have been observed at quarterly frequency. In vector form, $Z_t = \left(SP500_t, GDP_t, TB3_t, Expinfl_t, M2_t, CPIInfl_t, News_{t-1}\right)$ where $SP500_t$, GDP_t, $TB3_t$, $Expinfl_t$, $M2_t$, $CPIInfl_t$, $News_{t-1}$ respectively denote S&P 500 Stock Price Index growth, GDP growth rate, 3-month treasury bill rate, expected inflation rate, monetary aggregate M2 growth, CPI Inflation, and past federal spending growth as a percentage of GDP. The choice of macroeconomic variables is based on the empirical literature on the topic (Mumtaz and Theodoridis 2020; Agnello et al. 2013; Stoian and Iorgulescu 2020).

We follow Barsky and Sims (2011), Jinnai (2013) and Barsky et al. (2015) for identifying the government spending shock which evolves according to

$$g_t = \rho g_{t-1} + e_t \tag{7}$$

where the innovation e_t is the sum of two components

$$e_t = \epsilon_{1t} + \epsilon_{2t-1} \tag{8}$$

where ϵ_{1t} and ϵ_{2t-1} are independent and orthogonal such that $\sigma_{\epsilon_1}^2 + \sigma_{\epsilon_2}^2 = \sigma_{e_t}^2$. In (8), ϵ_{1t} and ϵ_{2t-1} denote respectively a surprise and a news component of e_t. However, because of the orthogonality between surprise and news shocks, the latter is anticipated one period in advance and does not predict the former such that $Var(e_t) = I$. Moreover, we assume that news about future changes in government spending can have large effects on the contemporaneous decisions of individuals (mostly investors). This introduces the main contribution of this paper, financial market expectation is more linked to the rational expectation behavior of economic agents based on all available information at time t, current government spending news included (ϵ_{2t-1}). This is the information transmission mechanism that influences market participants' decisions.

For simplicity, we use 6 variables in this order: Real Government spending as a percentage of GDP (generate the news shock), Real GDP, Federal Tax receipts, CPI Inflation, 3-month Treasury Rate, and Money supply M2. We estimate the VAR (11) to recover the coefficients B_j and the variance matrix of forecast errors.

We use a dual conditionality linear Kalman filtering/smoothing algorithm developed by Koop and Korobilis (2014) to estimate our model (1) to (6). See Appendix 1, section 1.2 for the details of the estimation procedure.

We compare our results to those obtained from a Bayesian VAR (BVAR) model which, similar to our baseline MF-TVP-FAVAR specification, uses time-varying parameters. Our main model uses a Cholesky decomposition scheme.

3 Data and Results

3.1 Data

Our data consists of 125 monthly and 8 quarterly macroeconomic indicators for the US economy. We divide the variables into five blocks, including real variables (such as industrial production), financial variables, prices (Consumer Price Index, Producer Price Index, and Personal Consumption Expenditure), monetary aggregates (simple sum and Divisia monetary aggregates), interest rates and Stock Price Indices, and an economic expectation survey. Variable details are available upon request. Our data sources include the FRED, the Board of Governor of Federal Reserve System, the Bureau of Economic Analysis (BEA), and Yahoo Finance. See Table 1 in Appendix 2 for variable descriptions and sources.

The S&P 500 Price Index extends from January 27th, 2000 to December 29th, 2022. See Figure 1 for the time plot and summary statistics. The variable is transformed to induce stationarity while ensuring that the transformed variables correspond to a monthly quantity when observed on the last Friday or Thursday (if Friday is a holiday) of the month. We compute the change in all stock price indices using the BIAS method proposed by Ren et al. (2020b) [1].

[1]BIAS calculates the percentage difference between a market index or closing price and a moving average. BIAS is computed only when a non-routine spending bill is passed in one chamber of Congress (House or Senate) and is pending approval in the next. Examples of non-routine spending include stimulus packages approved during the 2009 financial crisis or during COVID-19. We compute $\frac{SP500-SP500_{ti}}{SP500_{ti}}$ where $SP500$ is the closing stock price on the day the news of a bill's first approval is received while $SP500_{ti}$ is the moving average price of the stock after the ti^{th} day of news occurrence and until the bill's approval in the next chamber. For months with no spending news, we compute a 12-month moving average change (normal trend). Refer to Table 2 in Appendix 2 for a list of the bills included in the analysis.

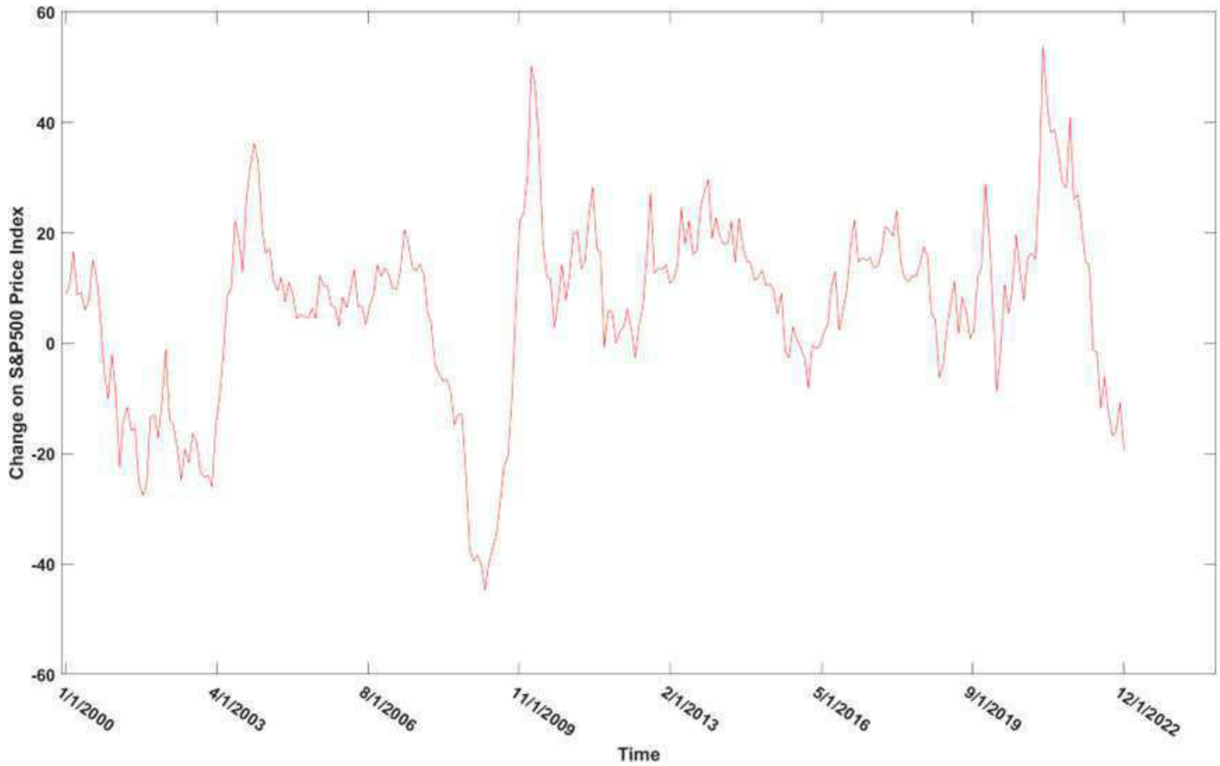

Figure 1: Monthly Change on S&P500 Price Index from January 2000 to December 2022

Notes: The official Change on S&P500 Price Index ranges between a minimum value of -44.7562 and a maximum value of 53.7100. It averages 6.4062 with a median value of 9.5550 and a mode of 1.7300. It has a standard deviation of 16.5850, a skewness of -0.5388 and kurtosis of 3.7394.

