Fiscal Policy and Financial Markets: Nonlinearity in Fiscal Policy Shocks

by

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Abstract

Linear Vector Autoregression (VAR) is a useful application of time-series models for analyzing multivariate relationships between key macroeconomic variables. Nevertheless, the linear multivariate system is not capable of capturing important nonlinear dynamics demonstrated by theoretical models. This essay employs a nonlinear VAR framework to re-examine previous findings that financial markets can act as a nonlinear propagator of shocks in the economy. A Threshold Vector Autoregression (TVAR) is estimated on U.S. quarterly data for the period 1980–2016 to compute state-dependent fiscal multipliers in relation to the financial market regime. In a TVAR model, a measure of 'tightness' in financial markets is included to endogenously determine the financial market regime in the multivariate system. I employ generalized impulse response functions (GIRFs) which allow for nonlinear dynamics such as regime-switching and asymmetric responses to shocks. With the GIRF approach, I examine the real effects of fiscal shocks in the following three dimensions: 1. whether fiscal policy shocks have different effects across 'tight' and 'normal' financial market regimes; 2. whether fiscal policy shocks of different magnitudes have disproportionate effects; 3. whether positive fiscal policy shocks have different effects from negative shocks. I find evidence of asymmetric/disproportionate output responses in all three dimensions. The results appear to be robust to different measures of financial 'tightness' and fiscal foresight.

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1 Introduction

It has long been recognized that both the dynamic behavior of economic variables as well as many relationships between them are inherently nonlinear. Nonlinearities can characterize a wide range of economic relationships. For example, Kocherlakota (2000) and Acemoglu and Scott (1997) show that business cycles are subject to the asymmetric amplification and propagation of shocks. However, capturing nonlinearities is a challenging exercise. Most empirical studies employ linear models which are not capable of capturing effects that may only materialize under particular states of an economy. As a result, empirical linear models often fail to capture effects that have been demonstrated in theoretical works. A prominent example is by Bernanke *et al.* (1998) on the financial accelerator mechanism where the pricing function for external financing regarding firms' net worth is convex. The concept has gained tremendous popularity and it has become an essential ingredient in business cycle models. However, it lacks empirical validation.

Important nonlinearities can be found in stabilization policies in relation to financial markets. The pervasiveness of financial frictions implies that financial markets play a central role in propagating shocks in a nonlinear way, potentially amplifying the magnitude and persistence.[1] A recession is associated with the period in which the quality of assets held by financial institutions deteriorates due to an increased ratio of non-performing loans and negative sentiment of investors depressing the value of other assets and increasing the perception of risk in the overall economy. Financial markets have also become a source of shocks generating business cycles. Ng and Wright (2013) shows that most of the recessions in the U.S. from the 1980s originated from financial market shocks having features distinguished from those of a standard 'textbook' recession.

Stabilization policies amid increased 'tightness' in financial markets could feed back

[1]See Gertler and Kiyotaki (2010) and Brunnermeier and Sannikov (2014).

into financial markets resulting in distinct macroeconomic responses. For example, after the financial crisis in 2007 the U.S. government engaged in active fiscal policy to support short-term GDP growth and the growth potential.[2] Such discretionary fiscal policy attracted much attention on the effectiveness of fiscal policy during a financial crisis. Blanchard and Leigh (2013), for example, find that fiscal consolidation pursued by many major economies after the financial crisis in 2007 unexpectedly produced stronger recessionary effects due to increased stress in financial markets.

Hence, during periods of increased 'tightness' in financial markets, effects of fiscal development on macroeconomic aggregates may be different from those observed in normal times. It is then important to investigate whether there are important nonlinearities at play in the transmission mechanism of fiscal policy shocks.

Indeed, discussions regarding fiscal policy in relation to financial markets are often two-sided. On the one hand, there are arguments against using discretionary fiscal policy as a stabilization tool as the policy may involve unsustainable sovereign debt that could increase the cost of borrowing for the whole economy due to an increased risk premium. This could crowd-out private spending as private sector borrowers face higher borrowing costs. In this case, the effect of fiscal policy in supporting the economy may be minimal. However, fiscal policy could stimulate demand without siphoning resources off the private sector. Fiscal policy can *improve* conditions in financial markets especially when agents face a higher degree of friction in the markets. Investment decisions are made based on future prospect of growth or demand in the economy. Lenders assess the risk of borrowers based on their beliefs about whether borrowers' investment can generate enough returns to finance debt service costs and pay back the principal. Thus, reflationary fiscal policy can improve credit supplies for the private sector by channeling more financial resources to them in exchange for claims on their future higher returns. This could actually crowd-in private demand resulting in more

[2] The Economic Stimulus Act (2008) and the American Recovery and Reinvestment Act (2009).

effective demand stimulation.[3]

The above circumstances pose a challenge to fiscal policies. Fiscal policy has become increasingly important as a stabilization tool but it is strongly interrelated with financial markets. Nevertheless, there is little research examining how the size of fiscal multipliers changes depending on the state of an economy. In fact, much of research in fiscal policy relies on a linear vector autoregression or first-order linearized DSGE models which cannot capture the state-dependent effect of fiscal policy.

By adopting a Threshold Vector Autoregressive (TVAR) model, this essay studies potential state-dependent responses of macroeconomic aggregates to fiscal policy shocks using U.S. quarterly data for the period 1980–2016. In a TVAR model, the Chicago Fed National Financial Conditions Index is included as the threshold variable that defines the financial market regime. The threshold variable is included as one of the endogenous variables in the TVAR model allowing for the possibility of an endogenous regime-change. To motivate the use of a nonlinear time-series model, I also conduct formal statistical tests for linearity. By adopting the methods suggested by Hansen (1999) and the literature on *supLR* tests (*e.g.* Galvão (2003) and Lo and Zivot (2001)), I conduct linearity tests on the sample data to provide statistical evidence of the presence of multiple regimes in financial markets.

Two main questions can be addressed based on a TVAR framework. First, the model can explore the dynamics of macroeconomic aggregates for given characteristics of fiscal shocks. In linear VAR models, for example, effects of shocks are symmetric in the sense that the sign and the size of the shock do not lead to different amplification effects. However, one can easily imagine that certain shock can trigger effects that differ depending on the magnitude and direction of the shock. With the nonlinear model, we can investigate the difference across varying nature of shocks. Secondly, one can study the difference in effects of a given shock conditional on the initial state of an economy. It may be the case that the mechanism of

[3]See Woodford (1990) and Holmstrom and Tirole (1996).

the shock operates differently if an economy is very vulnerable when the shock hits. These two questions can be answered by the use of a generalized impulse response function (GIRF) which is constructed based on a simulation method.

By rejecting the null hypothesis of linearity in the data, I find statistical evidence that the U.S. economy has more than one regime depending on conditions in its financial markets. Also, the GIRFs captures a strong and persistent difference in the output response across different financial market regimes. Specifically, the output response is stronger when the economy is in the 'tight' financial market regime. The GIRFs also show that fiscal shocks have asymmetric/disproportionate output responses across different signs and sizes of the shocks.

This essay also presents a series of robustness tests for the following two issues: 1. There is little consensus on a single variable that represents the overall condition of financial markets; 2. Fiscal shocks identified by the model may contain a forecastable component due to expectations about future fiscal policies. I carry out the same analysis using two alternative threshold variables: the BAA spread and the mix of bank loans and commercial paper in total firm external funding (Kashyap *et al.* (1993)). I also conduct the analysis based on the model controlling for fiscal foresight.

The rest of the essay is organized as follows. The following section discusses previous literature on the interrelation between financial markets and government stabilization policies. The section also looks at the empirical works investigating the asymmetric effects of fiscal shocks focusing on a specific source of multiple regimes in a given economy. Section 3 describes a TVAR model along with associated the linearity test and the generalized impulse response functions. Section 4 describes the data employed in the study. Section 5 presents empirical results and Section 6 discusses a series of robustness tests. Finally, Section 7 contains concluding remarks.

2 Related Research

2.1 Financial Markets as a Source of Nonlinearity

Financial markets can be a source of nonlinearity in the relationship between macroeconomic variables and fiscal policy shocks. The link between financial markets and the real economy comes from firms' need for external finance to fund their investment and production. There is an extensive literature on the relationship between financial markets and business cycles. The most notable study is by Bernanke *et al.* (1998) on the financial accelerator effect. They introduce a mechanism through which financial markets and macroeconomic development are interrelated by looking at how firms and households become credit-constrained following an adverse shock in the economy. Frictions in financial markets (*e.g.* asymmetric information or costs of contract enforcement) introduce a wedge between the cost of external financing and the opportunity cost of internal financing. This is often termed 'the premium for external funds'. Such a premium is endogenously determined and has an inverse relationship with the balance sheet strength of the borrower. Importantly, the borrowers' balance sheet position is often positively correlated with the aggregate economic activity. The procyclicality in borrowers' financial positions implies countercyclical movement in the premium for external funds. It is a financial feedback loop in which firms experience a vicious cycle of deterioration of their balance sheets and reduction of economic activities, that enables a small shock in financial markets to produce a significant change in economic conditions.[4]

In the presence of such frictions, fiscal policy can be considered as a shock that either alleviates or amplifies the friction for the private sector borrowers. When an economy is in

[4]For example, an adverse shock deteriorates the balance sheets of the firms causing the external finance premium to increase. A larger share of borrowers in the economy would have impaired access to credit markets. This causes a larger decline in spending and production than otherwise. Limited access to credit and fall in the value of asset used as collateral would further lead to decrease in aggregate economic activities resulting in a vicious cycle. See Gertler and Kiyotaki (2010) and Brunnermeier and Sannikov (2014) for additional explanation.

the 'tight' financial market regime, financial frictions limit the access to credit more severely in the private sector. By improving the prospect of the aggregate economic activity, an expansionary fiscal policy can be considered as a shock that improves conditions for private sector borrowers minimizing the crowd-out effect. Credit supplied to the private sector could also be reduced due to tighter collateral constraints during a recession. Then, a positive fiscal shock can relax such constraint by limiting the fall in the value of collateral, which tends to be real estate and equities. On the other hand, in the normal regime a positive fiscal policy shock may result in 'tighter' conditions in the financial market where firms face increasing external premia. This is a standard 'textbook' prediction where fiscal policy crowds out private investment.

The above view is often explained in the literature based on a DSGE model augmented with lending relationships in the financial market where countercyclicality of bank spreads plays a financial accelerator role in the propagation mechanism of technology shocks. In such a model, fiscal policy can act as a shock that either alleviates or amplifies countercylical movement in bank spreads and loan supply. Lending relationship is established as banks hold up borrowers since the former has an accumulated informational advantage over the latter's creditworthiness. Moreover, borrowers face switching costs associated with finding a new funding source as they need to start a signaling process again. Hence, during a recession banks raise the bank spread by more for bank-dependent borrowers as part of their profit maximization exploiting the deep habit formed by borrowers. This results in countercyclical movement in bank spreads. When the government conducts fiscal policy that improves the prospectives of future growth and thus higher returns on investment, lenders may find it more profitable in the longer-term to increase the supply of loans to lock new customers into lending relationships rather than exploiting the current customer base. As firms obtain a greater access to external financing for capital acquisition and the wage bill, investment and labour hours increase by more. This, in turn allows for a greater expansion in output. This can be considered as a second-round effect of fiscal policy on output. Thus, the presence of frictions allows for nonlinearity in effect of stabilization policy on the economy depending on the financial market regime. The higher the degree of deep habit formation in lending by firms is the more, in response to a positive fiscal shock, banks are willing to supply loans, causing a downward pressure on the lending rate.

The view has been explored in both RBC and New Keynesian models. Based on an RBC model augmented with lending relationship, Melina and Villa (2014) show that there is a financial accelerator as part of the transmission mechanism in fiscal policy. By incorporating the modeling device that allows firms to form deep habits in their borrowing decisions, they show that the lending relationship generates a counter-cyclical bank spread. They show that under the credit-constrained regime, a positive fiscal shock alleviates such friction in the financial market. Subsequently, it leads to a smaller bank spread and greater loan supply for firms.[5] Aliagadaz and Olivero (2010) also show that a countercyclical bank spread in an RBC model plays a financial accelerator role in the propagation mechanism of technology shocks. They argue that their finding provides additional grounds for stabilization policies in economies with stronger counter-cylicality in bank spreads. In the New Keynesian framework, Aksoy *et al.* (2013) show that the lending relationship is a crucial feature of financial intermediation. Hence, it is relevant for monetary policy decision.

2.2 Measuring Fiscal Policy Effects with a Nonlinear VAR

This essay adopts a nonlinear time-series model to explicitly account for potential nonlinearity in the effect of fiscal policy considering the financial market as a source of nonlinearity. A small but the growing literature has examined the conditional effect of fiscal policy with

[5]In the same paper, by adopting an SVAR framework using U.S. data, they find that lenders lower the external risk premia for borrowers after a positive fiscal shock and that fiscal policy has a greater effect on output under a 'tight' credit regime measured by the bank spread. This implies that fiscal consolidation would have larger recessionary effect on the economy when credit is constrained.

respect to the state of an economy.[6] Most of the studies employ nonlinear VAR models in order to capture the nonlinearity in responses of macroeconomic variables to a policy shock. The most commonly adopted model is a TVAR featuring a discrete endogenous regime-change or its special cases such as Smooth Transition TVAR (STVAR). GDP growth and the output gap have been studied as a source of multiple regimes most commonly by researchers. For example, Auerbach and Gorodnichenko (2012a,b) studied the nonlinearity in effects of fiscal policy over business cycle by estimating STVAR using data for U.S. and other OECD countries. Other examples include Baum and Koester (2011), Mittnik and Semmler (2012), and Bachmann and Sims (2011). Other sources of regimes previously studied are banking crises (*e.g.* Turrini *et al.* (2010)); public debt (*e.g.* Baum *et al.* (2012)); financial stress indexes (*e.g.* Afonso *et al.* (2011); corporate bond markets (*e.g.* Ferraresi *et al.* (2015)). A common result of these studies is that there is a statistically significant difference in the effect of fiscal policy across regimes and the effect tends to be greater during periods of crisis. For instance, using U.S. data, Auerbach and Gorodnichenko (2012b) and Bachmann and Sims (2011) find fiscal multipliers higher than 2 during recessions but around 1 in periods of expansion. Based on a TVAR, Baum *et al.* (2012) use the output gap as the threshold variable as it divides economic development in phases of under- and over-utilization (two regimes). They find that fiscal spending multipliers are much larger in times of a negative output gap but have only a very limited effect in times of a positive output gap.

There has been relatively less effort to study empirically the possible nonlinear relationship between the effect of fiscal policy and the state of financial markets based on a multi-equation framework. The closest antecedents to this essay are Afonso *et al.* (2011) and Ferraresi *et al.* (2015). Afonso *et al.* (2011) examine data from the U.S., U.K., Italy, and Germany to study

[6]In the field of monetary policy, based on threshold VAR (TVAR), Li and St-Amant (2010) examine nonlinearity in the effect of monetary policy by looking at how financial stress conditions play a role as as a nonlinear propagator of monetary policy shocks. They show that the effect of monetary policy is greater under the 'tight' credit regime as measured by the financial stress index constructed by Illing and Liu (2006). Similar results are supported by Atanasova (2003) and Balke (2000), who also adopt the TVAR framework.

possible nonlinearity in effects of fiscal policy vis-á-vis a financial-stress index (constructed by the IMF) encompassing bank, stock market and exchange rate dynamics. Ferraresi *et al.* (2015) aim to answer a similar question based on U.S. data but using the BAA spread as the threshold variable that defines regimes. They focus specifically on the corporate bond market conditions in order to capture variations in premia for external financing for firms. A common outcome of the two studies is that there are statistically significantly different regimes in credit markets and that the estimated response to a fiscal shock differs across regimes. However, their findings are mixed for the U.S.. Afonso *et al.* (2011) find no statistically significant difference in the output gap response to a fiscal shock between 'tight' and normal regimes while Ferraresi *et al.* (2015) find that the response of output to fiscal shocks is much stronger whenever firms are subject to increasing financing costs in the bond market.

2.3 Identification of Shocks and Choices of Fiscal Variables

There are two main complications when one studies fiscal policy based on a VAR framework. One is associated with the identification of fiscal policy shocks and the other is with the choice of fiscal variables. Empirical studies on the effectiveness of fiscal policy have a wide range of conclusions depending on factors such as sample period, choice of fiscal variables, and the identification scheme for fiscal shocks. Some studies find evidence of significant and large impact of fiscal policy on consumption/investment while others find no evidence of such impact. Estimation of the effect of fiscal policy is tricky as it is challenging to isolate the direct effect of a purely exogenous fiscal policy shock on macroeconomic variables. The identification problem arises since changes in fiscal variables may just be contemporaneous responses to changes in other macroeconomic variables. Fiscal policy automatically responds to changes in economic conditions and this must be distinguished from discrete fiscal action and from an exogenous shock to fiscal policy. The remaining two components must also be isolated in order to completely identify exogenous shocks. Moreover, fiscal foresight further complicates the identification problem. Fiscal policies are usually announced in advance so agents in the economy obtain information about the future fiscal policies and react accordingly even before the policy is implemented. Researchers have tried to circumvent this problem by focusing on the subset of exogenous fiscal shocks. However, there is little consensus in the literature on the method to extract the exogenous element from the observed fiscal data.

In line with most of the fiscal TVAR literature (*e.g.* Afonso *et al.* (2011) and Ferraresi *et al.* (2015)), I employ a recursive identification scheme with the Cholesky decomposition with the ordering of government spending measure (g) followed by net tax (τ)[7], real GDP (y), and the threshold variable which determines the financial market regime.[8]

In the literature exploring the macroeconomic effects of fiscal policy, there seem to be four main identification strategies employed. The most common identification strategy is the recursive identification scheme with the Cholesky decomposition. Examples are Fatas and Mihov (2001) and Favero (2002) although the specific ordering of variables in the identification scheme differs across the studies. The second method involves estimating a fiscal VAR based on more complex structure as suggested by Blanchard and Perotti (2002), where they impose a restriction on contemporaneous relationship between endogenous variables in VAR based on external information on the elasticities of output with respect to tax and fiscal spending change. This is to filter out the effect of automatic stabilizers. In the TVAR literature on fiscal policy, Auerbach and Gorodnichenko (2012a,b) and Baum and Koester (2011) are examples that rely on this approach. A third method involves the narrative approach (Ramey

[7] Government spending includes the following: Government consumption expenditures and gross investment (*Federal National Defense Gross Investment*, *Federal Non-defense Gross Investment, and State and Local Government Gross Investment*). Following Blanchard and Perotti (2002), net tax is computed by: *Current Tax Receipts* (the sum of *Personal Tax* and *Nontax Receipt*, *Corporate Profits Tax Receipts*, and *Indirect Business Tax* and *Nontax Accruals*) plus *Contributions for Social Insurance* less *Transfers Payments to Persons* and *Interest Payments*.

[8] Some empirical studies in the fiscal VAR and TVAR literature include inflation and a short-term interest rate. However, the Cholesky identification scheme could be too restrictive in a six dimensional TVAR. The number of coefficients in the TVAR and the linearity test increases in proportion to the number of coefficients in the standard linear VAR model. This significantly affects the size and power of the tests. Thus, I have chosen a more parsimonious model.

and Shapiro (1998); Edelberg *et al.* (1998); Burnside *et al.* (2004); Romer and Romer (2010)). The narrative approach uses external information regarding the fiscal policy released by governments and newspapers. In their famous paper, Ramey and Shapiro (1998) identify an external fiscal shock by constructing a dummy variable associated with periods that are known for exogenous changes in fiscal policy. Lastly, there is another less commonly used alternative approach: imposing sign restrictions. Caldara and Kamps (2008) compared the four existing approaches to identify fiscal policy shocks in VAR models using a dataset for the U.S.: the recursive identification scheme with the Cholesky decomposition; the Blanchard and Perroti (B&P) SVAR approach; the narrative approach; the sign-restriction approach proposed by Uhlig (2005). The authors argue that different identification schemes lead to similar results as far as the effect of government spending is concerned, *e.g.* the shock to government spending is likely to increase output. However, results are strongly diverging regarding the responses to changes in taxes.

Among these identification strategies, the recursive identification scheme with the Cholesky decomposition and B&P approach are the most commonly chosen strategies in empirical studies on fiscal policy. The B&P approach has an advantage over a simple recursive identification via Cholesky decomposition as I can explicitly identify the effect of automatic fiscal policy response on output by using external information on output elasticities with respect to tax and spending changes. However, Perrotti (2004) shows that there is no clear evidence of automatic fiscal response within a quarter in the U.S.. Also, the B&P approach is based on the assumption that fiscal multipliers do not vary over the business cycle. Auerbach and Gorodnichenko (2012b) argue that B&P's elasticities are likely to vary over the cycle, thereby introducing a bias of unknown magnitude and direction in the regime-specific estimates for their threshold model. For example, they have found that output responses to tax shocks in different regimes are very sensitive to the assumed elasticity. This approach may not be appropriate especially in a nonlinear time-series framework where the model explicitly aims to estimate state-dependent relationship between variables. Imposing an additional state-independent structure in the model does not seem to be plausible. Thus, I adopt the recursive identification scheme and rely on the Cholesky decomposition of the variance-covariance matrix of residuals in each regime.

Next, I provide explanation for the specific ordering of the variables. In order to establish a plausible ordering of the variables, I first discuss the components of fiscal policy action. The reduced-form residual for the fiscal variable equation is assumed to be a linear combination of the following three components; 1. automatic response 2. systematic discretionary response 3. random discretionary shocks. Component 2 is assumed to be absent in quarterly data as discretionary fiscal policy usually faces institutional constraints creating some implementation lags. Moreover, it takes time for the fiscal authority to identify changes in economic conditions as macroeconomic data are released with a considerable lag. Next, Perroti (2004) argues that there is no evidence of any substantial automatic response of government spending to GDP within a quarter in the U.S.. Hence, component 1 is assumed to be 0. The remaining component is a structural shock which would be identified by the Cholesky decomposition. I take fiscal variables as predetermined with respect to macroeconomic shocks. In other words, changes in government investment and consumption are undertaken for reasons other than immediate reaction to macroeconomic conditions.[9] However, fiscal spending is ordered before the tax variable and this amounts to assuming that tax decisions are taken only after spending is determined. The reason is that tax changes are decided on a yearly basis and largely pre-announced. I believe it is a plausible assumption but an untestable hypothesis in the SVAR.

[9]Ordering the policy instrument after GDP is common in monetary policy VARs with monthly data (Bernanke and Mihov (1998)) based on the assumption that a change in the policy rate has roughly 6-month lag in having effect on GDP. But if we order the fiscal variable after GDP this implies that a fiscal spending, for example crowds out 100 percent of private GDP contemporaneously as government spending is a component of GDP. Similarly, taxes are a component of disposable income. Thus, restricting the contemporaneous effect of taxes on private consumption, for example seems highly questionable.

The effect of a tax change is complicated. A mere change in levels of revenues as captured by the tax variable cannot fully represent the change in government's tax policy. Its effect on the economy is likely to be through the structure of taxes such as marginal tax rates. Moreover, most papers show that the spending has a more direct effect on output than taxes do. Thus, in this essay, I focus on the effect of a spending shock although I include the tax variable in the model.[10] I order the threshold variable last as I assume that changes in both policy and macroeconomic aggregates are transmitted to financial markets within a quarter.

Lastly, I briefly discuss the problem associated with fiscal foresight. Decision lags in fiscal policy may facilitate identification of exogenous shocks to fiscal variables. However, unlike monetary policy, changes in fiscal policy are often decided and announced well before the actual implementation. Thus, fiscal 'shocks' can be anticipated by firms and households. Note that innovations from a VAR are with respect to the information set of the econometricians not of the private sector. With announcement of fiscal policy decision, its effect is likely to be reflected immediately in macroeconomic variables. Thus, those variables would pick up the effects of the anticipated component of fiscal policy. In the benchmark specification, I do not control for expected changes in fiscal policy. However, I do so as one of the robustness test exercises using the data from the Survey of Professional Forecasters conducted by the Federal Reserve Bank of Philadelphia.

3 Statistical Method

3.1 Threshold Vector Autoregressive Model (TVAR)

Within the class of nonlinear models, this essay employs a Threshold Vector Autoregressive model (TVAR). This is one of the most widely used classes of models in the nonlinear

[10]Similarly, Fatas and Mihov (2001) leave the contemporaneous relationship between macroeconomic and tax variables unrestricted as they only focus on a fiscal spending shock.

time series literature. TVAR is a relatively simple way to capture nonlinearities such as regime switching, asymmetries and multiple equilibria (reflected in multimodal stationary distributions) implied by theoretical models of credit market imperfections. TVAR only allows a discrete regime change rather than a smooth transition to different regimes in an economy. To capture nonlinear dynamics, regimes are associated with recurring dichotomous (*i.e.* good and bad states of the economy). Unlike a Markov Switching VAR model, TVAR explicitly models the endogenous regime-switching process by identifying a variable that causes a regime switch. The threshold variable (variable that determines the regime) is one of the endogenous variables in the model. This way, the regime switching is tractable. Threshold models work by splitting the time series endogenously into different regimes. Within each regime the time series is assumed to be a linear model. Nonlinearities are reflected by changes in the parameters across regimes. Due to the limited number of observations, I assume that only two regimes exist - 'tight' and 'normal' financial regimes - once the hypothesis of linearity is rejected.

Consider a two-regime TVAR model. With the endogenous threshold variable, f_t, denote a set of stationary endogenous variables (fiscal variables, output measure, and the financial 'tightness' measure) as $w_t = (g_t, \tau_t, y_t, f_t)'$. Also, with a finite lag order ρ, let $\phi = (\phi_0, \phi_1, ..., \phi_\rho)$ and $X_t = (1, w_{t-1}, ..., w_{t-\rho})'$.

Then, the TVAR is represented by:

$$w_t = \phi_1 X_t + (\phi_2 X_t) I(f_{t-d} > \gamma) + u_t \tag{1}$$

In regime 1:

$$I(f_{t-d} \leq \gamma) = 0 \tag{2}$$

$$w_t = \phi_1 X_t + u_t \tag{3}$$

In regime 2:

$$I(f_{t-d} > \gamma) = 1 \tag{4}$$

$$w_t = (\phi_1 + \phi_2) X_t + u_t \tag{5}$$

where d is the delay lag of the threshold variable relevant for regime switches; ϕ_R is the matrix of coefficients for regime R (R = 1,2); and γ is the threshold value.

For example, if f at time $(t-d)$ is greater than the threshold value, γ, then the economy is in regime 2 at time t. The threshold value (γ) and d are to be estimated along with other parameters of the model. Each regime is characterized by Σ_R which is a variance-covariance matrix for reduced-form errors in regime R. Σ_R is estimated based on a set of residuals in each regime. We gather residuals within each regime to obtain a matrix of u_R. The size of u_1 and u_2 would be $(N_1 \times k)$ and $(N_2 \times k)$ respectively where N_1 and N_2 denote the number of observations in each regime and k denotes the number of endogenous variables. Then, Σ_R=E$[u'_R u_R]$ and $\hat{\Sigma}_R = \dfrac{1}{N_R - k}\hat{u}'_R\hat{u}_R$.

3.2 Estimation

As the model is linear within each regime, the TVAR is estimated by conditional least squares (CLS).[11] By definition, the least squares estimators minimize jointly the sum of the squared errors. It is conditional LS as we minimize the sum of squared residuals conditional on γ and d. Then the LS estimates are:

[11] Tsay (1998) proves consistency by conditional least squares and shows that the estimates are asymptotically normal.

$$\hat{\phi}_R(\gamma, d) = (\sum_t^R X_t(X_t)')^{-1}(\sum_t^R X_t(w_t)') \tag{6}$$

$$\hat{\Sigma}_R(\gamma, d) = \frac{\sum_t^R (w_t - X_t'\hat{\phi}_R(\gamma, d))(w_t - X_t'\hat{\phi}_R(\gamma, d))'}{N_R - k} \tag{7}$$

where $\sum_t^R$ denotes summation over observations in regime R.

Let us denote the sum of squared residuals by:

$$S(\gamma, d) = S_1(\gamma, d) + S_2(\gamma, d) \tag{8}$$

where $S_R(\gamma, d)$ denotes the trace of $(N_R - k)\hat{\Sigma}_R(\gamma, d)$.

We estimate the TVAR with CLS for a given γ and d. The estimates of γ and d are obtained by:

$$(\hat{\gamma}, \hat{d}) = \text{argmin}_{\gamma, d}\, S(\gamma, d) \tag{9}$$

where $1 \leq d \leq \bar{d}$ and $\gamma \in \Gamma$ for some $\bar{d}$ and Γ.

The threshold value (γ) is assumed to be restricted to a bounded set $\Gamma =[\underline{\gamma}; \bar{\gamma}]$, where Γ is an interval (trimmed) that covers the sample range of the threshold variable. For example, I can impose trim (T) = 0.15 such that I have at least 15% of observations in each regime. So, I only consider the values lying between Tth and $(1 - T)$th quantile of f.[12] This is to guarantee that we have sufficient number of observations for estimation in each regime.[13]

[12]The number of observations in each regime would be at least TN where T is the value of trim that I set and N is the total number of observations in my sample.

[13]The trim is chosen arbitrarily by the econometrician. There is no general guideline but 15% is most commonly chosen in the literature. The higher the number of observations, the less the econometricians is

Within this interval, I do a grid search for all possible γ for a given d. For each γ, I apply CLS to estimate the model. Then, I pick the one with the minimum SSR as in (9).

The delay parameter, d, is typically unknown so, it too must be estimated. The least squares principle described allows d to be estimated along with other parameters. Hansen (1996) suggests the estimation be augmented to include a search over d as well. Since the parameter space for d is discrete the LS estimate, $\hat{d}$ is super-consistent. So, for the purpose of inference on the other parameters we can act as if d is known with certainty. The total number of function evaluations from the joint grid search for (γ, d) would then be $m \cdot \bar{d}$ where m is the number of possible γ in Γ. However, when m and $\bar{d}$ are too large, a full grid search can be too costly especially for the Hansen (1999) bootstrap method that I describe in the following subsection for the inference. Hence, for simplicity, I suggest that one simply tests d in $1 \leq d \leq \rho$ (for each trial of a grid search for γ) and select the delay order that results in the minimum SSR.

Due to the limited number of observations associated with estimating the TVAR (especially in the 'tight' financial regime), the lag order of the endogenous variables is determined by the Schwarz's Bayesian information criterion (SBIC) which gives a relatively large penalty to the number of coefficients estimated in the model. Based on the SBIC, the optimal lag order for the baseline and all alternative specifications is one lag. For the alternative specifications where I use different threshold variables, the majority of the information criteria suggest a higher order (4 lags). However, I follow the SBIC as the cost of over-fitting in a TVAR model is quite high. The power of the linearity test, which is described in the following subsection decreases significantly for every additional parameter included in the model.[14]

restricted in choosing extreme trimming values.

[14]See Hansen (1996) for Monte-Carlo experiments.

3.3 Linearity Test

Before adopting the TVAR, I test the nonlinear alternative (TVAR) against a linear model (VAR without a threshold). Using the method suggested by Hansen (1999), I test the null hypothesis of a linear VAR versus the alternative of a TVAR with 2 regimes based on a nested hypothesis test. More precisely, the null hypothesis is that ϕ_2 in equation (1) is zero. However, the threshold parameter, γ and d are nuisance parameters as they are not identified under the null. Thus, we cannot apply standard inference (see Hansen (1996)).

Following a procedure suggested by Hansen (1999), I conduct a test which explicitly accounts for the fact that the threshold parameter is not identified under the null hypothesis. For a given d, a TVAR model is estimated by CLS for all possible threshold values (all values within the interval, $\Gamma =[\underline{\gamma}; \bar{\gamma}]$). Then, for each trial the LR statistic testing the hypothesis of no difference between VAR and TVAR is computed:

$$LR(\gamma, d) = T(ln(|\hat{\Sigma}|) - ln(|\hat{\Sigma}(\gamma, d)|)) \tag{10}$$

This LR test statistic is computed as the difference in log determinant of the estimated variance-covariance matrix of the model under the null and the alternative.[15]

I also calculate:

$$LR^{*} = supLR(\gamma, d) \tag{11}$$

$supLR$[16], which is the supremum of LR statistic over all possible threshold values over the grid, is obtained from the above exercise. The distribution of the test statistic does not follow a χ^2 as γ and d are not identified under the null. For a fixed (and known) γ and d,

[15] I follow the multivariate extension proposed by Lo and Zivot (2001) and Clements and Galvão (2004) of the linearity test of Hansen (1999) for univariate models.

[16] $LR(\gamma, d)$ is a monotonic function of the determinant of $\hat{\Sigma}(\gamma, d)$ but it is not necessarily the case that LR^{*} is $LR(\hat{\gamma}, d)$ where $\hat{\gamma}$ satisfies (9). It is important to note that the value of γ that satisfies (11) can be different from the CLS estimate of γ.

the test statistics would have an asymptotic chi-squared distribution. But (11) involves a large number of values for the parameter not just a single value. As a result, the asymptotic distributions of $supLR$ statistics are affected by the unidentified parameters under the null hypothesis of linearity, the so-called Davies problem (see Davies (1977, 1987)). In practice, simulation techniques must be adopted to evaluate the distributions on a case-by-case basis.[17] The simulation method suggested by Hansen (1996) and Hansen (1999), which involves simulating an empirical distribution of $supLR$, is used to conduct inference. The p-values from the bootstrap distributions are then obtained from B replications of the simulation procedure.[18]

3.4 Generalized Impulse Response Function (GIRF)

In a linear model, one set of impulse responses is sufficient to characterize the dynamics in the system. Using the Koop *et al.* (1996) terminology, the impulse response function of a linear model has a symmetry property (*i.e.* a shock of -1 has exactly the opposite effect of a shock of +1), a shock linearity property (*i.e.* a shock of size 2 has exactly twice the effect of a shock of size 1) and a history independent property. The impulse responses are constant over time as the structure of the covariance does not change.

However, these convenient properties do not carry over to a nonlinear model. In a

[17]In a separate study, I conducted Monte-Carlo experiments where I studied how the finite sample distribution of $supLR$ statistics is affected by the number of regressors in the model holding other factors constant. I found that the distribution changes monotonically with respect to a change in the number of regressors. Such observation is robust to introduction of covariance among vectors of error. Thus, the distribution of $supLR$ cannot be tabulated for general use. This motivates me to conclude that a case-by-case simulation for inference may be required in practice.