Table 1: Unit Root Tests for S&P 500 Stock Price Index

Asymptotic Critical values	MZ_α	MZ_t	MSB	MPT
1%	-13.8000	-2.5800	0.17400	1.78000
5%	-8.1000	-1.9800	0.23300	3.17000
10%	-5.7000	-1.6200	0.27500	4.45000
Level	-1.29802	-0.80986	0.62392	33.0974
Change	-22.9256***	-3.28893***	0.14346***	0.140136***

Notes: These tests are proposed by Ng and Perron (2001). *, **, and *** denote rejection of the unit root null at 10%, 5%, and 1%, respectively. Null hypothesis states that the S&P 500 Stock Price Index is not stationary.

Following Ng and Perron (2001), we perform the Generalized Least Square (GLS) detrended unit root tests to determine series stationarity. We use the modified information criteria (MIC) to select the lag length and compute the proposed statistics MZ_α, MZ_t,

MSB, and MPT to test for unit root (see Table 1 for the details). The S&P 500 Price Index is a RW because we fail to reject the unit-root null hypothesis at the 5% confidence level. However, the statistics show that the unit-root null hypothesis is rejected for the average change in S&P 500 with some BIAS. Thus, the latter is stationary.

3.2 Results

Figure 2 plots the estimated response to a 1 percent increase in government spending news shock as identified by the SVAR (11) and incorporated in our main MF-TVP-FAVAR models 1 to 6 using the full sample. Our results show that the change in the S&P 500 Price Index turns negative 4 months after a 1 percent increase in the variance of government spending news and continues to decline for 21 months. The immediate response is 10 percent and it reaches 30 percent after 15 months.

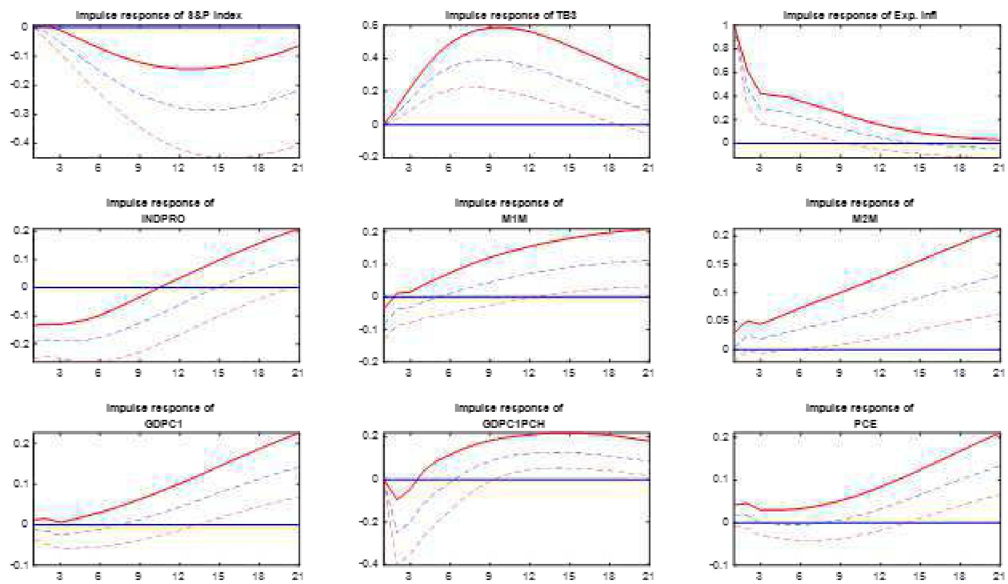

Figure 2: Impulse Response Functions (IRF) of Federal Spending Bill News Shocks (full sample)

We repeat the analysis for sub-samples of our study period surrounding the major economic downturns since 2000. The first sub-sample extends from January 2000 to November 2007, the period before the financial crisis between December 2007 and June 2009. Our results in Figure 3 show that spending news has no impact on the change in the S&P 500 Price Index. This is expected since there were no significant spending changes affecting investor expectations during this period.

The second sub-sample spans the financial crisis and beyond from December 2007 to December 2022. Figure 4 shows that the spending news has a short, negative impact on the change in the S&P 500 Price Index 6 months after the shock. The delay is longer compared to the 3 months for the full sample. The impact is short-lived, lasting only 8 months as compared to the 18 months for the full sample. This is expected since Congress passed unprecedentedly large spending bills during this period.

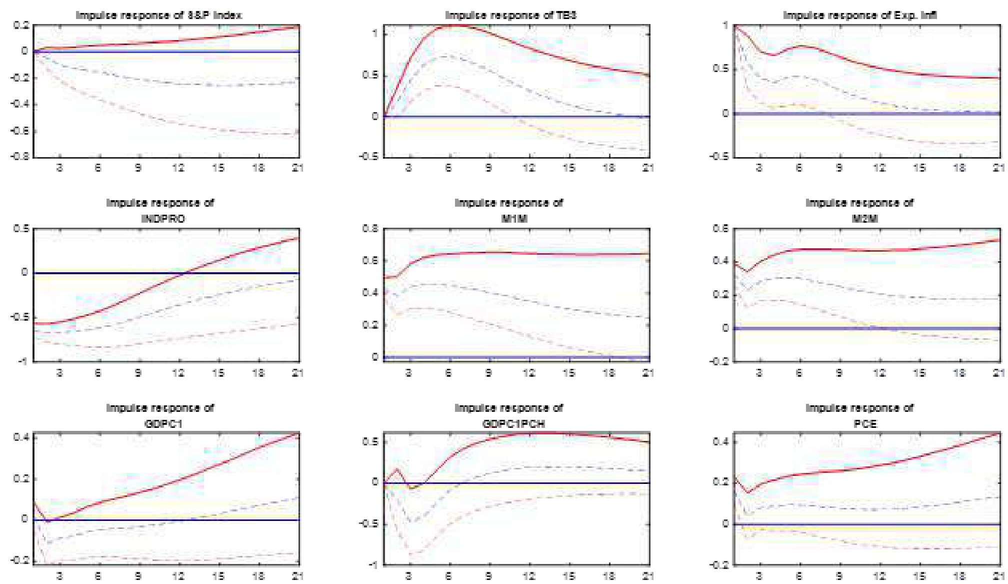

Figure 3: IRF of Federal Spending Bill News Shocks (01/2000 - 11/2007)

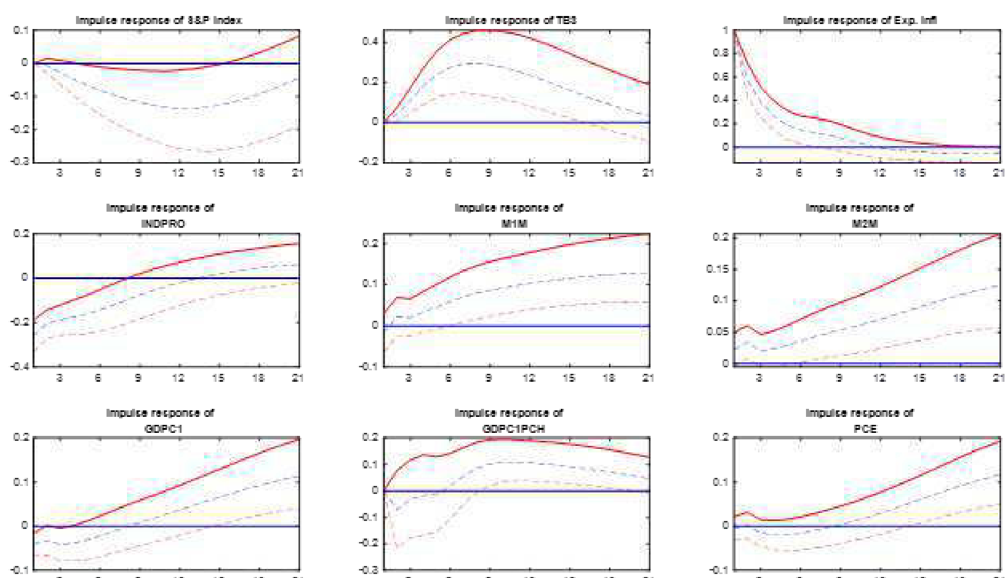

Figure 4: IRF of Federal Spending Bill News Shocks (12/2007 - 12/2022)

The third sub-sample stretches from January 2000 to December 2009 which is the period before the European Sovereign debt crisis. Our results in Figure 5 indicate that the spending news does not have any impact on the change in the S&P 500 Price Index.

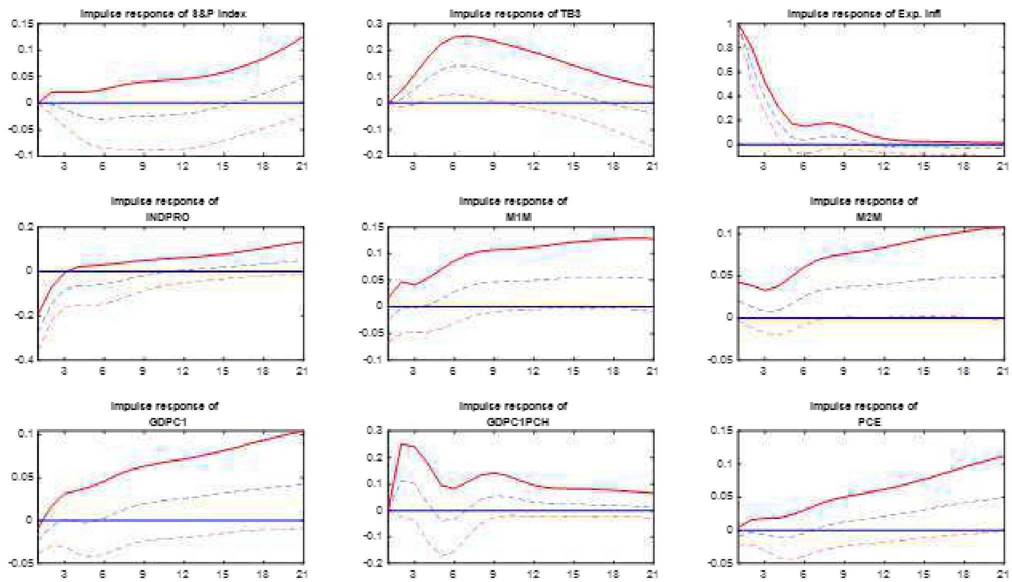

Figure 5: IRF of Federal Spending Bill News Shocks (01/2000 - 12/2009)

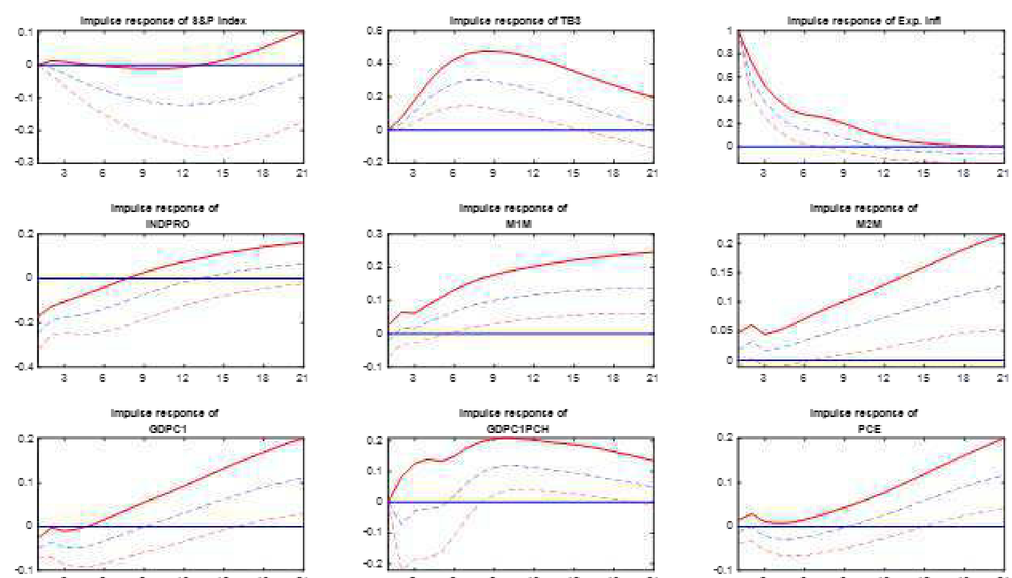

Figure 6: IRF of Federal Spending Bill News Shocks (01/2012 - 12/2022)

However, in the fourth and post-crisis sub-sample between January 2012 and December

2022, Figure 6 shows that the spending news shock has a short and delayed negative impact on the change in the S&P 500 Price Index.

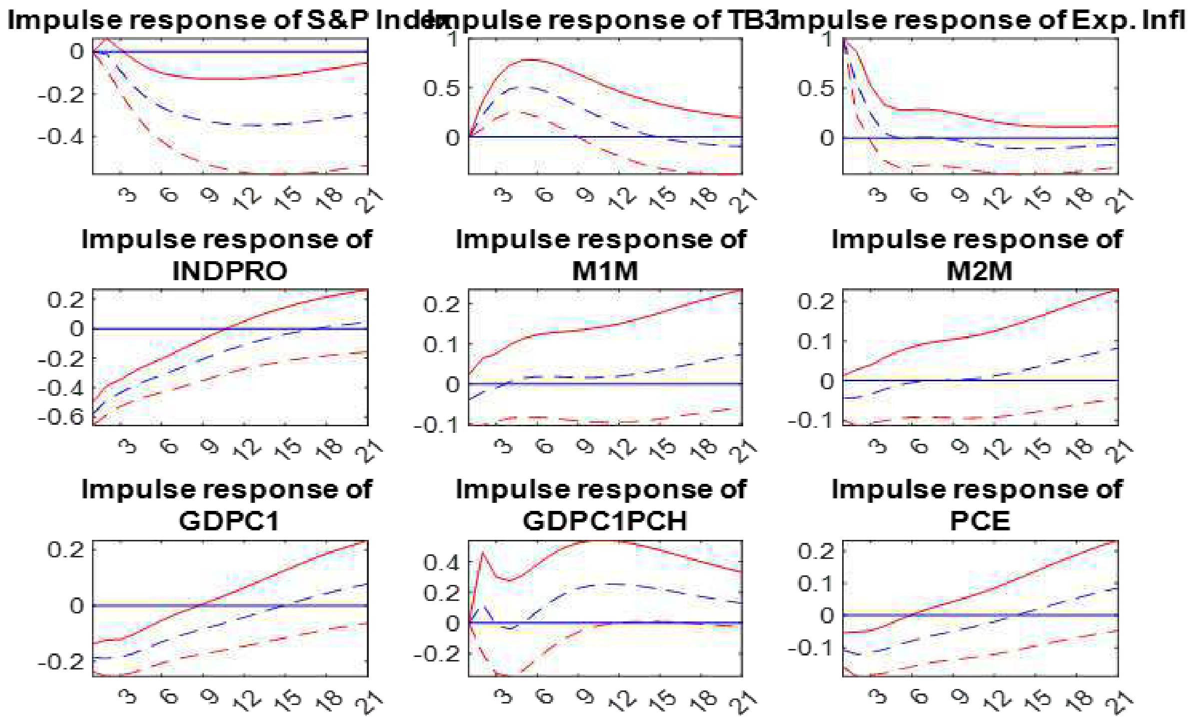

Figure 7: IRF of Federal Spending Bill News Shocks (01/2000 - 01/2020)

The fifth sub-sample spans all years before the Covid-19 recession, from January 2000 to January 2020. The impact is similar to the full sample (Figure 7). The sixth and final sub-sample excludes all the recessions between January 2000 and December 2022, spanning the periods January 2000 to February 2001, December 2001 to November 2007, July 2009 to January 2020, and May 2020 to December 2022. We find similar impacts as for the full sample as shown by Figure 8.