[18]The algorithm is as follows. Generate a random sample of u_t^*, t= 1,...,N by sampling with replacement from the OLS residuals of the model under the null. Then, using the fixed initial conditions (w_0, w_{-1},..., $w_{-\rho+1}$), recursively generate a sample w_t^* using estimated coefficients from the model under the null and u_t^*. Based on this simulated series, w_t^*, I compute the $supLR_b*$ (test statistics) as described in this essay. Then, I repeat the whole process B times. The bootstrap p-value is the percentage of simulated $supLR_b*$ that exceed the observed $supLR^*$. $p=\frac{1}{B}\sum_{b=1}^{B} I(supLR_b* > supLR^*)$. This is the algorithm suggested by Hansen (1996) and Hansen (1999) and used by many empirical papers that adopt TVAR. Examples are Li and St-Amant (2010), Ferraresi *et al.* (2015), Afonso *et al.* (2011), Balke (2000), and Atanasova (2003).

nonlinear framework with endogenous regime-switching, the reaction of endogenous variables to a shock largely depends on the entire past history of the system, the initial state of the economy at the time of a shock at t, the sign and size of a shock at t, and the sign and size of all shocks over the horizon (from $t+1$ to $t+h$ where h is the time horizon) of the impulse response function. The moving-average representation of a TVAR is not linear in the structural shocks and hence, their Wold decomposition does not exist. A shock at time t may lead to switches between the multiple regimes in the economy. As a result, impulse responses in a nonlinear framework cannot be constructed simply as the path that a given variable takes in response to a shock at time t. Moreover, the assumption that no shock hits the system over a given time horizon may result in misleading inferences regarding the underlying propagation mechanism (a shock at time t may trigger a regime switch at $t+d$). Such assumption essentially implies that the threshold effect is only active at time t and becomes inactive independent of the initial shock for the rest of the horizon (Koop *et al.* (1996)). Also, choosing a particular history of the system can introduce bias in the impulse responses.

Formally, the generalized impulse response function is defined as the change in the conditional expectation of w_{t+h} in response to a shock (u_t) to the variable of our interest at time t:

$$GIRF(h, \Omega_{t-1}, u_t) = E[w_{t+h}|\Omega_{t-1}, u_t] - E[w_{t+h}|\Omega_{t-1}] \tag{12}$$

where Ω_{t-1} is the information set at $t-1$.

The impulse response function must be conditional on the entire past history of the variables up to point t (reflected in Ω_{t-1}), and the size/sign of the shocks. In order to obtain the complete dynamics of the system, simulation methods are required to recover the GIRF. The conditional expectations in equation (12) must be computed by simulating a TVAR model with bootstrapped shocks for any possible starting point given the initial state of the system. Such simulation is repeated many times with new series of bootstrapped shocks for each trial. This way, the impulse responses are averaged over initial values taken from subsamples of the data. In other words, the impulse responses are averaged over the initial values that correspond to all observations that belong to a particular regime of the system. Via simulations, the effects of the past history and of all other shocks hitting the system after t would also be averaged out. The exercise is repeated by adding a shock of a specific size to the variable we are interested in at t given the initial regime of the system. Equation (12) would be the result of the difference of the two averages over the horizon, h. The program for computing the GIRF was written by the author based on the algorithm suggested by Koop *et al.* (1996). The algorithm can be found in Appendix B.

The majority of papers that adopt GIRFs do not compute confidence bands. First of all, there is no methodological work on computing confidence bands for GIRFs. Secondly, it is computationally quite intensive. For example, if I simulate over 100 different draws of shocks for each 100 different histories, computing GIRFs already involves 10,000 simulations. Confidence bands require additional simulations. For example, if I simulate over GIRFs 1000 times to construct a bootstrapped distribution of GIRFs (a distribution of *mean values* of simulated series) from which confidence bands are drawn, the total number of simulations reaches 10^6.

In this essay, I employ a quite simple alternative method to reduce this computational burden. I simply plot 2.5% and 97.5% quantiles of the simulated responses based on the average responses over all histories (given an initial regime) that are randomly drawn. For example, by simulating over 100 different draws of shocks for each of 100 different histories, I have a distribution of 100 average responses at each point over the time horizon. From the distribution, I draw 2.5% and 97.5% quantiles. Note that unlike linear time-series models with normal errors, in the TVAR framework, the distribution of simulated values of a given endogenous variable is not normal and is often intractable if the GIRF horizon is greater than d. This is due to the possibility of an endogenous regime-switch that could occur from $t+d$ in response to a shock at t.[19] Constructing 2.5% and 97.5% quantile of the simulated responses, for example, would also be useful if the mean response is inappropriate due to a possible multimodal or very skewed distribution.

4 Data

In this essay, U.S. quarterly data are employed from the FRED database of the Federal Reserve Bank of St. Louis and the Bureau of Economic Analysis of U.S. Department of Commerce.[20] The main sample period ranges from 1980q1 to 2016q3. The choice of the sample period is motivated by the fact that the period covers a relatively coherent time with respect to the characteristics of recessions in the U.S. economy. According to Ng and Wright (2013), the recessions since 1980s all have financial origins and have common features such as 'tight' credit conditions during recoveries and strong leverage cycles.

4.1 Threshold Variables

There is an additional complication associated with the TVAR framework. The choice of threshold variable that endogenously determines the financial market regime is tricky. There is little consensus on a single variable that represents the overall condition of financial markets. We have a variety of indicators that reflect particular aspects of financial markets in the economy. In this essay, I adopt three alternative measures of financial market 'tightness':

[19] As a result, there would be no uncertainty in impulse responses from t to $t+d$. We know the size of a given shock and the regime from t to $t+d$ based on a given initial history. Hence, from t to $t+d$, the *difference* between the average shocked and unshocked responses would always be the same across simulations trials although they may be different individually. This is reflected in Figure 3, where $d=1$ so that there is no uncertainty in responses at impact. If one had employed a bootstrap method to construct a confidence band by simulating over GIRFs then uncertainty would be introduced from t to $t+d$.

[20] For monthly series, I use the end of quarter values.

the Chicago Fed National Financial Conditions Index, the BAA spread, and the mix of bank loans and commercial paper in total firm external funding (MIX ratio) (Kashyap *et al.* (1993)). Although these indicators are not without controversy, I aim to choose a set of measures that complement each other in order to deliver robustness to empirical results.

4.1.1 Chicago Fed National Financial Conditions Index

I am interested in the state of financial markets for firms as I would like to reflect developments that directly affect firms' investment and production decisions which have important implications for real economic activity. However, the choice of such variable involves more than simply looking at spreads on corporate bonds. Empirical works on nonlinearity using the financial market condition as a source of multiple regimes often rely on a spread for corporate bonds. For example, Balke (2000), Atanasova (2003), and Ferraresi *et al.* (2015) all use spreads on investment-grade bonds and on commercial paper as threshold variables that determine the financial market regime in their TVAR models. However, those spreads may not be suitable to capture the entire picture of the financial market condition for corporate borrowers. Large firms are the majority borrowers in the corporate credit markets as small and medium-sized firms cannot easily issue commercial paper and bonds in capital markets. Thus, only large firms would be initially affected by increases in the spreads because they are the only firms that can participate in these capital markets. Moreover, in response to a shock to the spread, larger firms can easily substitute away from bonds to bank loans thereby cushioning the output effects of the initial shock. Some empirical literature on corporate bond markets in the U.S. has shown that neither credit and collateral channel is likely to be present in corporate borrowing for large firms.[21] Hence, it is important to consider an

[21] For example, Giesecke *et al.* (2014) show that the credit channel is likely to be absent in the corporate bond market as large firms can easily substitute away from bonds to bank loans. Furthermore, the vast majority of corporate bonds issued in the U.S. are in the form of unsecured debentures instead of mortgage or equipment-secured bonds. Thus, large firms that issue bonds in the capital markets are able to borrow against their future income streams, instead of being limited to their current collateral. So the collateral

indicator that takes into account various funding options faced by different sizes of firms given that developments in the corporate bond market alone may not affect all firms that engage in external funding in the economy.

Thus, I use the national financial conditions index constructed by the Chicago Fed as the threshold variable in the baseline specification in order to account for the overall financial market conditions.[22] One practical advantage of the index is that it is available from 1973 and is the longest financial stress index available in the U.S.. The Chicago Fed National Financial Conditions Index reflects several aspects of the financial market. One of the prominent features of the index is the use of 100 different financial variables. This helps identifying a wider range of the financial constraints faced by firms in the U.S.. It provides weekly and monthly updates on financial conditions in the three major market segments: money market; debt and equity market; banking system.[23]

A positive index reflects tighter financial conditions while a negative value reflects looser financial conditions. The degree of tightness or looseness of the financial market conditions is determined by the deviation of the index from its average, which is normalized to zero. The adjusted financial conditions index (ANFCI) is plotted in Figure 1.

4.1.2 BAA Spread and MIX Ratio

I also consider alternative measures that can directly represent the supply of/access to credits for corporate borrowers. Despite their imperfections, changes in spreads on corporate bonds may contain important signals regarding the current and future economic states and

channel is likely to be absent as well.

[22]Since the U.S. economic conditions tend to be highly correlated with financial conditions, an adjusted financial conditions index (ANFCI), which isolates a component of financial conditions uncorrelated with economic conditions is constructed to give more accurate interpretation of financial conditions relative to current economic states. In this essay, ANFCI is adopted. Also, I do not transform the ANFCI data as the autocorrelation is relatively low and fades away quite rapidly.

[23]The 100 financial variables used in the index comprise data with different frequencies (weekly, monthly, and quarterly). Hence, a dynamic factor analysis is applied to construct the index (see Doz *et al.* (2012)). This provides the technical capability of constructing a single index based on data which begins and ends in different time periods.

they should not be overlooked. To the extent that prices of investment-graded corporate bonds reflect a correct assessment of average default risk over the duration of the bond, short-term fluctuations in spreads could identify shifts in external finance premia. One indicator that I choose is the BAA spread. It is the difference between the rate on BAA-rated corporate bonds and the 10-year treasury constant-maturity rate. The spread allows one to capture long-term changes in lenders' perceived risk. According to the 'credit spread puzzle', spreads on corporate bonds are often wider than the extent implied by expected default losses alone. More than half of the variations in spread can be explained by time-varying liquidity premium, tax treatment and the compensation demanded by creditors for bearing the credit risk (Gilchrist and Zakrajsek (2011)) while less than half reflects the financial health of the issuer (e.g. Elton *et al.* (2001)).

Hence, in the presence of financial market imperfections, the corporate spread is supposed to capture the premium for external finance possibly linked to restrictions in the supply of credit to firms (Ernst *et al.* (2010)). Variations in credit spreads are considered to exhibit important signals with respect to developments in the real economy and risks to the economic outlook. This view on the yield spread on corporate bonds is supported by the large literature on the predictive content of credit spreads (or asset prices more generally) for economic activity.[24] Thus, I believe that fluctuations in the spread can capture lenders' changes in perceived long-term risks and in turn, the availability of credits. I choose the BAA spread over other available spreads on corporate borrowing. For example, Balke (2000), who employs a TVAR to study the nonlinearity caused by the financial market conditions, argues that the spread on (4-6 month) commercial paper can be a good candidate. However, its short maturity fails to capture lenders' perception of long-term economic risks and its low default rates make it a close substitute for treasury bills.

A second alternative measure is the MIX ratio which represents the quantity of bank loans

[24]See Gertler and Lown (2000) and Faust *et al.* (2013).

supplied in the overall economy. Specifically, the MIX is computed as the ratio between the total amount of loans in the liabilities of non-financial firms (corporate and non-corporate) and the sum of that amount plus the amount of commercial paper issued by non-financial corporate firms. A fall in the MIX ratio would indicate a limited supply of loans available to corporate/non-corporate borrowers as an alternative to raising funds in the bond market. The use of the MIX ratio becomes relevant especially when large firms can easily substitute between bonds and bank loans for external financing. It also accounts for the fact that non-corporate firms cannot typically rely upon commercial paper. Thus, the MIX can be a reliable measure that better captures restrictions in the overall supply of credit.[25]

The two alternative threshold variables are highly persistent. For example, the MIX ratio shows a clear downward trend from 1960s to 2000q1. We then observe an upward trend from 2000q1 to 2016q3. Thus, I carry out the analysis using the series in first differences. Moreover, as there are high frequency fluctuations in the first-differences of the two variables, I apply an MA filter to the variable in order to prevent implausibly frequent regime changes. Following Balke (2000) and Ferraresi *et al.* (2015), the windows of the moving averages are set such that the two threshold variables have similar autocorrelation functions. I apply an MA(2) to first differences of the BAA spread by simply taking the average growth rate of the two subsequent quarters. For the MIX ratio, I apply an MA(5) to its first-differenced series. With this approach, interpretation regarding this threshold variable would be as follows: The threshold value is estimated to be the moving average of the past rates of growth so that whenever the lagged (the lag order must be estimated as well) moving average rate of growth in the threshold variable crosses the threshold value, the economy is considered to be in the 'tight' financial market regime. The BAA spread and the MIX ratio are plotted along with their estimated threshold values in Figure 1.

[25] Bernanke *et al.* (1998) argue that the ratio can reflect a 'flight to quality' effect implied by models of financial contracting under asymmetric information.

Lastly, it should be noted that a problem may arise if the variations in the threshold variable closely follow business cycles. If so, the threshold variable would only be a proxy for output fluctuations and hence, cannot capture distinct financial market regimes. First of all, I compute the correlation between the first differenced real GDP and each of the threshold variables. The correlation for ANFCI is only -0.062. The correlations for the BAA spread and the MIX ratio (both in a first-differenced form) are -0.397 and -0.086 respectively. I also compare the observations in the 'tight' financial market regime with those in 'contractions' as defined by the NBER business cycle chronology. In the sample (1980q1 – 2016q3), we have 18 observations in the contractionary episode defined by NBER. The estimated threshold value for ANFCI is 0.31, which results in 10 out of 42 'tight' financial market regime observations overlapped with those in the NBER contraction regime. For the alternative model with BAA spread, I observe that 9 out of 25 'tight' corporate bond markets episodes in the sample overlap with the NBER contraction. For the MIX ratio, 5 out of 55 'tight' loan supply episodes overlap with the NBER contraction. To provide a more robust conclusion, I estimate a TVAR model under the same specification but with real GDP growth rate as the threshold variable. The estimated threshold value for the real GDP growth is 0.098. I compare the observations in the 'contractionary' regime as defined by the model and those in the 'tight' regime based on the baseline model (ANFCI). I find that only 10 observations overlap.[26] With the alternative models with the BAA spread and the MIX ratio, 8 and 19 observations overlap respectively.

4.2 Fiscal and Output Variables

The remaining variables are the two fiscal variables discussed in Section 2 and a measure of output. All variables are made stationary by taking first differences. For the output

[26] With the threshold of 0.098 for the real GDP growth to define the contractionary/expansionary regimes, we get 23 contractionary observations. Similarly, NBER defines 18 observations to be contractionary in the sample. 14 out of 23 contractionary observations overlap with the NBER indicator.

measure, I employ the real GDP growth rate (y). To obtain the logarithm of real GDP, I take the difference between the logarithm of nominal GDP and logarithm of the implicit GDP deflator. The two fiscal variables are the growth rate of real government spending (g) and the growth rate of real net tax (τ). The component of the two variables are explained in Section 2. To convert the nominal spending and taxes into real measures, I take the difference between the logarithm of the variable and the logarithm of the implicit GDP deflator. A detailed description of the data used in the analysis is given in Appendix A.

Table 1 shows the mean values of the variables in each regime. We have some interesting observations to be noted. First of all, the mean of y tends to be lower in the 'tight' financial market regime. However, we already saw that this does not necessarily result in a high correlation between low output growth and increased 'tightness' in the financial markets. Importantly, we can see that the mean of τ tends to be negative during the 'tight' regime defined by ANFCI and the BAA spread. This implies that during the 'tight' regime, on average, spending is often financed by borrowing rather than by increasing taxes. However, the opposite is found when the MIX ratio is used to define the financial market regime. The government tends to increase taxes and spend less when non-financial firms face 'tighter' loan supplies from banks.

5 Empirical Results

5.1 Results of Linearity Tests

First, I employ the standard method (the Augmented Dickey-Fuller and Phillips-Perron tests) to test for unit root processes. The Phillips-Perron test is carried out to correct for any serial correlation and heteroskedasticity in the errors in a non-parametric way. Table 2 presents the results for all variables considered in this essay. The test statistics indicate that the series are stationary by rejecting the null hypothesis of a unit root process.

The results of linearity tests are presented in Table 3. Linearity tests are performed using the method described in Section 3.3. Hansen's bootstrap method is conducted with 1000 replications for each test. The results suggest that there are multiple regimes in the U.S. financial market. For all threshold variables considered, we can see that the linearity hypothesis is rejected at the 1% significance level.

The estimated threshold values are reported in Table 4. The threshold value that minimizes the sum of squared residuals is 0.31 for ANFCI. With the delay order of one, this implies that whenever ANFCI increases above 0.31 in the previous quarter, the economy enters the 'tight' financial regime in the following period. According to the model, the economy spends approximately 28.6% of the time in the 'tight' financial regime as defined by ANFCI. With 0.31 as the threshold value, the average length of the 'tight' financial regime is 4.2 quarters for the U.S. economy. The maximum length is 11 quarters which occurs around the Savings and Loan Crash in the late 1980s. The collapse of the Lehman Brothers is associated with 3 quarters of the 'tight' financial regime which is quite close to the average length of the 'tight' regime in the sample. The length of 'tight' financial markets regime after the crisis is shorter than the length of the following recessionary period which lasts for 6 quarters according to NBER.