Our results are consistent with that of Mumtaz and Theodoridis (2020) who estimate a negative impact of fiscal expansions on real stock price index post-1980s. They detect a small impact of the expansions on output, consumption, and total factor productivity (TFP) while real wages decline and inflation and volatility increase. A plausible explanation is the diminishing importance of endogenous growth mechanism and the expanding role of international factors since 1980. Our results confirm the same findings for output, consumption, TFP, and inflation through the rational expectations theory. This theory states that investors forecast the future stock price based on all available information today. Therefore, rising concerns about government debt among investors may restrict growth in private investment and consumption.

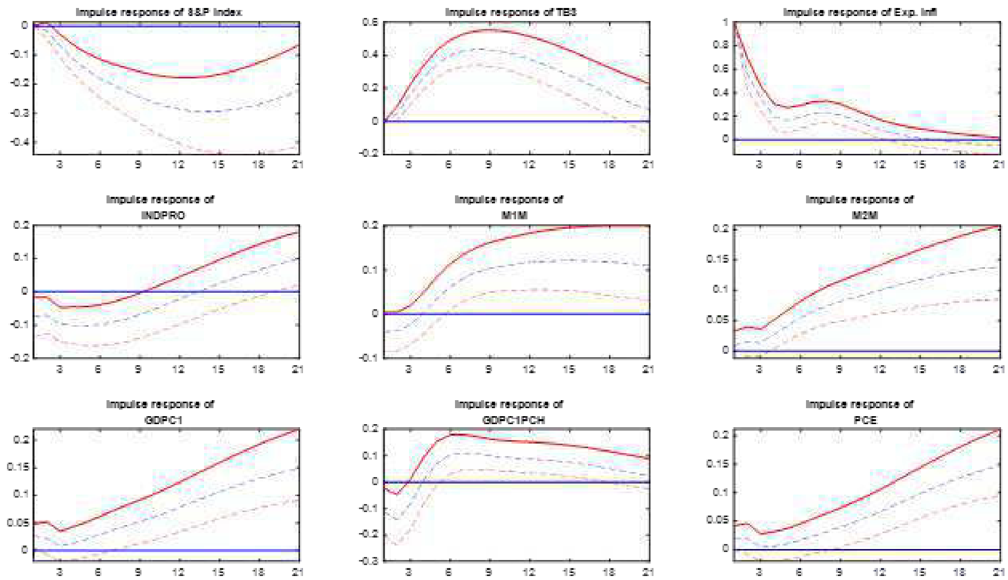

Figure 8: IRF of Federal Spending Bill News Shocks (excluding recessions)

For robustness checks, we use multiple alternative schemes. First, we estimate the impulse response functions of government spending news on two other stock price indices: Dow Jones and Nasdaq. Figures 9 and 10 show that the change in both indices responds negatively to the spending news shock with a delay of 6 months.

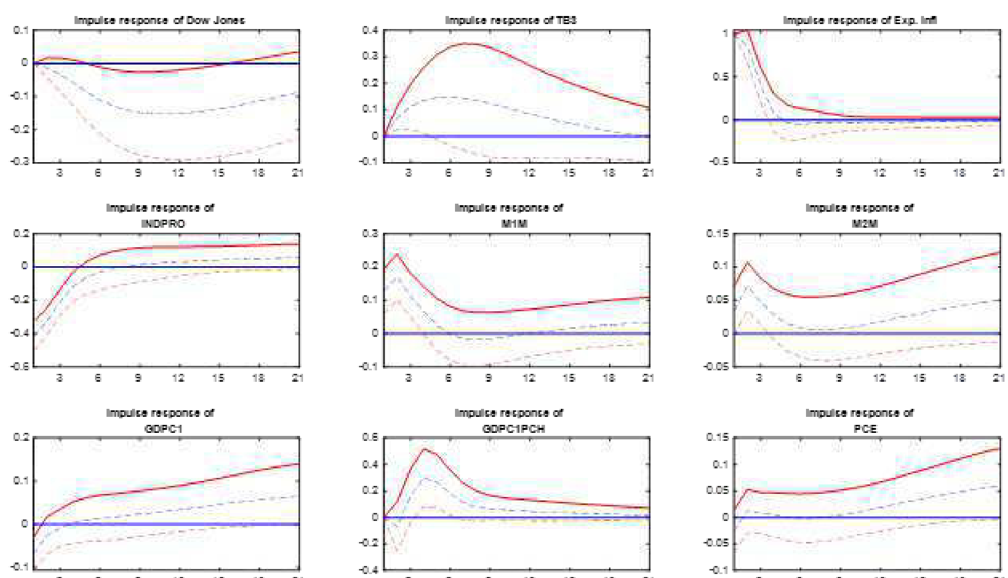

Figure 9: IRF of Federal Spending Bill News Shocks (Nasdaq)

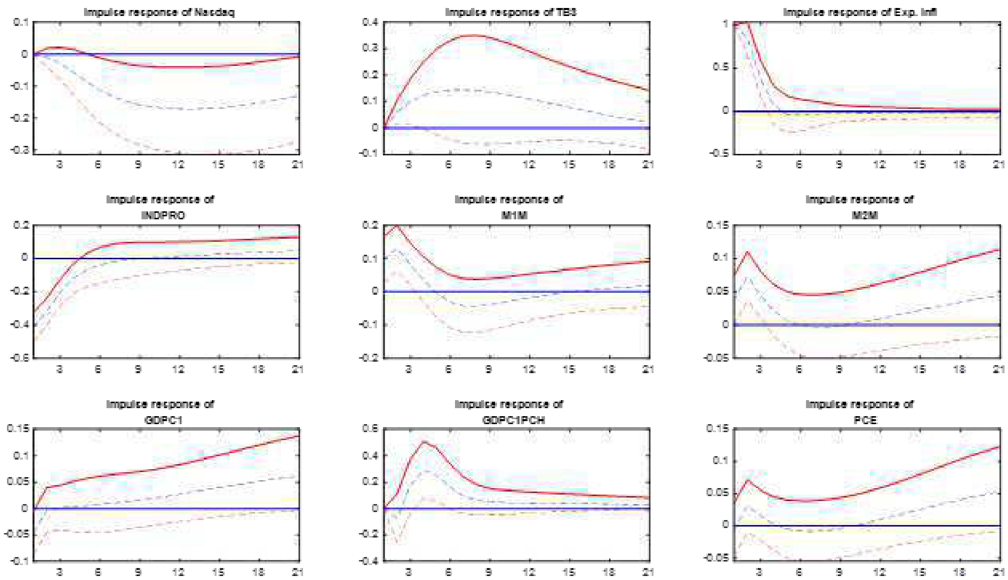

Figure 10: IRF of Federal Spending Bill News Shocks (Dow Jones)

The response of Dow Jones lasts 18 months while that of the Nasdaq Stock Price Index continues for 15 months. These responses are similar to the benchmark model and confirm our results.

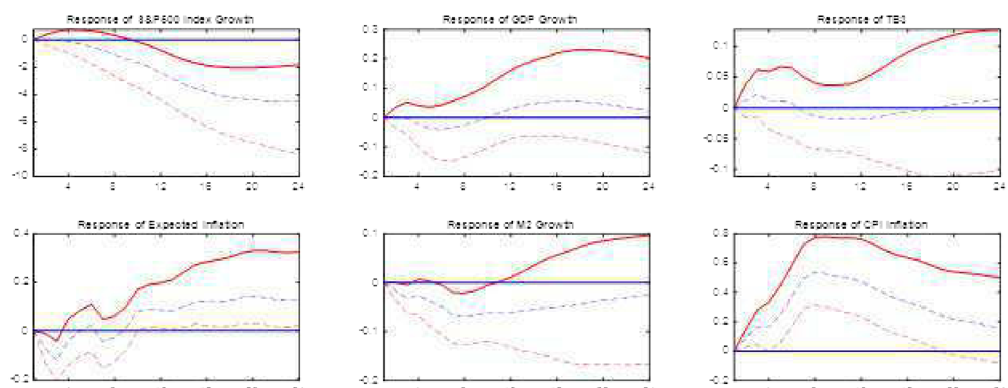

Figure 11: IRF of Federal Spending Bill News Shocks (BVAR model)

Furthermore, we use a Bayesian VAR to estimate the responses of the change in the stock price indices to spending shocks. The response of the S&P 500 remains similar to our benchmark model (See Figure 11).