5.2 Nonlinear Responses to Fiscal Policy Shocks

By employing a generalized impulse response function, I explore the nonlinearity in effects of fiscal policy shocks on macroeconomic aggregates in the following three dimensions: first, whether fiscal policy shocks have different effects across 'tight' and 'normal' financial market regimes; second, whether fiscal policy shocks of different magnitudes have disproportionate effects; and third, whether positive fiscal policy shocks have different effects from negative shocks. All three issues can be explored through GIRFs. For comparison, impulse response functions from estimating a linear VAR are provided in Figure 2.

I start by examining the average regime-specific response to fiscal policy shocks. Figure 3 shows regime-specific GRIFs of real GDP growth (y) to a 1% standard deviation shock to the growth of government consumption and investment normalized to obtain a 1% increase in spending (g). The figure also includes the 2.5% and 97.5% quantiles of the simulated responses. The GIRFs appear to capture a nonlinear response of real GDP growth to fiscal policy shocks. The responses of y in each regime clearly differ in terms of the magnitude and persistence from those reflected in the linear IRFs (see Figure 2). Moreover, one can see that the contemporaneous response of y is greater when the initial state is the tight financial regime. In the tight regime, on average, y increases by 0.19% contemporaneously in response to a 1% shock to g while in the normal regime, it increases by 0.12% on average.

Cumulative responses of y further show that there is pronounced nonlinearity in the effects especially over the medium term (see Figure 4). With the normal regime as the initial state, the cumulative increase in y peaks at 0.23% after two quarters and it returns slowly towards zero over the horizon. For the tight regime, the cumulative increase continues over the horizon. The difference in cumulative responses between the two regimes is amplified over the medium term. For example, at the 4th quarter, the cumulative increase associated with the tight regime is roughly four times the increase associated with the normal regime. At the 8th or 12th quarter, the differences become even greater. Such findings imply that fiscal policy seems to be successful in stimulating the economy during the period of increased 'tightness' in the overall financial market. However, the policy is less effective during normal times for financial markets.

The nonlinearity is also present when we consider negative g shocks as shown in Figure 3. We can see that the asymmetric patterns are parallel with those of a positive shock. In the normal financial regime, a 1% decrease in g is associated with a smaller fall in y relative to the case in the tight financial regime. There are also large differences in the cumulative responses in y (see Figure 4). In the tight regime, the cumulative decrease in y after 2 quarters is twice the extent of the decrease in the normal regime. The magnitude increases by a factor of four after 12 quarters. This implies that fiscal consolidation policies during the tight regime may slow down the economy significantly over the short/medium term.

To obtain a more precise quantitative result, I compute the fiscal multipliers associated with the GIRFs reported above. The multiplier at time h is computed by dividing the cumulative response up to h by the average ratio of government spending and the real GDP (in terms of levels) over the whole sample. We can compute the peak multiplier by following the same procedure using the maximum cumulative response over the time horizon. The resulting multiplier would be in terms of constant dollars (2009 dollars). The estimated fiscal multipliers are reported in Table 5.

Table 5 captures the nonlinear responses reflected in the GIRFs. For comparison, the estimated fiscal multipliers based on the linear VAR are presented in Table 9. The impact fiscal multiplier from the linear VAR is 0.68 which is smaller than the impact multipliers associated with the tight financial regime but greater than the multiplier associated with the normal financial regime. The estimated fiscal multipliers associated with the 'tight' regime and the 'normal' regime appear to be consistent with the upper and lower bound of the estimated fiscal multipliers (respectively) from the existing empirical works using linear models.[27] According to the impact multipliers, g shock has a greater impact when the economy is initially under the tight financial market regime. The difference in the multipliers between the two regimes is quite significant up to the 2nd quarter as implied by Figure 3 where the 2.5% quantile of the simulated responses under the tight regime is above the 97.5% quantile of the simulated responses for the normal regime up to the 2nd quarter.

Over the 12-quarter horizon, the estimated fiscal multipliers are clearly larger if a g shock occurs when ANFCI implies increased 'tightness' in the financial market. With the tight

[27] *e.g.* Ramey (2011); Blanchard and Perotti (2002); Eichenbaum and Fisher (2005); Barro and Redlick (2009)

regime as the initial state, for a 1% standard deviation g shock, we see that the multiplier rises from 0.99 to 2.09 after 12 quarters. In contrast, the multipliers associated with the normal regime decrease over time and stay below one.[28] The peak fiscal multiplier in the tight regime occurs after 20 quarters.[29] For the normal regime, the peak occurs after 2 quarters at which point the multiplier starts decreasing quickly. This indicates that the effect of typical fiscal shocks is of relatively short duration during normal times for the financial market. In sum, we can say that fiscal shocks during the tight financial market regime generally result in greater and more persistent impacts on the output.

Similar observations are also found in different sizes of the fiscal shock. Figure 3 also shows $\pm 2\%$ and $\pm 3\%$ shocks to g respectively. We observe the general result that for a given g shock, y responds to a greater extent in the tight financial regime. The estimated fiscal multipliers also follow similar patterns (see Table 5).

Next, I examine potential asymmetry in terms of *disproportionate* responses with respect to the size of fiscal shocks. Figure 5 plots cumulative responses of y with respect to different sizes of g shocks. Dotted lines represent cumulative responses that are proportionate to the shock size (linear cumulative response). The dotted responses would be the ones we expect to see if there is no disproportionate response across different sizes of g shocks. In general, we see greater disproportionate responses over the medium term. More importantly, the larger the size of a shock is the greater the disproportionate responses are. However, there does not seem to be any significant extent of disproportionate responses for 'positive shocks' and 'negative shocks associated with the normal financial market regime'. For example, a 2% standard deviation shock to g results in the cumulative responses that are approximately

[28] Despite the clear differences in the multipliers over the horizon, one would need to conduct a formal test to decide whether such difference is significant. However, in a TVAR framework, it is computationally quite intensive to conduct such testing as it involves an infeasible number of simulations to construct a bootstrapped distribution of mean responses for each period over the horizon.

[29] The multiplier continues to increase over some time. So, the peak is at the end of the horizon that I choose for the GIRFs.

twice the size of those associated with a 1% standard deviation shock. Different sizes of shocks (3%, 4%, 5%, and 6% standard deviation) are also examined as larger shocks may trigger disproportionate responses. However, the results are similar in that the responses are roughly proportionate to the shock size.[30] I get similar results when I consider negative shocks with the normal financial market regime as the initial state of the economy.

However, it is interesting to find that the extent of disproportionate responses is notably greater for 'negative fiscal shocks associated with the tight financial market regime'. The differences between the linear and nonlinear cumulative responses are greater than the other three cases. It would be meaningful to examine such disproportionate responses in terms of fiscal multipliers. For example, in response to a negative 1% shock to g, I estimate fiscal multiplier as 1.88 at the 4th quarter. In response to a negative 3% shock, the estimated multiplier is 6.09, which is greater by a factor of 3.29. In response to a negative 5% shock, the estimated multiplier is 10.47, which is 5.57 times the multiplier associated with the 1% shock. With the linear IRFs, we should see the multiplier of 9.4 for a negative 5% shock. In other words, such disproportionate responses result in an additional dollar (in 2009 dollars) decrease in GDP for every dollar of fiscal tightening when the economy is initially in the tight financial market regime.[31] Such a finding suggests that a large scale fiscal consolidation may cause an additional fall in the output over the medium term when the economy is experiencing increased 'tightness' in financial markets.

Lastly, we look at whether positive fiscal policy shocks have different effects from negative shocks. Based on Figure 5 and the estimated fiscal multipliers in Table 5, we observe some asymmetric responses between positive and negative shocks. In the normal regime, positive g shocks appear to have greater output effects especially when the shock size is large. Conversely,

[30] Positive g shocks under the normal financial market regime appear to trigger some disproportionate responses only when the shock size is significantly large.

[31] Larger negative shocks were also tried and the results indicated that there was a even greater extent of disproportionate responses of the output. For example, with the negative 7% shock, the disproportionate response resulted in additional 1.64 dollar decrease in output after four quarters.

in the tight regime, negative shocks appear to have greater output effects. However, it is unclear whether such asymmetry is statistically significant as the difference seems small.

All dimensions of asymmetry in output responses discussed so far indicate that there is a significant nonlinearity in effects of fiscal policy shocks with respect to the financial market regime: 1. fiscal shocks associated with the tight financial market regime, on average, generate greater responses in real GDP growth; 2. Given a negative fiscal shock in the tight financial market regime, the shock causes disproportionately greater decreases in output as the shock size increases; 3. Negative fiscal shocks in general have greater impacts on output than positive shocks do if they occur in the tight financial market regime.

It is worthwhile to note the following additional observation regarding different patterns in responses of output following a given g shock. Figure 3 shows that g shocks in the normal financial regime generate opposite movements in y *over the medium term*. If positive g shocks occur in the normal regime, they tend to have pronounced negative effects on y in the following periods. After a jump at impact, y seems to fall endogenously below zero after 2 quarters. The 97.5% quantile of the simulated responses stays negative until the 5th quarter at which point it touches the positive region. However, we do not see such pronounced opposite movement in y when the economy is initially in the tight financial regime. The observation appears to be general in that the same patterns are found across different sizes of g shocks.

Together with the finding that impact multipliers are greater under the tight regime as the initial state, this additional observation is consistent with the conjecture that a positive shock to fiscal spending is more likely to crowd in the private consumption and investment when the agents face 'tighter' financial markets. Conversely, in normal times, the effect of a positive shock on the real GDP may be minimized as the private demand is likely to be crowded out over the medium term.[32]

[32]To be more precise, one needs to include private spending in the model rather than GDP to argue this way. See Ramey (2012) as an example. The author include private spending in her VAR model by subtracting

The nonlinearity in the effect of fiscal policy shocks on output seems to be strong in that the responses at impact are significantly different between the two regimes and such difference persists over time despite potential endogenous regime-switches that could occur following the fiscal policy shock.[33] This motivates me to further explore the relationship between financial markets and fiscal policy shocks. Specifically, it is important to study the average response of ANFCI with respect to fiscal shocks and how likely is the economy to experience a regime-switch after a fiscal shock conditional on the initial regime of the financial market. Based on these two exercises, we can shed more light on the difference in the output responses between the two financial markets regimes.

5.3 Financial Markets and Fiscal Policy Shocks

First, it is interesting to observe a mean-reverting response in ANFCI to a fiscal policy shock. Figure 6 shows the GIRF for ANFCI with respect to a 1% standard deviation shock to g. A positive g shock in the tight financial regime leads to 'less tight' financial markets. ANFCI falls below zero at impact and stays negative over the horizon. This means that the economy starts experiencing a below-average 'tightness' in the financial market when there is a positive g shock. When a positive shock occurs in the economy experiencing the normal financial regime, the 'tightness' increases over time. ANFCI jumps at impact and stays positive over the horizon.

Thus, it is the case that on average, ANFCI moves in such a way to potentially offset the difference in the output responses between the two regimes. If the model did not allow for an endogenous regime-switch, we would have seen an even greater difference in output responses between the two regimes. We have already observed that such difference in the responses

government spending from GDP.

[33]Note that the difference still exists if one compares the 2.5% quantile of the simulated responses for the tight regime and the 97.5% quantile for the normal regime. Given the small number of observations in the tight regime, this implies that the difference is very significant.

between the two regimes exists even if we consider different sign and sizes of g shocks. Hence, it appears to be a general case that there is a *pronounced* difference in the effect of fiscal policy shocks between the two financial market regimes despite the offsetting movement of ANFCI.

I have shown the direction of the response in ANFCI with respect to g shocks. Nevertheless, it is unclear whether the response of ANFCI is significant enough to induce a regime-switch. Note that in the TVAR, nonlinearities are reflected by changes in the parameters across regimes. Thus, it requires an actual regime-switch to have asymmetric responses. Although the GIRFs presented earlier do take into account endogenous regime switches following a given shock, they do not explicitly show whether such switches actually occur and if so, when they occur. Thus, I conclude the empirical exercise by answering the following question: If the economy is currently in the tight (normal) financial market regime, how likely is an expansionary fiscal policy shock to induce a switching to the normal (tight) financial market regime?

To answer the question, I conduct simulations to estimate the probability of an endogenous regime-switch in response to a given g shock conditional on the initial financial market regime. I compare the conditional probabilities of this shock scenario to the conditional probability in the baseline case where there is no g shock at t. The baseline case shows estimated probabilities of switching to the tight (normal) financial regime conditional on the economy initially being in the normal (tight) financial regime without any information about fiscal policy shocks. This exercise produces concrete statistical evidence not only for how strong the nonlinearity is in the output responses but also for a potential role of fiscal policy shocks in the evolution of the financial market regime.

The probability of a regime-switch can be estimated from a TVAR model by specifying initial conditions and shocks.[34] Given the initial information set (Ω_{t-1}) at $t-1$ and a

[34] The procedure is similar to that of the GIRFs. See Section 3 and Appendix B for calculation details.

particular realization of a shock (u_t) at t, the probabilities of being in the tight and normal financial market regime at period h are respectively,

$$Pr[I(f_{t-d+h} > \gamma)|\Omega_{t-1}, u_t] \tag{13}$$

$$Pr[I(f_{t-d+h} \leq \gamma)|\Omega_{t-1}, u_t] \tag{14}$$

The 'empirical probability' of a regime-switch at period h is then derived from the number of times the threshold variable crosses the estimated threshold value given the initial regime reflected in Ω_{t-1}. The 'empirical' counterparts of the above two probabilities would be:

$$\frac{1}{n}\sum_{i=1}^{n} I[f^i_{t-d+h} > \gamma)|\Omega_{t-1}, u_t] \tag{15}$$

$$\frac{1}{n}\sum_{i=1}^{n} I[f^i_{t-d+h} \leq \gamma)|\Omega_{t-1}, u_t] \tag{16}$$

where f^i_{t-d+h} is a simulated realization of the threshold variable at period h for the given information set, Ω_{t-1} and shock, u_t. n is the product of the number of initial values randomly drawn and the number of random draws of shocks (see Appendix B for details).

Figure 7 presents the estimated transition probabilities conditional on the tight and normal financial market regimes. The figure indicates that a large expansionary fiscal policy shock (2% standard deviation) to the economy experiencing 'tight' financial markets increases the likelihood of switching to the normal financial market regime. The maximum impact on the transition probability appears to occur 3 quarters after the shock. At the third quarter, the transition probability with the positive g shock is roughly twice as high relative to that in the baseline case. After the third quarter, the increase in the probability tails off gradually and converges to that in the baseline case. A negative g shock does decrease the likelihood of switching to the normal regime but its impact is relatively smaller.

When the economy is initially in the normal financial market regime, a large expansionary fiscal policy shock (2% standard deviation) tends to increase the likelihood of switching to the tight regime. The maximum impact on the transition probability occurs 2 quarters after the positive g shock, at which point the transition probability is roughly twice as high. Similarly, a negative g shock decreases the transition probabilities to the tight regime but its impacts are smaller relative to its positive counterpart.

Overall, under the tight financial market regime as the initial state, a positive fiscal shock increases the probability of a regime-switch to normal financial markets. Similarly, if the economy is initially in the normal financial market regime, a positive fiscal policy shock leads to a higher probability of experiencing a regime-switch to tight financial markets relative to the baseline case. In summary, a fiscal policy shock produces different output responses depending on the financial market regime and such difference is strong enough to exist and to persist over time despite a higher probability of an endogenous regime-switch caused by the shock. Lastly, these results also suggest that fiscal policy shocks (especially expansionary shocks) can have substantial impacts on the conditions in financial markets and thus, play an important role in the evolution of the financial market regime in the U.S..

6 Robustness Tests

6.1 Alternative Threshold Variables: BAA spread and MIX ratio

One should note that ANFCI captures financial conditions in three major financial market segments: money market; debt and equity market; and banking system. The transmission mechanism of fiscal policy shocks may work differently depending on the form of financial 'tightness'. Hence, it may result in output responses which differ in terms of the sign and the magnitude. To explore this issue, I consider two alternative threshold variables: the BAA spread and the MIX ratio.

The estimated threshold value for the BAA spread is 0.217 (see Table 4). If, in the last quarter, the variation of the BAA spread accelerates on average by more than 21.7 basis points, the economy is expected to enter the tight financial regime (tight corporate bond markets) in the next quarter. With the BAA spread as the threshold variable, the economy spends approximately 20.5% of the time in the tight financial regime. With the BAA spread, the average length of the tight regime is 1.56 quarters with the maximum length of 3 quarters in the early 1980s. The BAA spread tends to move together with ANFCI. However, with the BAA spread, the incidence of the tight regime is more frequent but the length is shorter relative to ANFCI. The shorter length of the tight regime seems to make sense as ANFCI reflects a wider range of financial market conditions than the BAA spread which is supposed to reflect the condition mostly for (large) corporate borrowers. Brief periods of the tight regime are clustered around the 1990s, the periods associated with the Savings and Loan Crash, the Junk Bond Market Collapse, and the Nikkei Crash. Around the collapse of the Lehman Brothers, a tight financial episode tends to last longer (See Figure 1).

For the MIX ratio, the threshold value is estimated to be 0.002. Unlike the other two threshold variables, the economy is in the tight financial regime when the variation of the mix ratio *decelerates* on average by more than 0.2%.[35] As shown in Figure 1, the incidence of a tight loan supply episode is more frequent than the BAA spread. The longest episode of tight loan supply starts around the late 1980s and continues until the early 1990s. The episode coincides with the Savings and Loan Crash.

I briefly discuss different effects of a fiscal policy shock across the tight and normal regimes based on the two alternative threshold variables. I start with the alternative model with the BAA spread. The GIRFs for responses of y with respect to various sizes of shocks to g are

[35] With the MIX ratio, I imposed 35% restriction on the minimum number of observations for a regime since the 15% restriction resulted in an implausibly large number of observations in the tight regime.

provided in Figure 8. In general, response of y is larger when firms face tight bond markets. In the tight regime, response of y is slightly larger at impact than that in the normal regime. Moreover, y stays positive for 2 quarters after a positive g shock. Its 2.5% quantile of the simulated responses stays above zero implying that the positive effect is quite significant. In the normal regime, y jumps at impact in response to a positive g shock but falls abruptly to the negative territory in the following quarter. The negative y appears to be quite persistent as the 97.5% quantile of the simulated responses stays below zero up to the 7th quarter.

Table 6 reports the estimated fiscal multipliers. Relative to the multipliers estimated based on the linear model (see Table 9), the multipliers in the tight regime are larger while for the normal regime, they are lower. This is similar to what we observe with the baseline model with ANFCI. Relative to the baseline model, the multipliers are smaller over the horizon of the GIRF. However, it is still true that the fiscal multipliers are significantly greater in the tight regime. Moreover, unlike the baseline model, we see negative fiscal multipliers for the normal regime responses. This is a clear sign that expansionary fiscal policies during the normal financial regime are likely to be less successful. Although the difference in the output responses between the two regimes is quite small at impact, the difference becomes notably greater than the baseline case over the horizon.

In Table 6, we can also see that response of y is not symmetric as positive g shocks have different effects from negative shocks over the horizon. In general, for a given magnitude of the shock, a positive g shock has greater fiscal multipliers than a negative g shock. However, we do not see any significant extent of disproportionate response across different sizes of a g shock. The estimated multipliers are roughly proportional to the size.

Lastly, we examine the response of the BAA spread itself. See Figure 9 for the GIRF of the BAA spread in response to a 1% g shock. Similarly, we observe a mean-reverting response of the BAA spread after the g shock. Hence, it appears that the there exists a strong difference in response of y between the two regimes despite the mean-reverting response of the threshold variable potentially offsetting the difference. However, the mean-reverting response in the tight regime is of relatively short-duration as the negative growth of the spread lasts for 2 quarters after the positive g shock. This may be responsible for the larger difference in y responses between the two regimes relative to the baseline model. In the baseline model, we observe a quite persistent mean-reverting movement in the threshold variable. For example, as Figure 6 shows, ANFCI falls (less tight) in the tight regime in response to a positive g shock and its 97.5% quantile of the simulated responses stays below zero for 10 quarters after the shock.

Next, I consider the alternative model using the MIX ratio. The GIRFs for y responses with respect to various sizes of a g shock are provided in Figure 10. We can see that response of y is stronger when firms face tight loan supplies. The difference in the response is significant as the lower bound of the 2.5% quantile of the simulated responses for the tight regime is above the 97.5% quantile for the normal regime. Such a difference exists across different sign and sizes of g shocks.

Table 7 presents the estimated fiscal multipliers based on the alternative model with the MIX ratio. First, relative to the multipliers based on the linear model (see Table 9), the multipliers in the tight regime are notably greater while those in the normal regime are smaller. Similarly, the difference in y response between the two regimes is notably greater than the baseline model with ANFCI. The effects on y in the tight regime do not seem to differ significantly from those in the baseline model. However, one can find that the fiscal multipliers associated with the normal regime are much smaller. The fiscal multipliers in the normal regime are above 1 only when the g shock is significantly large (3%). Hence, the larger difference observed with the alternative model stems from smaller effects of g shocks in the normal regime.

With the MIX ratio, we observe some asymmetric response between positive and negative g shocks. The estimated fiscal multipliers in response to positive shocks are greater if the shocks occur in the normal financial regime. In the tight regime, y responses to positive g shocks are greater but not to the extent we observe in the normal regime. Next, we see largely disproportionate multipliers across different sizes of g shocks. The disproportionate response appears to be more pronounced for the normal regime responses. For example, in response to a -1% g shock, the multiplier at 4th quarter in the normal regime is 0.16 while it is 0.88 in response to a -3% g shock.

Interestingly, we do not see a mean-reverting movement of the MIX ratio for the *normal* regime in response to a positive g shock. See Figure 11 for the GIRF of the MIX ratio. In both regimes, the MIX ratio jumps in response to a positive g shock and then slowly decreases over the horizon. In the tight regime, the MIX ratio jumps (more abundant loan supplies) and the 2.5% quantile of the simulated responses stays above zero for three quarters after the g shock. Hence, the MIX ratio moves in such a way to revert the current tight regime to the normal regime. However, the mean-reverting response appears to have a low persistence. For the normal regime response, the MIX ratio does not exhibit a mean-reverting response after the g shock. Also, relative to the tight regime, the MIX ratio jumps by more and its 2.5% quantile of the simulated responses stays above zero for a longer period (for the first 5 quarters). Hence, the absence of mean-reverting movement of the MIX ratio in the normal regimes could be responsible for the larger difference in y responses between the two financial regimes relative to the baseline model.

Overall, the result that the output response is greater in the tight financial market regime seems to be robust to different threshold variables that define the financial market regime: tightness in the overall financial market; tightness in corporate bond markets; and tightness in loan supplies for non-financial firms. Fiscal policy has, on average, greater impacts on output growth when firms face increased 'tightness' in the financial markets. However, it is interesting to see that the alternative models imply a greater extent of difference in the output responses between the two financial market regimes. Such difference can be explained by either less persistent (the BAA spread) or the absence of (the MIX ratio) mean-reverting responses in the threshold variable.

6.2 Fiscal Foresight

Unlike monetary policy, changes in fiscal policy are often decided and announced in advance. As a result, fiscal 'shocks' sometimes can be anticipated by economic agents. The information set of the econometricians may not coincide with that available to the private sector and policymakers. According to Ramey (2011), the timing of a fiscal policy shock is a crucial factor to consider when one identifies the effect of fiscal policy shocks. Hence, I control for expectations not reflected in the VAR using real-time forecasts from the Survey of Professional Forecasters conducted by the Federal Reserve Bank of Philadelphia.

The forecasts for the real spending of the federal, state and local government are available from the Survey of Professional Forecasters (SPF).[36] However, the forecasts for the government spending are available from 1981q3. Thus, for the period 1980q1–1981q2, I use the data from Auerbach and Gorodnichenko (2012b). For 1980q1–1981q2, they use the forecasts from the Greenbook prepared by the FRB staff for FOMC.[37] The properties of the Greenbook forecasts are similar to those of the SPF forecasts. Thus, following Auerbach and Gorodnichenko (2012b) (A&G), I combine the two forecasts to construct a continuous forecast series for 1980q1–2016q3.

The forecasts from SPF are provided over different forecast horizons.[38] The forecasts for the government spending are available from 0-step-ahead forecast (nowcast) to 4-step ahead forecast. For example, the survey for 0-step-ahead forecasts conducted at t is the forecast made for the current period, t. Hence, I use 1-step-ahead forecasts, the forecast made using

[36] In Ramey (2011), the SPF is shown to Granger-cause the standard VAR shocks, hence the forecast is likely to have fewer anticipation effects than shocks from a standard VAR.

[37] They take Greenbook forecasts which is the closest to the middle of the quarter so that the forecasts would be comparable to SPF forecasts

[38] I use mean forecasts from the SPF. Median forecasts are also available.

$t-1$ information for the period t government spending. I sum all the forecasts for levels of federal, state, and local government spending and then, I compute quarter-over-quarter growth rates.[39]

Figure 12 shows the importance of controlling for fiscal foresight. The residuals from projecting forecasted and actual g on the information contained in the lags of the variables in the baseline TVAR are plotted. One can see that the two residuals are correlated. Thus, government spending net of the information provided by the baseline TVAR contains some forecastable component which can be explained by the professional forecasts.

One straightforward way to control for the forecastable components of VAR residuals is to expand the vector of endogenous variables to include their forecasts. Define the forecasts made using $t-1$ information for a given variable, x at t as $x^F_{t|t-1}$. Then, the expanded vector of endogenous variables would be:

$$[g^F_{t|t-1} \quad \tau^F_{t|t-1} \quad y^F_{t|t-1} \quad f^F_{t|t-1} \quad g_t \quad \tau_t \quad y_t \quad f_t] \tag{17}$$

I order the forecasts first as it is obvious that shocks to a given variable at t cannot contemporaneously affect the forecast made at $t-1$ for that variable. Although this approach is attractive adding four more variables is very costly in practice due to the limited number of observations in each financial market regime. Thus, I augment the baseline model with only the forecast of g. The expanded vector of endogenous variables is:

$$[g^F_{t|t-1} \quad g_t \quad \tau_t \quad y_t \quad f_t] \tag{18}$$

In this specification, a structural shock (orthogonal to $g^F_{t|t-1}$) to g_t can be interpreted as an unanticipated shock to government spending. Following Ramey (2011) and A&G, I also

[39]The Greenbook forecasts from A&G are in terms of quarter-over-quarter growth rates, expressed as annualized percentage points. I converted them to quarter-over-quarter growth rates so that they are consistent with the SPF forecasts and other variables in the TVAR.

consider an alternative specification where I replace $g^F_{t|t-1}$ in (18) by $FE^g_{t|t-1}$ which is the forecast error or news for growth rates of government spending (computed as the difference between g_t and $g^F_{t|t-1}$). In this alternative specification, a shock to this news measure can be interpreted as an unanticipated shock to government spending.

Figure 13 shows the GIRFs of y in response to an unanticipated shock to government spending. ANFCI is used as the threshold variable in the specification. In line with the baseline model, the effect on output growth is stronger when the economy is in the tight financial market regime. This is true for both specifications. Table 8 shows the estimated fiscal multipliers from the model controlling for fiscal foresight. The multipliers confirm the result that fiscal policy shocks have greater impact in the tight regime. Relative to the baseline model, the multipliers associated with the normal regime are much smaller. Hence, controlling for foresight appears to amplify the crowd-out effect of fiscal expansion over the medium term.

7 Conclusion

This essay contributes to the fiscal policy vector autoregression (VAR) literature by estimating state-dependent fiscal multipliers based on a threshold vector autoregression (TVAR) framework with regime-switching determined by a financial 'tightness' measure. The application of this nonlinear model is motivated by the potential two-way relationship between financial markets and fiscal policy. The empirical adequacy of the nonlinear model is confirmed by formal tests. Using the Chicago Fed Financial Conditions Index to define the financial market regime, I show that linearity tests support the presence of two distinct regimes in financial markets in the U.S.. The presence of different regimes is still supported when I consider alternative threshold variables: the BAA spread; the MIX ratio. With evidence for the presence of multiple regimes in financial markets, I conjecture that fiscal shocks would have stronger effects on output when frictions in financial markets worsen the conditions faced by economic agents or when the economy is hit by shocks associated with increased 'tightness' in financial markets.

By computing generalized impulse response functions (GIRFs), this essay provides empirical evidence for important nonlinearities at play in the mechanism of fiscal policy shocks. Nonlinearities are studied in three different perspectives: regime-dependent output responses; disproportionate output responses across different sizes of fiscal policy shocks; and asymmetric output responses between positive and negative fiscal policy shocks.

Based on the GIRFs using the simulation method to compute the average difference in the output response between the shocked and unshocked scenarios, I show that on average, the effect of government spending shocks on output is greater when economic agents face above-average 'tightness' in financial markets. Even after controlling for fiscal foresight, the general result remains the same. The result that the output response is greater in the 'tight' financial market regime is robust to different threshold variables that define the financial market regime. On average, the output effect is greater when firms face increasing financing costs in bond markets or when they face 'tighter' loan supplies.

I also show that there is some disproportionate response in output across different sizes of fiscal policy shocks especially when the economy is in the 'tight' financial market regime. We observe some asymmetric responses between negative and positive shocks but the asymmetry appears to be small in magnitude. With the two alternative models, however, such asymmetric responses are quite significant.

With the alternative financial 'tightness' measures, the GIRFs captures different output responses in terms of the magnitude and persistence. Also, the two threshold variables show quite different responses to fiscal shocks implying the transmission mechanism of fiscal shocks could work differently depending on the form of finanial 'tightness' in the economy. Lastly, fiscal policy shocks appear to feed back into the financial conditions and play a role in the evolution of the financial market regimes in the U.S. as they substantially affect the transition probability in the economy.

On the normative side, the empirical results suggest that policymakers should take into account the current state of financial markets in the economy as fiscal policies and financial markets are closely interrelated. In periods when economic agents face 'tighter' conditions in financial markets, expansionary fiscal policy could be highly effective in stimulating aggregate economic activities as it may also relax financial conditions. In contrast, fiscal tightening can be preferred in the 'normal' financial regime as its potential negative effect on the output appears to be minimized. Lastly, fiscal policy should be conducted with recognition that it could substantially affect conditions in financial markets leading to a transition to different financial market regimes in the economy.

References

Acemoglu, D. and Scott, A. (1997). Asymmetric business cycles: Theory and time-series evidence. *Journal of Monetary Economics*, 40(3):501–533.

Afonso, A., Baxa, J., and Slavk, M. (2011). Fiscal developments and financial stress: A threshold VAR analysis. Working Paper Series 1319, European Central Bank.

Aksoy, Y., Basso, H., and Coto-Martinez, J. (2013). Lending relationships and monetary policy. *Economic Inquiry*, 51(1):368–393.

Aliagadaz, R. and Olivero, M. (2010). Macroeconomic implications of deep habits in banking. *Journal of Money, Credit and Banking*, 42(8):1495–1521.

Atanasova, C. (2003). Credit market imperfections and business cycle dynamics: A nonlinear approach. *Studies in Nonlinear Dynamics & Econometrics*, 7(4):1–22.

Bachmann, R. and Sims, E. R. (2011). Confidence and the transmission of government spending shocks. Working Paper 17063, National Bureau of Economic Research.

Balke, N. S. (2000). Credit and economic activity: Credit regimes and nonlinear propagation of shocks. *The Review of Economics and Statistics*, 82(2):344–349.

Barro, R. J. and Redlick, C. J. (2009). Macroeconomic effects from government purchases and taxes. Working Paper 15369, National Bureau of Economic Research.

Baum, A. and Koester, G. (2011). The impact of fiscal policy on economic activity over the business cycle - Evidence from a threshold VAR analysis. Discussion Paper Series 1: Economic Studies 03/2011, Deutsche Bundesbank, Research Centre.

Baum, A., Poplawski-Ribeiro, M., and Weber, A. (2012). Fiscal multipliers and the state of the economy. IMF Working Papers 12/286, International Monetary Fund.

Bernanke, B., Gertler, M., and Gilchrist, S. (1998). The financial accelerator in a quantitative business cycle framework. Working Paper 6455, National Bureau of Economic Research.

Blanchard, O. and Leigh, D. (2013). Growth forecast errors and fiscal multipliers. NBER Working Papers 18779, National Bureau of Economic Research.

Blanchard, O. and Perotti, R. (2002). An empirical characterization of the dynamic effects of changes in government spending and taxes on output. *The Quarterly Journal of Economics*, 117(4):1329–1368.

Brunnermeier, M. K. and Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421.

Burnside, C., Eichenbaum, M., and Fisher, J. D. (2004). Fiscal shocks and their consequences. *Journal of Economic Theory*, 115(1):89 – 117.

Caldara, D. and Kamps, C. (2008). What are the effects of fiscal policy shocks? A VAR-based comparative analysis. Working Paper Series 877, European Central Bank.

Clements, M. P. and Galvão, A. B. (2004). A comparison of tests of nonlinear cointegration with application to the predictability of U.S. interest rates using the term structure. *International Journal of Forecasting*, 20(2):219–236.

Doz, C., Giannone, D., and Reichlin, L. (2012). A quasi-maximum likelihood approach for large, approximate dynamic factor models. *The Review of Economics and Statistics*, 94(4):1014–1024.

Edelberg, W., Eichenbaum, M., and Fisher, J. (1998). Understanding the effects of a shock to government purchases. NBER Working Papers 6737, National Bureau of Economic Research.

Eichenbaum, M. and Fisher, J. (2005). Fiscal policy in the aftermath of 9/11. *Journal of Money, Credit and Banking*, 37(1):1–22.

Elton, E., Gruber, M., and Agrawal, D. Mann, C. (2001). Explaining the rate spread on corporate bonds. *Journal of Finance*, 56(1):247–277.

Ernst, E., Mittnik, S., and Semmler, W. (2010). Interaction of labor and credit market frictions: A theoretical and empirical analysis. *Paper prepared for the Winter Meeting of the Econometric Society, Atlanta.*

Fatas, A. and Mihov, I. (2001). The effects of fiscal policy on consumption and employment: Theory and evidence. CEPR Discussion Papers 2760, C.E.P.R.

Faust, J., Gilchrist, S., Wright, J., and Zakrajsek, E. (2013). Credit spreads as predictors of real-time economic activity: A Bayesian model-averaging approach. *Review of Economics and Statistics*, 95(5):1501–1519.

Favero, C. (2002). How do european monetary and fiscal authorities behave? CEPR Discussion Papers 3426, C.E.P.R.

Ferraresi, T., Roventini, A., and Fagiolo, G. (2015). Fiscal policies and credit regimes: A TVAR approach. *Journal of Applied Econometrics*, 30(7):1047–1072.

Galvão, A. B. (2003). Multivariate threshold models: TVARs and TVECMs. *Brazilian Review of Econometrics*, 23(1):143–171.