4 Conclusion

We model the response of S&P 500 index to unexpected spending announcements from the Congress using an MF-TVP-FAVAR framework and detect a negative impact of such news shocks on stock prices. Our results align with previous studies that show a negative impact of expansionary fiscal policy on stock market indices (Darrat 1988; Agnello et al. 2013; Mumtaz and Theodoridis 2020). Our findings indicate that important spending bills influence the stock price index even before their formal adoption as a policy because investors adjust their expectations about the future based on current news and alter their stock portfolios.

It is worth mentioning that we use monthly data on the stock price index due to the unavailability of federal spending and output (gross domestic product) data at a monthly frequency. These variables are only available quarterly. This is a limitation of our study. Our future work may focus on extending the modeling framework to incorporate triple or quadruple-frequency time series data and exploit the weekly or daily information from stock price indexes for a more robust analysis.

References

Afonso, A. and Sousa, R. M. (2011). What are the effects of fiscal policy on asset markets? *Economic Modelling*, 28(4):1871–1890.

Afonso, A. and Sousa, R. M. (2012). The macroeconomic effects of fiscal policy. *Applied Economics*, 44(34):4439–4454.

Agnello, L., Furceri, D., and Sousa, R. M. (2013). How best to measure discretionary fiscal policy? assessing its impact on private spending. *Economic Modelling*, 34:15–24.

Ankargren, S., Unosson, M., and Yang, Y. (2020). A flexible mixed-frequency vector autoregression with a steady-state prior. *Journal of Time Series Econometrics*, 12(2).

Ardagna, S. (2009). Financial markets' behavior around episodes of large changes in the fiscal stance. *European Economic Review*, 53(1):37–55.

Baker, S. R., Bloom, N., Davis, S. J., and Kost, K. J. (2019). Policy news and stock market volatility. Technical report, National Bureau of Economic Research.

Baker, S. R., Davis, S. J., and Levy, J. A. (2022). State-level economic policy uncertainty. *Journal of Monetary Economics*, 132:81–99.

Banbura, M., Giannone, D., and Reichlin, L. (2011). Nowcasting with daily data. *European Central Bank, Working Paper*, page 18.

Banerjee, A., Marcellino, M., and Masten, I. (2008). *Forecasting macroeconomic variables using diffusion indexes in short samples with structural change*. Emerald Group Publishing Limited.

Barsky, R. B., Basu, S., and Lee, K. (2015). Whither news shocks? *NBER macroeconomics annual*, 29(1):225–264.

Barsky, R. B. and Sims, E. R. (2011). News shocks and business cycles. *Journal of monetary Economics*, 58(3):273–289.

Bates, B. J., Plagborg-Møller, M., Stock, J. H., and Watson, M. W. (2013). Consistent factor estimation in dynamic factor models with structural instability. *Journal of Econometrics*, 177(2):289–304.

Bjørnland, H. C. and Leitemo, K. (2009). Identifying the interdependence between us monetary policy and the stock market. *Journal of Monetary Economics*, 56(2):275–282.

Blanchard, O. J. (1981). Output, the stock market, and interest rates. *The American Economic Review*, 71(1):132–143.

Breitung, J. and Eickmeier, S. (2011). Testing for structural breaks in dynamic factor models. *Journal of Econometrics*, 163(1):71–84.

Carlin, B. I., Longstaff, F. A., and Matoba, K. (2014). Disagreement and asset prices. *Journal of Financial Economics*, 114(2):226–238.

Conover, C. M., Jensen, G. R., and Johnson, R. R. (1999). Monetary environments and international stock returns. *Journal of Banking & Finance*, 23(9):1357–1381.

Dal Bianco, M., Camacho, M., and Quiros, G. P. (2012). Short-run forecasting of the euro-dollar exchange rate with economic fundamentals. *Journal of International Money and Finance*, 31(2):377–396.

Darrat, A. F. (1988). On fiscal policy and the stock market. *Journal of money, credit and banking*, 20(3):353–363.

Engelberg, J. E. and Parsons, C. A. (2011). The causal impact of media in financial markets. *the Journal of Finance*, 66(1):67–97.

Fama, E. F. and French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of financial economics*, 25(1):23–49.

Gertler, M. and Gilchrist, S. (1993). The role of credit market imperfections in the monetary transmission mechanism: arguments and evidence. *The Scandinavian Journal of Economics*, pages 43–64.

Jansen, D. W., Li, Q., Wang, Z., and Yang, J. (2008). Fiscal policy and asset markets: A semiparametric analysis. *Journal of Econometrics*, 147(1):141–150.

Jensen, G. R. and Johnson, R. R. (1995). Discount rate changes and security returns in the us, 1962–1991. *Journal of Banking & Finance*, 19(1):79–95.

Jinnai, R. (2013). News shocks and inflation. *Economics Letters*, 119(2):176–179.

Koop, G. and Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, 71:101–116.

Laopodis, N. T. (2010). Dynamic linkages between monetary policy and the stock market. *Review of Quantitative Finance and Accounting*, 35:271–293.

Manela, A. and Moreira, A. (2017). News implied volatility and disaster concerns. *Journal of Financial Economics*, 123(1):137–162.

Mariano, R. S. and Murasawa, Y. (2003). A new coincident index of business cycles based on monthly and quarterly series. *Journal of applied Econometrics*, 18(4):427–443.

Mumtaz, H. and Theodoridis, K. (2020). Fiscal policy shocks and stock prices in the united states. *European Economic Review*, 129:103562.

Ng, S. and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*, 69(6):1519–1554.

Patelis, A. D. (1997). Stock return predictability and the role of monetary policy. *the Journal of Finance*, 52(5):1951–1972.

Ren, Y., Liao, F., and Gong, Y. (2020a). Impact of news on the trend of stock price change: An analysis based on the deep bidirectiona lstm model. *Procedia Computer Science*, 174:128–140.

Ren, Y., Liao, F., and Gong, Y. (2020b). Impact of news on the trend of stock price change: an analysis based on the deep bidirectiona lstm model. *Procedia Computer Science*, 174:128–140. 2019 International Conference on Identification, Information and Knowledge in the Internet of Things.

Schorfheide, F. and Song, D. (2015). Real-time forecasting with a mixed-frequency var. *Journal of Business & Economic Statistics*, 33(3):366–380.

Shiller, R. J. (2017). Narrative economics. *American economic review*, 107(4):967–1004.

Stock, J. H. and Watson, M. (2009). Forecasting in dynamic factor models subject to structural instability. *The Methodology and Practice of Econometrics. A Festschrift in Honour of David F. Hendry*, 173:205.

Stoian, A. and Iorgulescu, F. (2020). Fiscal policy and stock market efficiency: An ardl bounds testing approach. *Economic Modelling*, 90:406–416.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of finance*, 62(3):1139–1168.

Thorbecke, W. (1997). On stock market returns and monetary policy. *The Journal of Finance*, 52(2):635–654.

Van Aarle, B., Garretsen, H., and Gobbin, N. (2003). Monetary and fiscal policy transmission in the euro-area: evidence from a structural var analysis. *Journal of Economics and Business*, 55(5-6):609–638.