Gertler, M. and Kiyotaki, N. (2010). Financial intermediation and credit policy in business cycle analysis. *In Handbook of Monetary Economics*, pages 547–599.

Gertler, M. and Lown, C. (2000). The information in the high yield bond spread for the business cycle: Evidence and some implications. NBER Working Papers 7549, National Bureau of Economic Research.

Giesecke, K., Longstaff, F. A., Schaefer, S., and Strebulaev, I. A. (2014). Macroeconomic effects of corporate default crisis: A long-term perspective. *Journal of Financial Economics*, 111(2):297 – 310.

Gilchrist, S. and Zakrajsek, E. (2011). Credit spreads and business cycle fluctuations. NBER Working Papers 17021, National Bureau of Economic Research.

Hansen, B. (1999). Testing for linearity. *Journal of Economic Surveys*, 13(5):551–576.

Hansen, B. E. (1996). Estimation of TAR models. Boston College Working Papers in Economics 325, Boston College Department of Economics.

Holmstrom, B. and Tirole, J. (1996). Private and public supply of liquidity. Working Paper 5817, National Bureau of Economic Research.

Illing, M. and Liu, Y. (2006). Measuring financial stress in a developed country: An application to Canada. *Journal of Financial Stability*, 2(3):243–265.

Kashyap, A. K., Stein, J. C., and Wilcox, D. W. (1993). Monetary policy and credit conditions: Evidence from the composition of external finance. *American Economic Review*, 83(1):78–98.

Kocherlakota, N. R. (2000). Creating business cycles through credit constraints. *Quarterly Review*, 24(3):2–10.

Koop, G., Pesaran, M., and Potter, S. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Li, F. and St-Amant, P. (2010). Financial stress, monetary policy, and economic activity. Staff Working Papers 10-12, Bank of Canada.

Lo, M. C. and Zivot, E. (2001). Threshold cointegration and nonlinear adjustment to the law of one price. *Macroeconomic Dynamics*, 5(4):533–576.

Melina, G. and Villa, S. (2014). Fiscal policy and lending relationships. *Economic Inquiry*, 52(2):696–712.

Mittnik, S. and Semmler, W. (2012). Regime dependence of the fiscal multiplier. *Journal of Economic Behavior and Organization*, 83(3):502–522.

Ng, S. and Wright, J. (2013). Facts and challenges from the great recession for forecasting and macroeconomic modeling. *Journal of Economic Literature*, 51(4):1120–1154.

Pesaran, M. and Shin, Y. (1996). Cointegration and speed of convergence to equilibrium. *Journal of Econometrics*, 71(1-2):117–143.

Ramey, V. (2012). Government spending and private activity. NBER Working Papers 17787, National Bureau of Economic Research.

Ramey, V. A. and Shapiro, M. D. (1998). Costly capital reallocation and the effects of government spending. *Carnegie-Rochester Conference Series on Public Policy*, 48(1):145–194.

Romer, C. D. and Romer, D. H. (2010). The macroeconomic effects of tax changes: Estimates based on a new measure of fiscal shocks. *American Economic Review*, 100(3):763–801.

Tsay, R. S. (1998). Testing and modeling multivariate threshold models. *Journal of the American Statistical Association*, 93(443):1188–1202.

Turrini, A., Rger, W., and Szekely, I. P. (2010). Banking crises, output loss and fiscal policy. CEPR Discussion Papers 7815, C.E.P.R.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.

Woodford, M. (1990). Public debt as private liquidity. *American Economic Review*, 80(2):382–88.

8 Appendix A: Data Sources

The data have been recovered from the FRED database, provided by the Federal Reserve Bank of St. Louis and from the Bureau of Economic Analysis. Nominal variables are transformed to obtain real values using the GDP implicit deflator. The series employed in the essay are:

- Gross domestic product (GDP)
- GDP implicit deflator (GDPDEF)
- Government consumption expenditures and gross investment (GCE)
- Government current receipts and expenditures: Current tax receipt; Contributions for government social insurance; Government social benefits to persons; Interest payments (B.E.A. Table 3.1.)
- Moody's seasoned BAA corporate bond yield (BAA)
- 10-year treasury constant maturity rate (GS10)
- Commercial paper, assets balance sheet of non-farm nonfinancial corporate business (CPLBSNNCB)
- Bank loans liabilities balance sheet of non-farm nonfinancial corporate business (BLNECLB-SNNCB)
- Bank loans liabilities balance sheet of non-farm nonfinancial non-corporate business (BLNECLBSNNB)
- Chicago Fed Adjusted National Financial Conditions Index (ANFCI)

For fiscal foresight, I augment my forecast series with the following data set from Auerbach and Gorodnichenko (2012b). The data set is available from:

www.aeaweb.org/articles?id=10.1257/pol.4.2.1

- Greenbook/SPF spliced series for government spending.

9 Appendix B: Algorithm for Generalized Impulse Response Function

1. Pick a history Ω^r_{t-1}. The history is the observed value of the endogenous variables at time $t-1$.

2. Randomly draw a sequence of shocks, u^*_{t+h}. The shocks are drawn with replacement from the residuals of the estimated model, taking into account the different variance-covariance matrices characterizing each regime. As the shocks are assumed to be jointly distributed I draw a k-vector of residuals in each draw.[40]

3. Given the history Ω^r_{t-1}, the future evolution of all variables is simulated using the shock process and the estimated coefficients. Denote the resulting sequence as $w_{t+h}(\Omega^r_{t-1}|u^*_{t+h})$

4. Step 3 is repeated but the first row of the matrix of randomly drawn shocks is replaced by a k-vector with a shock of a certain size to a given variable. Denote such row as u_0 and the resulting sequence as $w_{t+h}(\Omega^r_{t-1}|u_0, u^*_{t+h})$

5. Repeat step 2 to 4 B times to iterate over a large number of draws of shock sequence which are expected to average out.

6. Repeat step 1 to 5 R times to obtain an average over the respective regime histories.

7. The GIRF is the following.

$$GIRF(h, \Omega_{t-1}, u_0) = \frac{1}{R}\sum_{r=1}^{R} \frac{w_{t+h}(\Omega^r_{t-1}|u_0, u^*_{t+h}) - w_{t+h}(\Omega^r_{t-1}|u^*_{t+h})}{B} \tag{19}$$

The package for GIRF was written in R by the author. The program can be obtained upon request.

[40] As I do not assume that errors are Gaussian or in some other parametric form, I resample residuals based on my estimates of variance-covariance matrix for each regime. By following Koop *et al.* (1996), I first transform the residuals to contemporaneous independence by using the inverse of a Cholesky factorization of the estimated variance-covariance matrix. Then, individually independent draws are grouped into k-vectors and the estimated Cholesky factor is used to return the dependence. See Pesaran and Shin (1996) and Koop *et al.* (1996) for details.

10 Appendix C: Tables and Figures

Table 1: Mean Values of the Variables in each Regime

Financial Market Regime (defined by f)	g	τ	y
Normal (AFNCI)	0.46	0.97	0.66
Tight (AFNCI)	0.77	-1.08	0.59
Normal (BAA spread)	0.56	0.95	0.76
Tight (BAA spread)	0.50	-2.36	0.06
Normal (MIX ratio)	0.61	-0.20	0.64
Tight (MIX ratio)	0.45	1.36	0.64

Notes: The sample period (1980q1 – 2016q3) is used. All variables are in log first differences.

Table 2: Unit Root Tests: ADF and Phillips-Perron

Variable	Lag Order	Augmented Dickey-Fuller	Phillips-Perron
g	3	-2.91 (0.044)	-10.17 (0.000)
τ	3	-3.78 (0.003)	-10.23 (0.000)
y	8	-3.67 (0.005)	-7.79 (0.000)
ANFCI	7	-3.58 (0.006)	-5.04 (0.000)
MA(2) of BAA spread	7	-5.92 (0.000)	-7.12 (0.000)
MA(5) of MIX ratio	6	-3.15 (0.023)	-4.79 (0.000)

Notes: p-values are in parentheses. All variables are in first differences except for ANFCI. All tests include the constant term. The lag order for ADF is determined according to t-tests conducted downward from 8 lags. The results indicate that all variables (except for ANFCI) are I(1). Therefore, I include them in the TVAR in terms of growth rates.

Table 3: Results of *supLR* Linearity Tests

Threshold Variable	*supLR*	95% critical value
ANFCI	94.79 (0.000)	41.04
BAA spread	93.95 (0.000)	42.07
MIX ratio	55.39 (0.000)	42.27

Notes: p-values are in parentheses. 1000 replications were conducted for each test. The null is that a linear VAR is a better specification for the sample data than the alternative of a TVAR. The *supLR* statistics are far greater than the 95% critical values resulting in p-values less than 0.01. Hence, we reject the null of linearity. Note that the lag order for endogenous variables is one. As a result, only possible delay order for the threshold variables is one as well.

Table 4: Estimated Threshold Values

Threshold Variable	Threshold Value	No. Obs (tight/normal)
ANFCI	0.31	42/105
BAA spread	0.217	25/122
MIX ratio	-0.002	55/92

Notes: Due to the limited number of observations, I assume the existence of two regimes once the linearity is rejected. The total number of observations is 147. The threshold values are estimated by conditional least squares as described in Section 3.

Table 5: Estimated Fiscal Multipliers with ANFCI

g Shock	Impact	4-quarter	8-quarter	12-quarter	peak
1% S.D.	0.99/0.61	1.87/0.79	1.99/0.57	2.09/0.56	2.14/1.19
2% S.D.	1.98/1.22	3.71/1.60	3.98/1.20	4.20/1.19	4.34/2.41
3% S.D.	2.97/1.83	5.49/2.47	5.84/1.90	6.18/1.90	6.39/3.65
-1% S.D.	0.99/0.61	1.88/0.77	1.96/0.53	2.01/0.51	2.04/1.17
-2% S.D.	1.98/1.22	3.98/1.49	4.19/1.01	4.28/0.98	4.34/2.31
-3% S.D.	2.97/1.83	6.09/2.21	6.41/1.45	6.52/1.39	6.59/3.45

Notes: The numbers on the left-hand side of the forward slash are the estimated fiscal multipliers for the tight regime. The numbers of on the right-hand side are the estimated fiscal multipliers for the normal regime (*i.e.* tight/normal). Fiscal multipliers are estimated over a 12-quarter horizon. The peak multipliers over the horizon of GIRFs are also reported.

Table 6: Estimated Fiscal Multipliers with the BAA spread

g Shock	Impact	4-quarter	8-quarter	12-quarter	peak
1% S.D.	0.89/0.74	0.97/-0.47	0.97/-1.29	0.99/-1.40	1.01/0.74
2% S.D.	1.78/1.48	2.01/-1.09	2.06/-2.99	2.09/-3.30	2.10/1.48
3% S.D.	2.67/2.22	3.02/-1.61	3.12/-4.74	3.18/-5.31	3.19/2.22
-1% S.D.	0.89/0.74	0.84/-0.45	0.81/-1.15	0.82/-1.24	0.97/0.74
-2% S.D.	1.78/1.48	1.61/-0.71	1.53/-1.98	1.53/-2.16	1.90/1.48
-3% S.D.	2.67/2.22	2.41/-0.77	2.30/-2.41	2.29/-2.64	2.85/2.22

Notes: The numbers on the left-hand side of the forward slash are the estimated fiscal multipliers for the tight regime. The numbers of on the right-hand side are the estimated fiscal multipliers for the normal regime (*i.e.* tight/normal). Fiscal multipliers are estimated over a 12-quarter horizon. The peak multipliers over the horizon of GIRFs are also reported.

Table 7: Estimated Fiscal Multipliers with the MIX ratio

g Shock	Impact	4-quarter	8-quarter	12-quarter	peak
1% S.D.	1.13/0.40	1.78/0.16	1.87/0.17	1.88/0.19	1.89/0.40
2% S.D.	2.26/0.80	3.48/0.43	3.64/0.48	3.65/0.52	3.65/0.80
3% S.D.	3.39/1.20	5.37/0.88	5.64/1.02	5.66/1.09	5.66/1.20
-1% S.D.	1.13/0.40	1.74/0.07	1.81/0.06	1.82/0.07	1.82/0.40
-2% S.D.	2.26/0.80	3.29/0.04	3.40/0.02	3.40/0.05	3.41/0.80
-3% S.D.	3.39/1.20	4.84/0.01	5.00/0.07	5.02/0.05	5.03/1.20

Notes: The numbers on the left-hand side of the forward slash are the estimated fiscal multipliers for the tight regime. The numbers of on the right-hand side are the estimated fiscal multipliers for the normal regime (*i.e.* tight/normal). Fiscal multipliers are estimated over a 12-quarter horizon. The peak multipliers over the horizon of GIRFs are also reported.

Table 8: Estimated Fiscal Multipliers with Fiscal Foresight

g Shock	Impact	4-quarter	8-quarter	12-quarter	peak
1% S.D.	1.09/0.29	1.09/-0.36	1.18/-0.44	1.23/-0.46	1.24/0.29
1% S.D.	1.10/0.36	1.07/-0.17	1.12/-0.20	1.14/-0.22	1.14/0.36

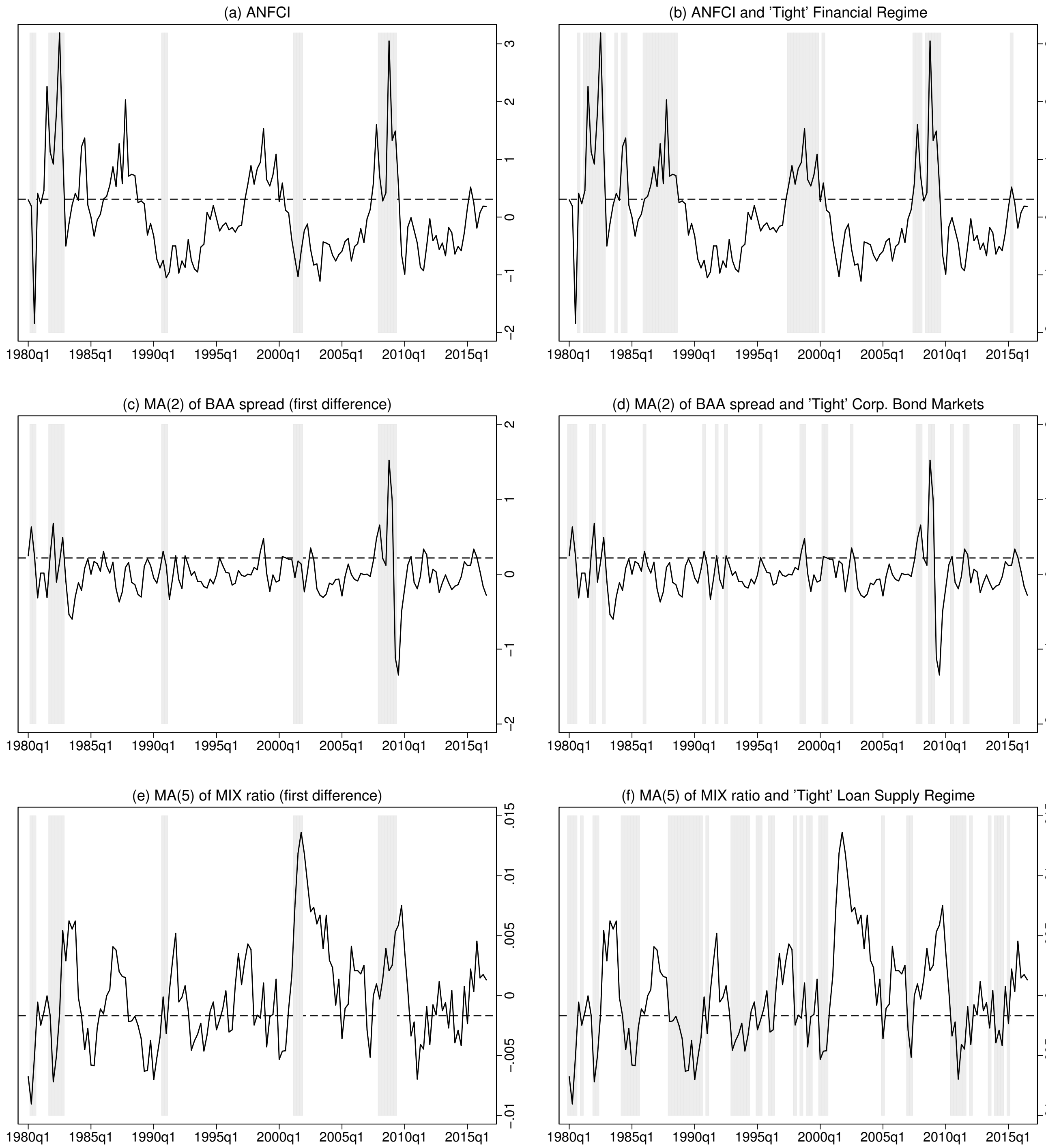
Notes: These are the multipliers with respect to an unanticipated shock to government spending. The first row of multipliers is based on the model augmented with the forecasted g. The second row is based on the model augmented with the news measure. ANFCI is used as the threshold variable. The numbers on the left-hand side of the forward slash are the estimated fiscal multipliers for the tight regime. The numbers of on the right-hand side are the estimated fiscal multipliers for the normal regime (*i.e.* tight/normal). Fiscal multipliers are estimated over a 12-quarter horizon. The peak multipliers over the horizon of GIRFs are also reported.