Yemba, B. P., Otunuga, O. M., Tang, B., and Biswas, N. (2023). Nowcasting of the short-run euro-dollar exchange rate with economic fundamentals and time-varying parameters. *Finance Research Letters*, 52:103571.

Appendix 1: Model Description

1.1 Data Transformation

To transform the quarterly data to monthly form, we rewrite equation (3) as follows

$$Y_t = \begin{pmatrix} Y_{mt} \\ Y_{qt} \end{pmatrix} = \begin{pmatrix} I_{n_m} & 0 \\ 0 & M_{qt}^Y \end{pmatrix} \begin{pmatrix} I_{n_m} & 0 \\ 0 & \Lambda_q^Y \end{pmatrix} Z_t = M_t^Y \Lambda^Y Z_t \tag{9}$$

where the subscripts m and q denote monthly and quarterly frequency respectively, $Z_t = \left(Z_{mt}^{'}, Z_{qt}^{'}\right)^{'} = \left(z_t^{'}, ..., z_{t-p+1}^{'}\right)$, $t = 1, ..., t_b$, t_b denotes the final time period where all the monthly variables are observed. Therefore, when $t \leq t_b$, all monthly series are observed. However, if all the quarterly series are observed at time t, both M_{qt}^y and Λ_q^y are identity matrices of dimension n_q so that $Y_{qt} = \begin{pmatrix} 0 & \Lambda_q \end{pmatrix}$.

For the remaining period (for $t > t_b$), M_q is an empty matrix such that $Y_t = Y_{mt}$. In this case, the matrix Λ_q^y contains scheme of unobserved high-frequency latent observations Z_{qt} into some observed low-frequency observations Y_{qt}.

Following Mariano and Murasawa (2003) and Dal Bianco et al. (2012), we use quarterly difference of Y_{qt} to construct the observed growth rate:

$$\begin{aligned} Y_{qt} &= Y_{qt}^* - Y_{qt-3}^* \\ &= \frac{1}{3}\left[(Z_{qt}^* - Z_{qt-3}^*) + (Z_{qt-1}^* - Z_{qt-4}^*) + (Z_{qt-2}^* - Z_{qt-5}^*)\right] \\ &= \frac{1}{3}\left[\Delta Z_{qt}^* + 2\Delta Z_{qt-1}^* + 3\Delta Z_{qt-2}^* + 2\Delta Z_{qt-3}^* + \Delta Z_{qt-4}^*\right] \end{aligned} \tag{10}$$

where Y_{qt}^* denotes the observed quarterly log-level (for $t \leq t_b$) and the latent variable quarterly log-levels (for $t > t_b$). The latent variable is defined as $Y_{qt-3}^* = 3\Delta Z_{qt}^*$.

The efficient compact formulation of the state-space model (1) to (6) can be improved by eliminating, for $t = 1, ..., t_b$, the monthly observations Y_{mt} from the state vector Z_t that appears in the measurement equation (3). Even though the monthly variables are observed for all points of time, there are some observations that are missing at the end of the sample, called as a ragged edge (Banbura et al., 2011), which generates unbalanced monthly data for $t = t_b + 1$. The dimension of the state-space model is reduced from np to $n_q(p+1)$. This treatment is more convenient for handling the factor variables, F_t of our FAVAR in equation (4).

1.2 Estimation procedure

We use a dual conditionally linear Kalman filtering/smoothing algorithm developed by Koop and Korobilis (2014) to estimate our model (1) to (6) by Kalman Filter and smoothers. First of all, we use the approach of Mariano and Murasawa (2003) and its adaptation in (Schorfheide and Song, 2015) described above to modify the state space model (1) - (6).

Then, we implement a simplified version of the algorithm developed by Koop and Korobilis (2014) for estimating our MF-TVP-FAVAR model ($\theta_t = (\Gamma_t, \beta_t)$). The variance discounting methods combined with the Kalman filter are used to obtain analytically consistent results for the posteriors of the state variable F_t and the time-varying parameters $\theta_t = (\Gamma_t, \beta_t)$. The identification of our model proceeds as standard, restricting the variance-covariance matrix R_t to be diagonal and applying a Cholesky decomposition with sign restrictions.

A simplified version of the algorithm developed by Koop and Korobilis (2014) for estimating our MF-TVP-FAVAR model is given in the following steps:

Algorithm 1 Simulation scheme

Given initial parameters Γ_0, β_0, R_0, Q_0, p
for $j = 1$ to p **do**,
    Evaluate the principal components estimates of the factors, $\tilde{F}_t$
    Estimate the time varying parameters θ_t given $\tilde{F}_t$.
    Estimate R_t, Q_t, W_t,and V_t using variance discounting.
    Estimate Γ_t and β_t, given (R_t, Q_t, W_t, V_t), using the Kalman filter and smoother.
Estimate the factors F_t given θ_t using the Kalman filter and smoother.
end for

Appendix 2: Data and sources

Table 2: Time Series variables

Variable Name	Description	Source
DTB3	3-Month Treasury Bill Secondary Market Rate	Board of Governor FED
HQMCB1YR	1-Year High Quality Market (HQM) Corporate Bond Spot Rate	Board of Governor FED
DBAA	Moody's Seasoned Baa Corporate Bond Yield	Board of Governor FED
HQMCB12YR	12-Year High Quality Market (HQM) Corporate Bond Spot Rate	Board of Governor FED
HQMCB10YR	10-Year High Quality Market (HQM) Corporate Bond Spot Rate	Board of Governor FED
HQMCB5YR	5-Year High Quality Market (HQM) Corporate Bond Spot Rate	Board of Governor FED
HQMCB20YR	20-Year High Quality Market (HQM) Corporate Bond Spot Rate	Board of Governor FED
HQMCB3YR	3-Year High Quality Market (HQM) Corporate Bond Spot Rate	Board of Governor FED
HQMCB6MT	6-Month High Quality Market (HQM) Corporate Bond Spot Rate	Board of Governor FED
DTB6	6-Month Treasury Bill Secondary Market Rate	Board of Governor FED
DTB1YR	1-Year Treasury Bill Secondary Market Rate	Board of Governor FED
RIFLGFCM01_N.M	Market yield on U.S. Treasury securities at 1-month constant maturity	Board of Governor FED
RIFLGFCM03_N.M	Market yield on U.S. Treasury securities at 3-month constant maturity	Board of Governor FED
RIFLGFCM06_N.M	Market yield on U.S. Treasury securities at 1-year constant maturity	Board of Governor FED
RIFLGFCY01_N.M	Market yield on U.S. Treasury securities at 2-year constant maturity	Board of Governor FED
RIFLGFCY02_N.M	Market yield on U.S. Treasury securities at 3-year constant maturity	Board of Governor FED
RIFLGFCY03_N.M	Market yield on U.S. Treasury securities at 5-year constant maturity	Board of Governor FED
RIFLGFCY05_N.M	Market yield on U.S. Treasury securities at 5-year constant maturity	Board of Governor FED
RIFLGFCY05_XII_N.M	Market yield on U.S. Treasury securities at 7-year constant maturity	Board of Governor FED
RIFLGFCY07_N.M	Market yield on U.S. Treasury securities at 7-year constant maturity	Board of Governor FED

Table 2: Time Series variables (continued)