Table 9: Estimated Fiscal Multipliers with the Linear VAR

g Shock	Impact	4-quarter	8-quarter	12-quarter	peak
1% S.D. (ANFCI)	0.68	0.86	0.91	0.92	0.92
1% S.D. (BAA spread)	0.73	0.82	0.80	0.78	0.81
1% S.D. (MIX ratio)	0.66	0.72	0.89	1.02	1.11

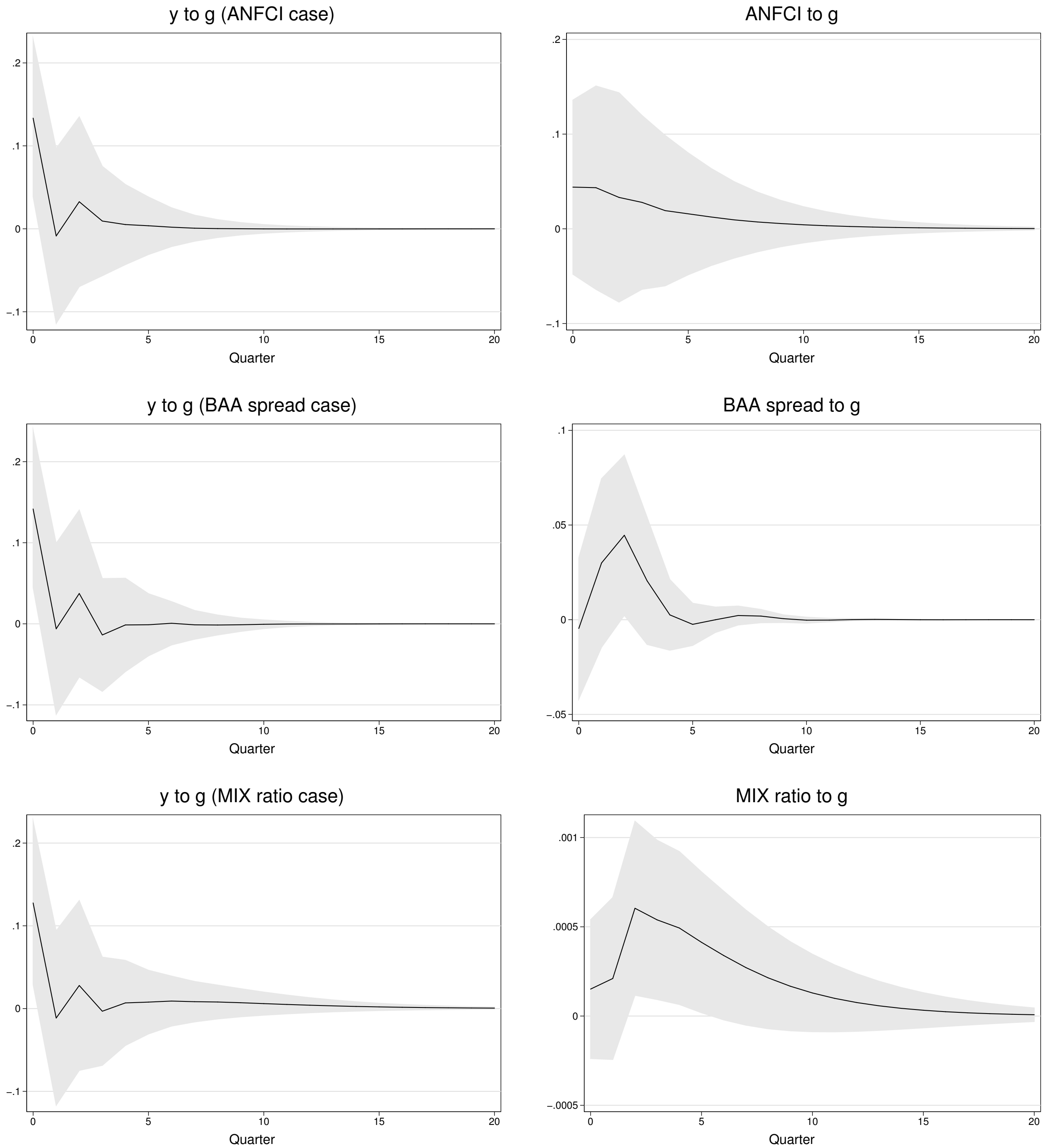
Notes: Since the fiscal multipliers are computed based on the linear VAR, one set of impulse responses is sufficient to characterize the dynamics of y in response to a shock to g. Fiscal multipliers are estimated over a 12-quarter horizon. The peak multipliers over the horizon of GIRFs are also reported.

Figure 1: Threshold Variables and Estimated Threshold Values



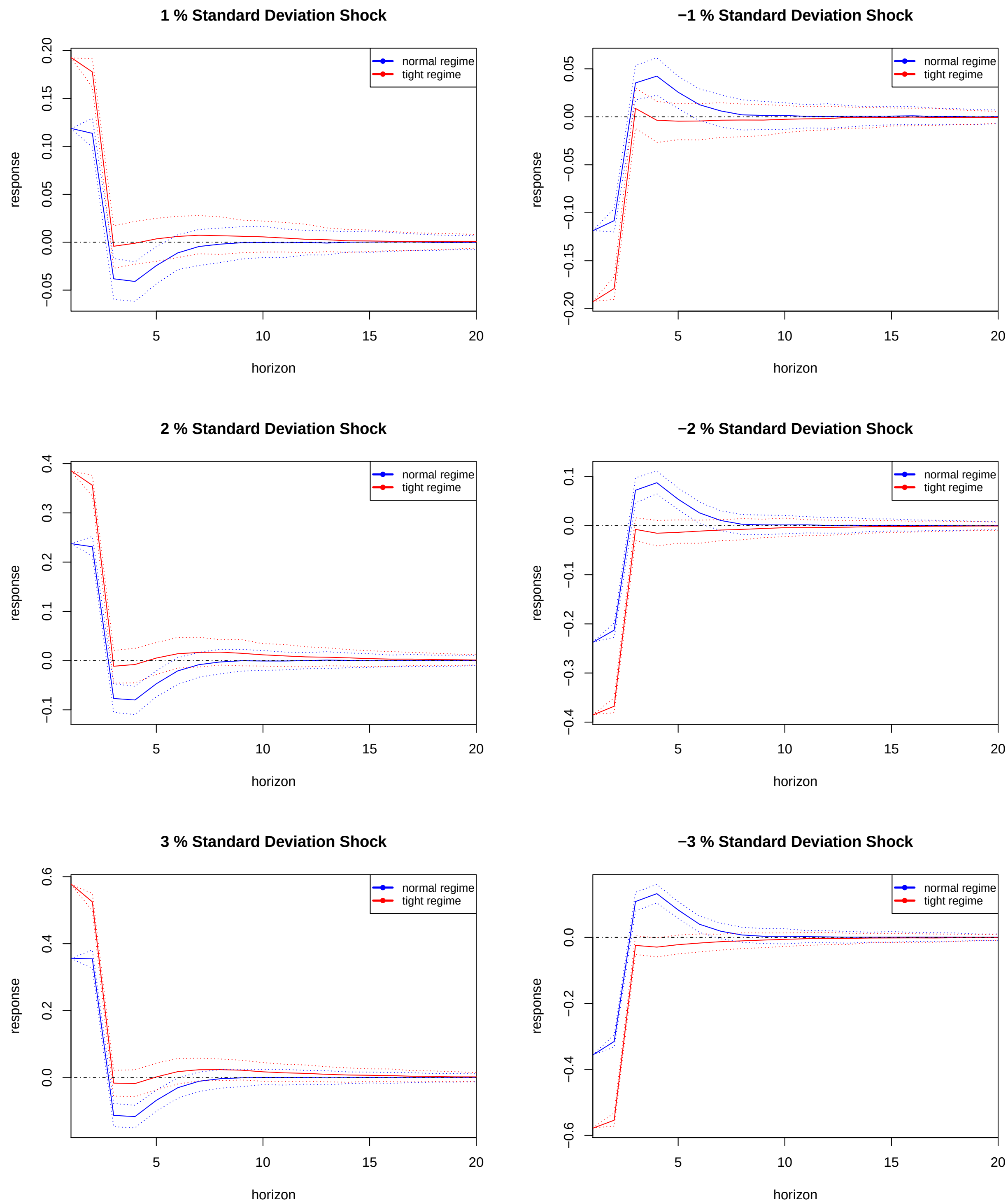
Notes: Shaded areas in the first column (a,c, and e) indicates contractions defined by NBER. In the second colmum (b, d, and f), the shaded areas indicate 'tight' regimes defined by the corresponding threshold variable. The dashed line indicates an estimated threshold value. Note that for the MIX ratio, the observations *below* the threshold line belong to the 'tight' regime.

Figure 2: Linear Impulse Responses



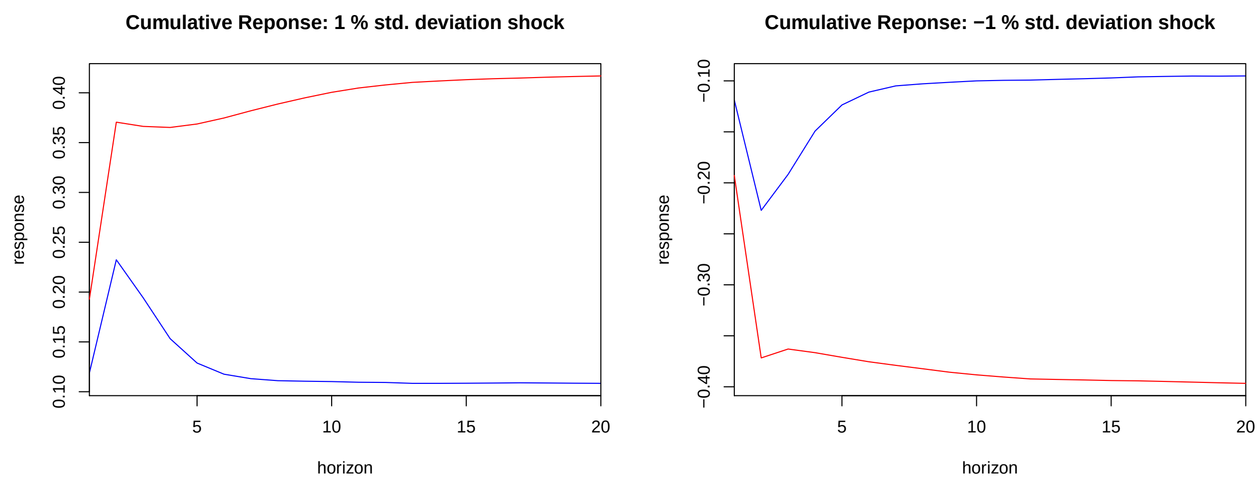
Notes: The first column shows responses of y to a 1% standard deviation shock to g. The second column shows the responses of the threshold variable to the same shock. The results from the baseline model (ANFCI) and the two alternative models (the BAA spread and the MIX ratio) are presented by each row. The shaded areas represent 95% confidence bands.

Figure 3: GIRF of y to g (ANFCI case)



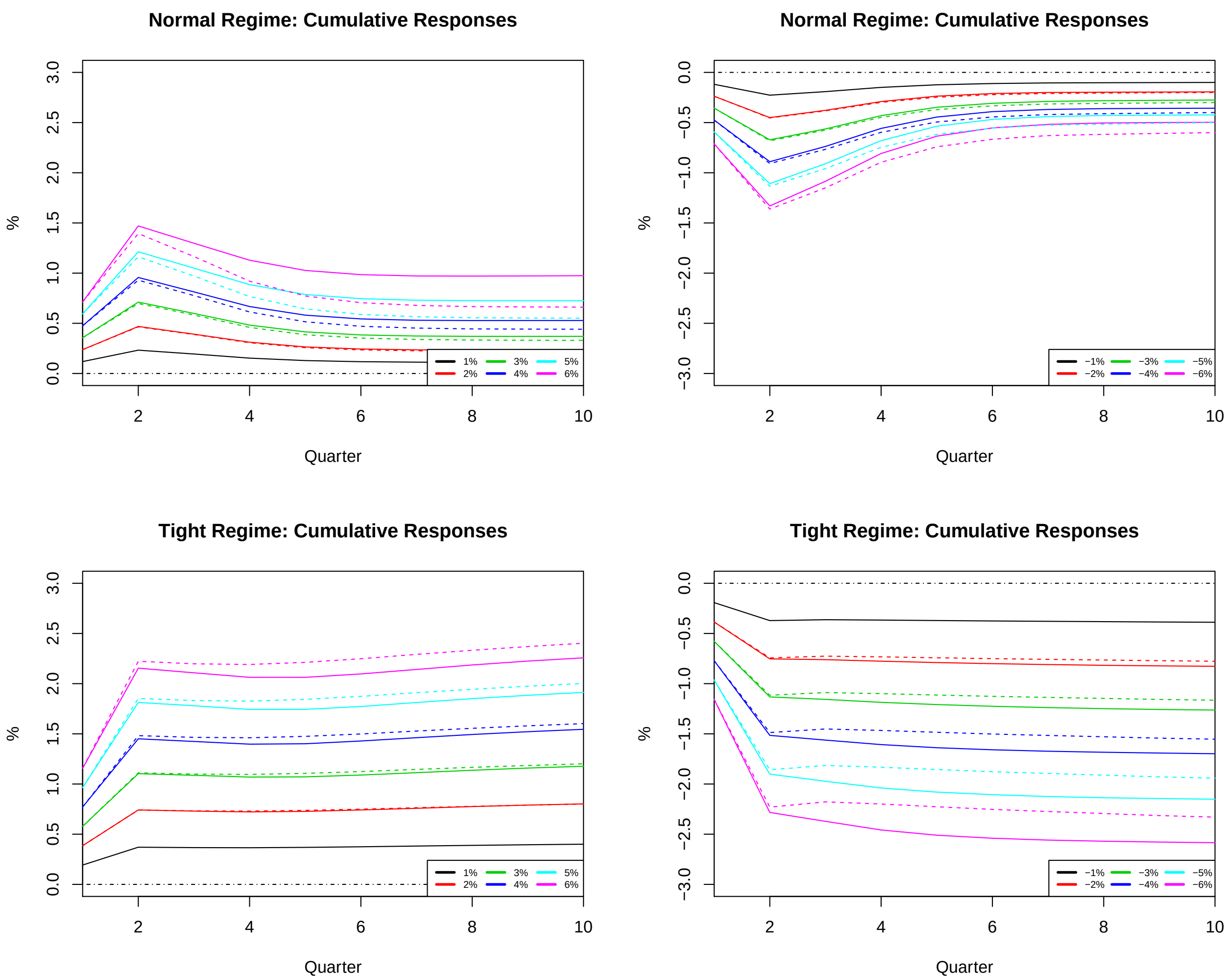
Notes: Responses of y to $\pm 1\%, 2\%, 3\%$ standard deviation shock to g based on the baseline model with ANFCI. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500). Dotted lines represent 2.5% and 97.5% quantile of simulated responses.

Figure 4: Cumulative Responses of y to g (ANFCI case)



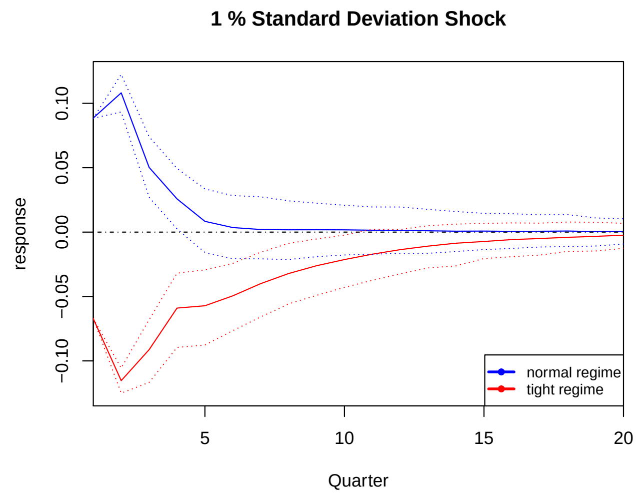
Notes: Cumulative responses of y to $\pm 1\%$ standard deviation shock to g based on the baseline model with ANFCI. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500).

Figure 5: Regime-Specific Cumulative Responses of y by Different Size of g Shocks



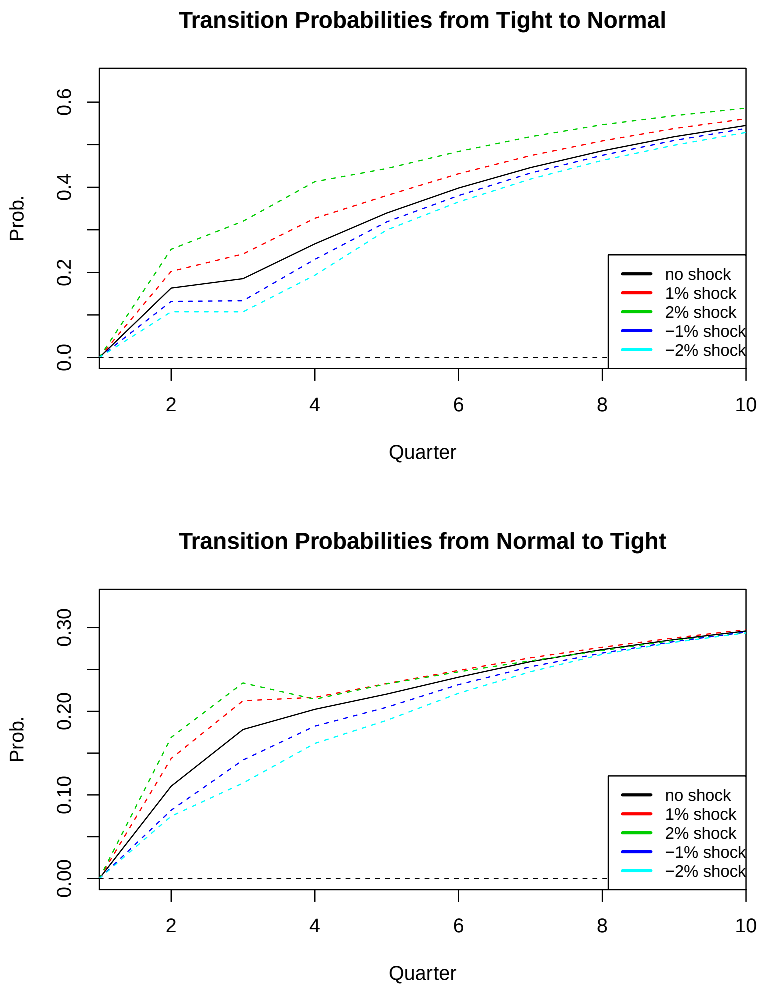
Notes: Cumulative responses of y to a given sign/size of shock to g based on the baseline model with ANFCI. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500). Dotted lines represent cumulative responses proportional to the shock size (linear cumulative responses).

Figure 6: GIRF of ANFCI to g



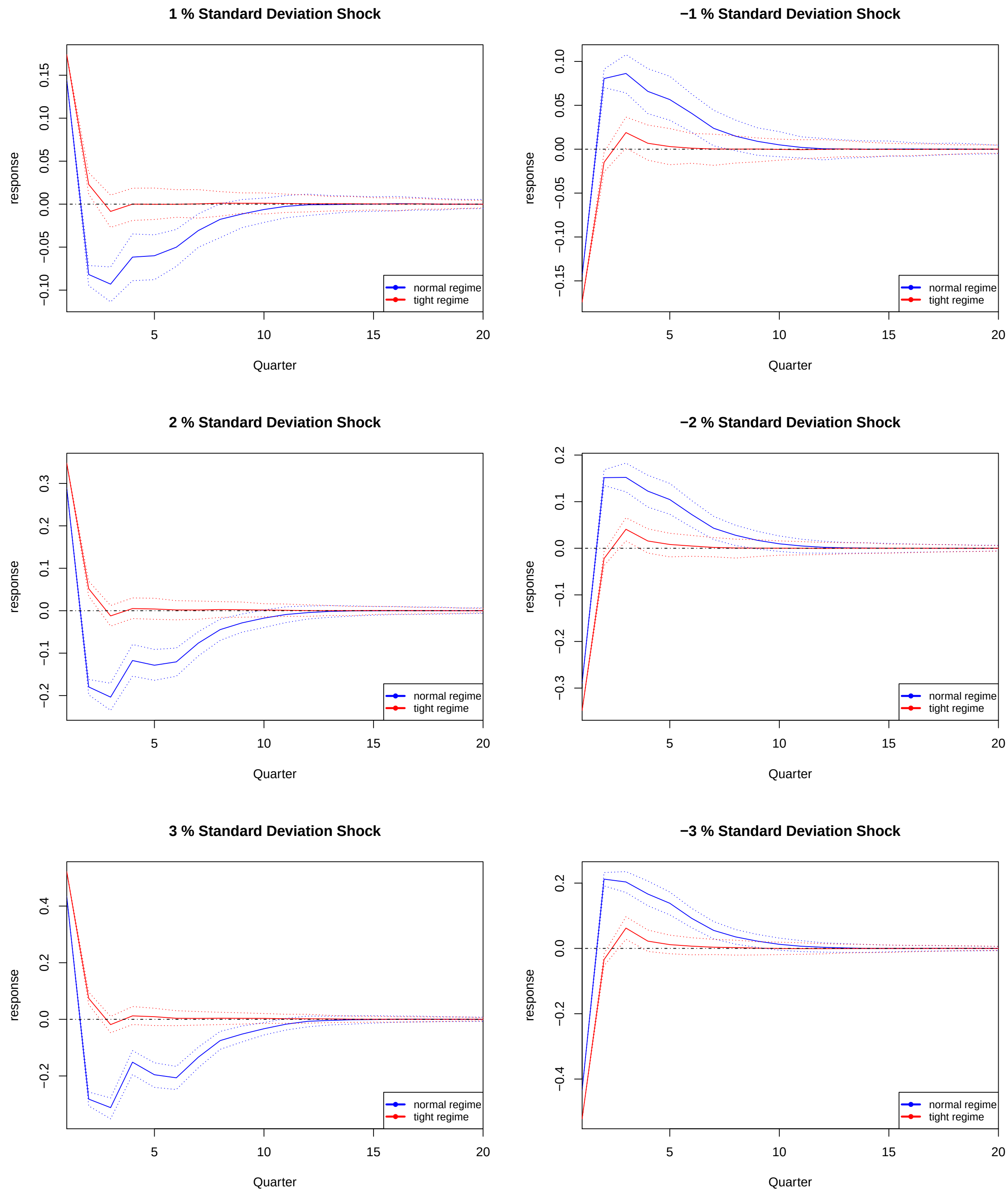
Notes: Responses of ANFCI to a 1% standard deviation shock to g. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500). Dotted lines represent 2.5% and 97.5% quantile of simulated responses.

Figure 7: The Impacts of g Shocks on the Transition Probability



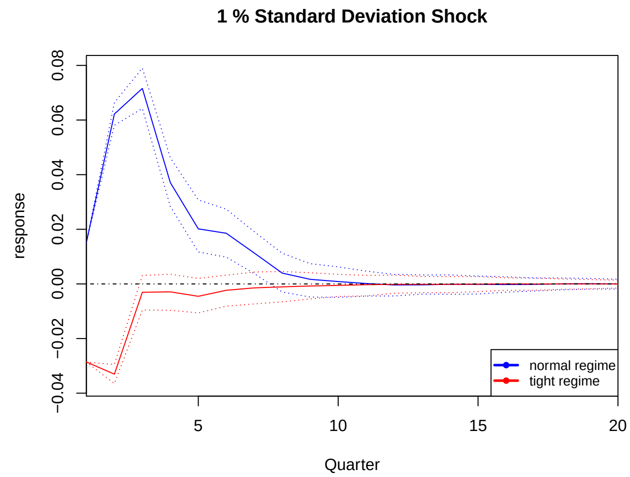
Notes: The black solid line represents the baseline scenario with no g shock at t=0. Dotted lines represent shocked scenarios with different signs and sizes of a g shock at t=0. Comparing the two would show impacts of a given g shock on the transition probabilities over the horizon. The transition probability at each time period is computed using a similar simulation method used for GIRFs. The probabilities are computed by $2.5X10^5$ simulations (B=500 and R=500). The baseline model with ANFCI is used.

Figure 8: GIRF of y to g (BAA spread case)



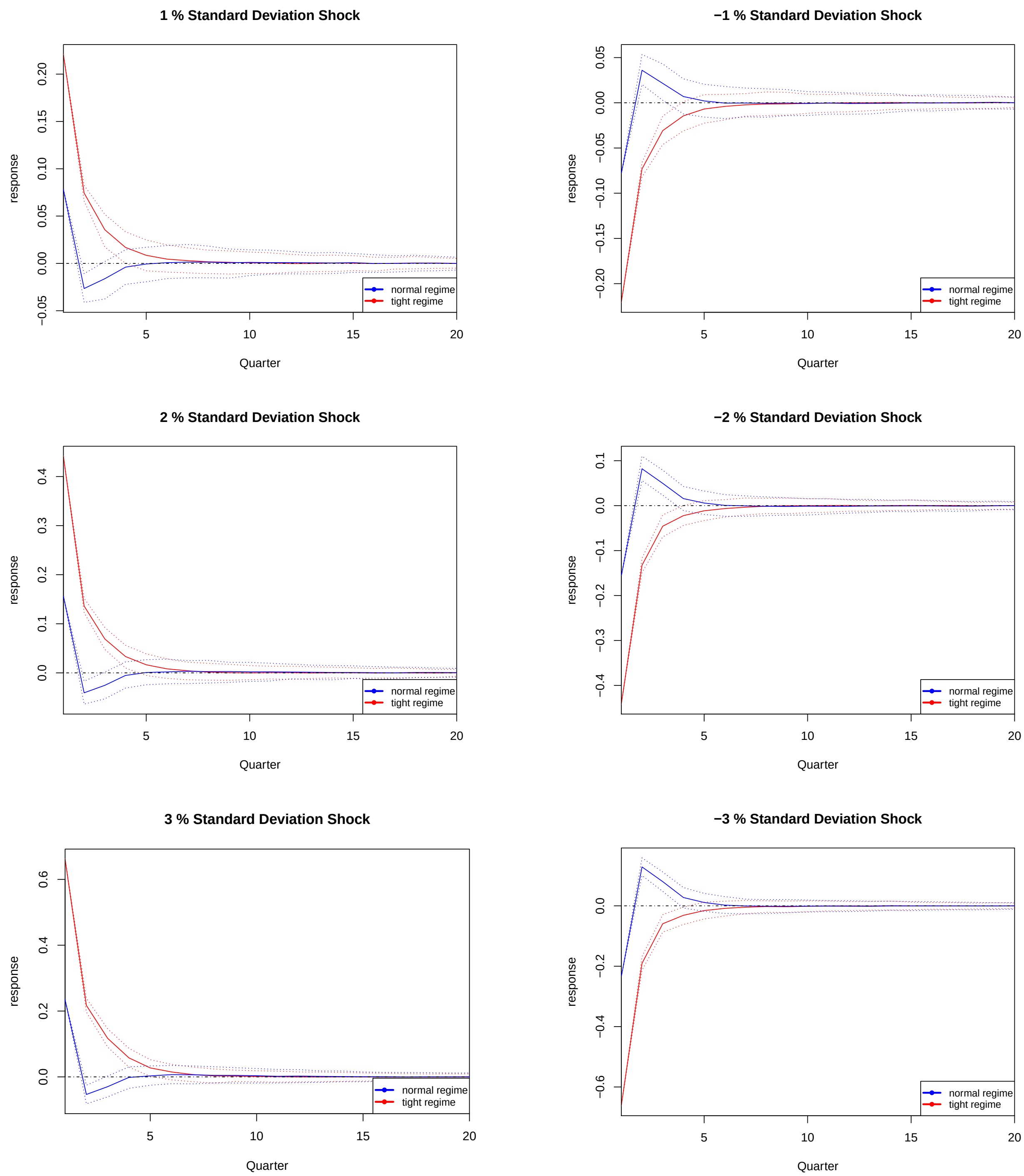
Notes: Responses of y to $\pm 1\%, 2\%, 3\%$ standard deviation shock to g based on the alternative model with the BAA spread. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500). Dotted lines represent 2.5% and 97.5% quantile of simulated responses.

Figure 9: GIRF of the BAA spread to g



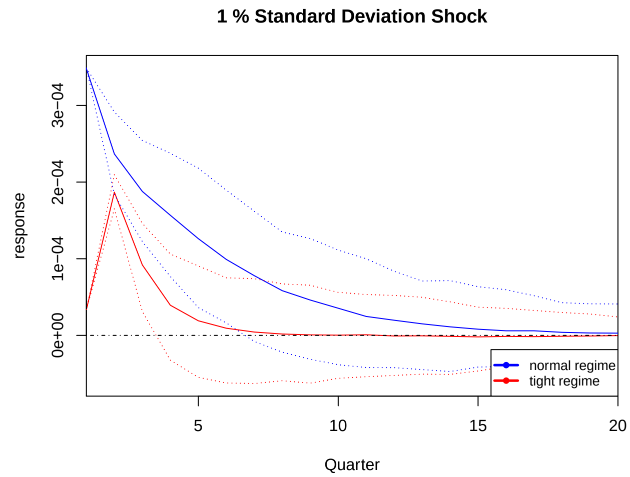
Notes: Responses of the BAA spread to a 1% standard deviation shock to g based on the alternative model with the BAA spread. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500). Dotted lines represent 2.5% and 97.5% quantile of simulated responses.

Figure 10: GIRF of y to g (MIX ratio case)



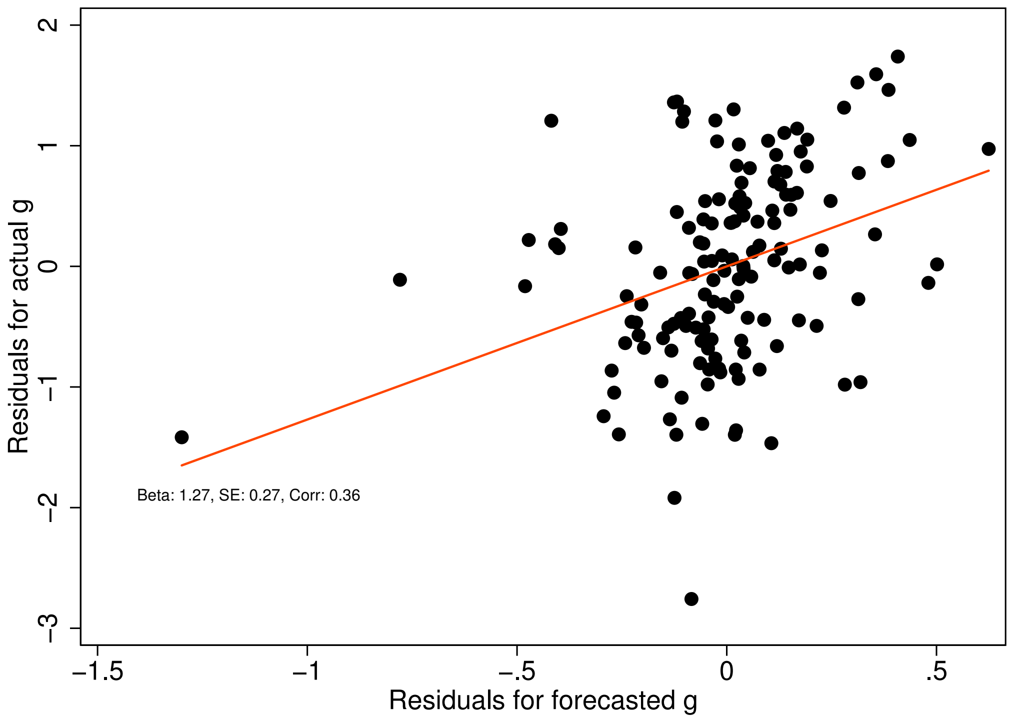
Notes: Responses of y to $\pm 1\%, 2\%, 3\%$ standard deviation shock to g based on the alternative model with the MIX ratio. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500). Dotted lines represent 2.5% and 97.5% quantile of simulated responses.

Figure 11: GIRF of the MIX ratio to g



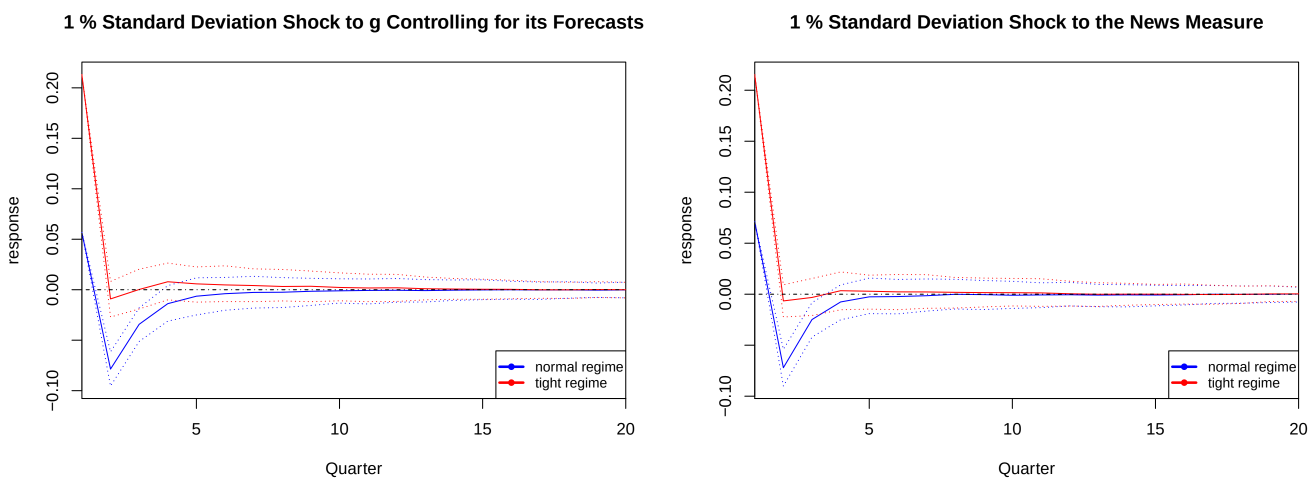
Notes: Responses of the MIX ratio to a 1% standard deviation shock to g. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500). Dotted lines represent 2.5% and 97.5% quantile of simulated responses.

Figure 12: Forecastable Component of Shocks to g



Notes: The residuals from projecting forecasted and actual g on the information contained in the lags of the variables in the baseline TVAR are plotted. The results of regressing residuals for actual g on those for forecasted g are presented in the figure.

Figure 13: GIRF of y to g (Fiscal Foresight)



Notes: Responses of y to a 1% unanticipated shock to government spending based on the models controlling for fiscal foresight. ANFCI is used as the threshold variable to define the financial market regime. GIRFs were constructed by $2.5X10^5$ simulations (B=500 and R=500). Dotted lines represent 2.5% and 97.5% quantile of simulated responses.