Variable Name	Description	Source
RIFLGFCY07_XII_N.M	Market yield on U.S. Treasury securities at 10-year constant maturity	Board of Governor FED
RIFLGFCY10_N.M	Market yield on U.S. Treasury securities at 10-year constant maturity	Board of Governor FED
RIFLGFCY10_XII_N.M	Market yield on U.S. Treasury securities at 20-year constant maturity	Board of Governor FED
RIFLGFCY20_N.M	Market yield on U.S. Treasury securities at 20-year constant maturity	Board of Governor FED
RIFLGFCY20_XII_N.M	Market yield on U.S. Treasury securities at 30-year constant maturity	Board of Governor FED
RIFLGFCY30_N.M	Market yield on U.S. Treasury securities at 30-year constant maturity	Board of Governor FED
RIFLGFCY30_XII_N.M	Market yield on U.S. Treasury securities at 30-year constant maturity	Board of Governor FED
RIFLGFL_XII_N.M	Treasury long-term average (over 10 years)	Board of Governor FED
RIFSGFSM03_N.M	3-month Treasury bill secondary market rate	Board of Governor FED
RIFSGFSM06_N.M	6-month Treasury bill secondary market rate	Board of Governor FED
RIFSGFSW04_N.M	4-week Treasury bill secondary market rate	Board of Governor FED
RIFSGFSY01_N.M	1-year Treasury bill secondary market rate	Board of Governor FED
RIFSPPFAAD30_N.M	30-Day AA Financial Commercial Paper Interest Rate	Board of Governor FED
RIFSPPFAAD60_N.M	60-Day AA Financial Commercial Paper Interest Rate	Board of Governor FED
RIFSPPFAAD90_N.M	90-Day AA Financial Commercial Paper Interest Rate	Board of Governor FED
RIFSPPNAAD30_N.M	30-Day AA Nonfinancial Commercial Paper Interest Rate	Board of Governor FED
RIFSPPNAAD60_N.M	60-Day AA Nonfinancial Commercial Paper Interest Rate	Board of Governor FED
RIFSPPNAAD90_N.M	90-Day AA Nonfinancial Commercial Paper Interest Rate	Board of Governor FED
M1.M	M1	Board of Governor FED
M2.M	M2	Board of Governor FED
MCU.M	Currency	Board of Governor FED

Table 2: Time Series variables (continued)

Variable Name	Description	Source
MDD.M	Demand deposits	Board of Governor FED
MDTS.M	Small-denomination time deposits - Total	Board of Governor FED
MMFGB.M	Retail money market funds	Board of Governor FED
RESMO14A_N.M	Monetary base	Board of Governor FED
RESMOB14A_N.M	Monetary base	Board of Governor FED
RESMOC14A_N.M	Monetary base	Board of Governor FED
DTCNLN_N.M	Nonrevolving securitized consumer credit	Board of Governor FED
DTCNLN_XDF_BA_N.M	Nonrevolving securitized consumer credit	Board of Governor FED
DTCNLNHD_N.M	Nonrevolving consumer credit securitized by depository institutions	Board of Governor FED
DTCNLNHD_XDF_BA_N.M	Nonrevolving consumer credit securitized by depository institutions	Board of Governor FED
DTCOLHC_N.M	Total consumer credit owned by credit unions	Board of Governor FED
DTCOLHC_XDF_BA_N.M	Total consumer credit owned by credit unions	Board of Governor FED
DTCOLHD_N.M	Total consumer credit owned by depository institutions	Board of Governor FED
DTCOLHD_XDF_BA_N.M	Total consumer credit owned by depository institutions	Board of Governor FED
DTCOLHF_N.M	Total consumer credit owned by finance companies	Board of Governor
DTCOLHF_XDF_BA_N.M	Total consumer credit owned by finance companies	Board of Governor FED
DTCOLHG_N.M	Total consumer credit owned by federal government	Board of Governor FED
DTCOLHG_XDF_BA_N.M	Total consumer credit owned by federal government	Board of Governor FED
DTCOLNHC_N.M	Nonrevolving consumer credit owned by credit unions	Board of Governor FED
DTCOLNHC_XDF_BA_N.M	Nonrevolving consumer credit owned by credit unions	Board of Governor FED
DTCOLNHD_N.M	Nonrevolving consumer credit owned by depository institutions	Board of Governor FED

Table 2: Time Series variables (continued)

Variable Name	Description	Source
DTCOLNHD_XDF_BA_N.M	Nonrevolving consumer credit owned by depository institutions	Board of Governor FED
DTCOLNHF_N.M	Nonrevolving consumer credit owned by finance companies	Board of Governor FED
DTCOLNHF_XDF_BA_N.M	Nonrevolving consumer credit owned by finance companies	Board of Governor FED
DTCOLNHG_N.M	Nonrevolving consumer credit owned by federal government	Board of Governor FED
DTCOLNHG_XDF_BA_N.M	Nonrevolving consumer credit owned by federal government	Board of Governor FED
DTCOLRHC_N.M	Revolving consumer credit owned by credit unions	Board of Governor FED
DTCOLRHC_XDF_BA_N.M	Revolving consumer credit owned by credit unions	Board of Governor FED
DTCOLRHD_N.M	Revolving consumer credit owned by depository institutions	Board of Governor FED
DTCOLRHD_XDF_BA_N.M	Revolving consumer credit owned by depository institutions	Board of Governor FED
DTCOLRHF_N.M	Revolving consumer credit owned by finance companies	Board of Governor FED
DTCOLRHF_XDF_BA_N.M	Revolving consumer credit owned by finance companies	Board of Governor FED
DTCTLHD_N.M	Total consumer credit owned and securitized by depository institutions institutions	Board of Governor FED
DTCTLHD_XDF_BA_N.M	Total consumer credit owned and securitized by depository institutions	Board of Governor FED
DTCTLHF_N.M	Total consumer credit owned and securitized by finance companies	Board of Governor FED
DTCTLHF_XDF_BA_N.M	Total consumer credit owned and securitized by finance companies	Board of Governor FED
DTCTLNHD_N.M	Nonrevolving consumer credit owned and securitized by depository institutions	Board of Governor FED
DTCTLNHD_XDF_BA_N.M	Nonrevolving consumer credit owned and securitized by depository institutions	Board of Governor
DTCTLNHF_N.M	Nonrevolving consumer credit owned and securitized by finance companies	Board of Governor FED
DTCTLNHF_XDF_BA_N.M	Nonrevolving consumer credit owned and securitized by finance companies	Board of Governor FED

Table 2: Time Series variables (continued)

Variable Name	**Description**	**Source**
DTCTLRHD_N.M	Revolving consumer credit owned and securitized by depository institutions	Board of Governor FED
DTCTLRHD_XDF_BA_N.M	Revolving consumer credit owned and securitized by depository institutions	Board of Governor FED
DTCTLRHF_N.M	Revolving consumer credit owned and securitized by finance companies	Board of Governor FED
DTCTLRHF_XDF_BA_N.M	Revolving consumer credit owned and securitized by finance companies	Board of Governor FED
CPIAUCSL_PCH	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average	Saint Louis FED
EXPINF2YR	2-Year Expected Inflation	Board of Governor FED
EXPINF1YR	1-Year Expected Inflation	Board of Governor FED
CPILFESL_PC1	Consumer Price Index for All Urban Consumers: All Items Less Food and Energy in U.S. City Average	Saint Louis FED (FRED)
CPIAUCSL_PC1	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average	FRED
INDPRO	Industrial Production: Total Index, Index 2017=100, Monthly	Board of Governor FED
INDPRO_PC1	Industrial Production: Total Index, Percent Change from Year Ago Monthly	Board of Governor FED
UNRATE	Unemployment Rate, Percent, Monthly	FRED
W068RCQ027SBEA	Government total expenditures,	Bureau of Economic Analysis (BEA)
	Billions of Dollars, Quarterly	BEA
GDPC1	Real Gross Domestic Product, Billions of Chained 2012 Dollars Quarterly	BEA
GDPC1_PCH	Real Gross Domestic Product, Percent Change Quarterly	BEA
A955RL1Q225SBEA	Real Government Consumption Expenditures, Percent Change from Preceding Period, Quarterly	BEA
FEDFUNDS	Federal Funds Effective Rate, Percent, Monthly	FRED

Table 2: Time Series variables (continued)

Variable Name	Description	Source
BOPSTB	Trade Balance: Services, Balance Payments Millions of Dollars, Monthly	BEA
BOPGTB	Trade Balance: Goods, Balance of Payments Millions of Dollars, Monthly	BEA
BOPGSTB	Trade Balance: Goods and Services, Balance of Payments, Millions of Dollars, Monthly	BEA
UNEMPLOY	Unemployment Level, Thousands of Persons, Monthly	
PCEND	Personal Consumption Expenditures:	BEA
PCES	Nondurable Goods, Billions of Dollars, Monthly	BEA
PCEDG	Personal Consumption Expenditures: Services, Billions of Dollars, Monthly	BEA
PCEPILFE	Personal Consumption Expenditures: Durable Goods, Billions of Dollars, Monthly	BEA
PCEPILFE	Personal Consumption Expenditures Excluding Food and Energy (Index 2012=100), Monthly	BEA
PCEPI	Personal Consumption Expenditures: Chain-type Price Index, Index 2012=100, Monthly	BEA
PCE	Personal Consumption Expenditures Billions of Dollars, Monthly	BEA
PCETRIM12M159SFRBDAL	Trimmed Mean PCE Inflation Rate Percent Change from Year Ago, Monthly	FRED
IPMAN	Industrial Production: Manufacturing (NAICS) Index 2017=100, Monthly	FRED
DTCNL_N.M	Total securitized consumer credit	Board of Governor FED
DTCNL_XDF_BA_N.M	Total securitized consumer credite	Board of Governor FED
DTCNLHD_N.M	Total consumer credit securitized by depository institutions	Board of Governor FED
DTCNLHD_XDF_BA_N.M	Total consumer credit securitized by depository institutions	Board of Governor FED
PCETRIM12M159SFRBDAL	Industrial Production: Total Index, Index 2017=100, Monthly	FRED

Table 2: Time Series variables (continued)

Variable Name	**Description**	**Source**
IPMAN	University of Michigan: Inflation Expectation Percent, Monthly	FRED
INDPRO	Consumer Price Index: All Items for the USA Index 2015=100, Monthly	FRED
MICH	Consumer Price Index: Total All Items for the USA, Growth rate previous period, Monthly	FRED
USACPIALLMINMEI	Median Consumer Price Index % Change at Annual Rate, Monthly	FRED
CPALTT01USM657N	Sticky Price Consumer Price Index, % Change, Monthly	FRED
MEDCPIM158SFRBCLE	Sticky Price Consumer Price Index less Food and Energy, % Change from year ago, monthly	FRED
STICKCPIM157SFRBATL	Personal Saving Rate, %, Monthly	FRED
CORESTICKM159SFRBATL	Real Government Consumption Expenditures and Gross Investment, Billions of Chained 2012 Dollars, Quarterly	BEA
PSAVERT	Growth Rate Real Government ConsumptionExpenditures and Gross Investment, Quarterly	BEA
GCEC1	Real Government Consumption Expenditures and Gross Investment, Quarterly	BEA
GCEC1PC	Growth Rate Real Government Consumption Expenditures and Gross Investment, Quarterly	BEA
M2REAL_PC1	Real M2 Money Stock % Change from Year Ago, Monthly	FRED
S&P500	stock market index tracking the stock performance of 500 of the largest companies listed on stock exchanges in the United States	Yahoo Finance
Dow Jones	a stock market index of 30 prominent companies listed on stock exchanges in the United States	Yahoo Finance
Nasdaq	stock market index that includes almost all stocks listed on the Nasdaq stock exchange	Yahoo Finance

Table 3: List of Spending Bills

Congress	**Bill**	**Date Signed**
106	H.R. 1141	May 21, 1999
106	H.R. 2116	November 30, 1999
106	S.791	December 9, 1999
106	H.R. 1000	April 5, 2000
106	H.R. 434	May 18, 2000
106	H.R. 2559	June 20, 2000
106	H.R. 4425	July 13, 2000
106	H.R. 4578	October 11, 2000
106	H.R. 4811	November 6, 2000
106	H.R.2498	November 13, 2000
106	H.R. 5528	December 27, 2000
107	H.R.2926	September 22, 2001
107	H.R. 2291	December 14, 2001
107	H.R. 1	January 8, 2002
107	H.R. 3338	January 10, 2002
107	H.R. 2646	May 13, 2002
107	H.R. 3009	August 6, 2002
107	H.R. 5531	October 21, 2002
107	S. 2017	December 13, 2002
108	H.R. 1559	April 16, 2003
108	H.R. 1298	May 27, 2003
108	S. 222	June 23, 2003
108	S. 189	December 3, 2003
108	H.R. 1	December 8, 2003
109	H.R. 6	August 8, 2005
109	H.R. 3	August 10, 2005
109	H.R. 4133	November 21, 2005
109	H.R. 1973	December 1, 2005
109	H.R. 2863	December 30, 2005
109	S.1932	February 8, 2006
109	S. 2275	March 23, 2006
109	H.R. 4939	June 15, 2006
109	H.R. 6198	September 30, 2006
109	H.R. 5574	October 6, 2006
109	H.R. 6111	December 20, 2006
110	H.R. 2206	May 25, 2007
110	H.R. 1429	December 12, 2007
110	H.R. 6	December 19, 2007
110	H.R. 6081	June 17, 2008
110	H.R. 2642	June 30, 2008
110	H.R. 5501	July 30, 2008
110	H.R. 4137	August 14, 2008
110	H.R. 1424	October 3, 2008

Table 3: List of Spending Bills (continued)

Congress	Bill	Date Signed
110	H.R. 2638	October 3, 2008
111	H.R. 1	February 17, 2009
111	H.R. 1388	April 21, 2009
111	H.R. 2346	June 24, 2009
111	H. R. 3590	March 23, 2010
111	H.R. 4872	March 30, 2010
111	S. 1963	May 5, 2010
111	H. R. 4899	July 29, 2010
111	H.R. 1586	August 10, 2010
111	H.R. 4783	December 8, 2010
111	S. 3307	December 13, 2010
111	H.R. 847	January 2, 2011
112	H.J.Res. 44	March 2, 2011
112	S. 365	August 2, 2011
112	H.R. 658	February 14, 2012
112	H.R. 3630	February 22, 2012
112	H.R. 4348	July 6, 2012
112	H.R. 8	January 2, 2013
113	H.R. 152	January 29, 2013
113	H.J.Res. 59	December 26, 2013
113	H.R. 2642	February 7, 2014
113	S. 25	February 15, 2014
113	H.R. 3080	June 10, 2014
113	H.R. 3230	August 7, 2014
113	H.R. 5771	December 19, 2014
114	H.R. 719	September 30, 2015
114	H.R. 1314	November 2, 2015
114	H.R. 22	December 4, 2015
114	S. 599	December 11, 2015
114	H.R. 2029	December 18, 2015
114	H.R. 2028	December 10, 2016
114	H.R. 34	December 13, 2016
114	S. 612	December 16, 2016
115	S. 442	March 21, 2017
115	H.R. 2266	October 26, 2017
115	H.R. 2810	December 12, 2017
115	H.R. 1	December 22, 2017
115	H.R. 1370	December 22, 2017
115	H.R. 1625	March 23, 2018
115	S. 188	March 27, 2018
115	H.R. 5515	August 13, 2018
115	H.R. 6157	September 28, 2018
116	H.J.Res. 31	February 15, 2019

Table 3: List of Spending Bills (continued)

Congress	**Bill**	**Date Signed**
116	H.R. 2157	June 6, 2019
116	H.R. 3401	July 1, 2019
116	H.R. 6074	March 6, 2020
116	H.R. 6201	March 18, 2020
116	H.R. 748	March 27, 2020
116	H.R. 266	April 24, 2020
116	H.R. 133	December 27, 2020
117	H.R. 1319	March 11, 2021
117	H.R. 3237	July 30, 2021
117	H.R. 5305	September 30, 2021
117	H.R. 3684	November 15, 2021
117	H.R. 2471	March 15, 2022
117	H.R. 4346	August 9, 2022
117	H.R. 5376	August 16, 2022
117	H.R. 6833	September 30, 2022