MEASURING THE OUTPUT RESPONSES TO FISCAL POLICY

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Abstract

A key issue in current research and policy is the size of fiscal multipliers when the economy is in recession. Using a variety of methods and data sources, we provide three insights. First, using regime-switching models, we estimate effects of tax and spending policies that can vary over the business cycle; we find large differences in the size of fiscal multipliers in recessions and expansions with fiscal policy being considerably more effective in recessions than in expansions. Second, we estimate multipliers for more disaggregate spending variables which behave differently in relation to aggregate fiscal policy shocks, with military spending having the largest multiplier. Third, we show that controlling for predictable components of fiscal shocks tends to increase the size of the multipliers.

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1. Introduction

The impact of fiscal policy on output and its components has long been a central part of fiscal policy analysis. But, as has been made clear by the recent debate over the likely effects and desired composition of fiscal stimulus in the United States and abroad, there remains an enormous range of views over the strength of fiscal policy's macroeconomic effects, the channels through which these effects are transmitted, and the variations in these effects and channels with respect to economic conditions. In particular, the central issue is the size of fiscal multipliers when the economy is in recession.

Recent theoretical work by Christiano et al. (2009), Woodford (2010) and others emphasizes that government spending may have a large multiplier when the nominal interest rate is at the zero bound, which occurs only in recessions. These novel theoretical findings for models where markets clear echo earlier Keynesian arguments that government spending is likely to have larger expansionary effects in recessions than in expansions. Intuitively, when the economy has slack, expansionary government spending shocks are less likely to crowd out private consumption or investment. To the extent discretionary fiscal policy is heavily used in recessions to stimulate aggregate demand, the key empirical question is how the effects of fiscal shocks vary over the business cycle. The answer to this question is not only interesting to policymakers in designing stabilization strategies but it can also help the economics profession to reconcile conflicting predictions about the effects of fiscal shocks across different types of macroeconomic models.

Despite these important theoretical insights and strong demand by the policy process for estimates of fiscal multipliers, there is little, if any, empirical research trying to assess how the size of fiscal multiplies varies over the business cycle. In part, this dearth of evidence reflects the fact that much of empirical research in this area is based on linear structural vector autoregressions (SVARs) or linearized dynamic stochastic general equilibrium (DSGE) models which by construction rule out state-dependent multipliers.[1] The limitations of these two approaches became evident during the recent policy debate in the United States, when government economists relied on neither of these approaches, but rather on more traditional large-scale macroeconometric models, to estimate the size and timing of U.S. fiscal policy interventions being undertaken then (e.g., Romer and Bernstein 2009, Congressional Budget Office 2009). This reliance on a more traditional approach, in turn, led to criticisms based on conflicting predictions which used SVAR and DSGE approaches (e.g., Barro and Redlick, 2009, Cogan et al., 2009, Leeper et al., 2009). Thus, a main objective of this paper is to explore this gray area and to provide estimates of state-dependent fiscal multipliers.

Our starting point is the classic paper by Blanchard and Perotti (2002), which estimated multipliers for government purchases and taxes on quarterly US data with the identifying assumptions that (1) discretionary policy does not respond to output within a quarter; (2) non-discretionary policy responses to output are consistent with auxiliary estimates of fiscal output elasticities; (3) innovations in fiscal variables not predicted within the VAR constitute unexpected fiscal policy innovations; and (4) fiscal multipliers do not vary over the business cycle. These multipliers are still commonly cited, although subsequent research has questioned whether the innovations in these SVARs really represent unanticipated changes in fiscal policy,

[1] Alternative identification approaches, notably the narrative approach of Ramey and Shapiro (1998) and Romer and Romer (2010), rely instead on published information about the nature of fiscal changes. But while the narrative approach offers a potentially more convincing method of identification, it imposes a severe constraint on its own, that the effects of only a very specific class of shocks can be evaluated (respectively, military spending build-ups and tax changes unrelated to short-term considerations such as recession or the need to balance spending changes). Furthermore, the narrative approach tends to provide qualitative assessments of the effects of fiscal policy shocks while policymakers are most interested in quantitative estimates of the effects. Romer and Romer (2010) and Ramey (2009) are exceptions that provide quantitative estimates of fiscal multipliers.

the challenge relating both to expectations and to whether the changes in fiscal variables represent actual changes in policy, rather than other changes in the relationship between fiscal variables and the included SVAR variables.

Building on Blanchard and Perotti (2002) and the subsequent studies, our paper extends the existing literature in three ways. First, using regime-switching SVAR models, we estimate effects of tax and spending policies that can vary over the business cycle.[2] We find large differences in the size of fiscal multipliers in recessions and expansions with fiscal policy being considerably more effective in recessions than in expansions. Second, to measure the effects for a broader range of policies, we estimate multipliers for more disaggregate spending variables, which often behave quite differently in relation to aggregate fiscal policy shocks. Third, we provide a more precise measure of unanticipated shocks to fiscal policy. Specifically, we have collected and converted into electronic form the quarterly forecasts of fiscal and aggregate variables from the University of Michigan's RSQE macroeconometric model. We also use information from the Survey of Professional Forecasters (SPF) and the forecasts prepared by the staff of the Federal Reserve Board (FRB) for the meetings of the Federal Open Market Committee (FOMC). We include these forecasts in the SVAR to purge fiscal variables of "innovations" that were predicted by professional forecasters. We find that the forecasts help explain a considerable share of the fiscal innovations, and that controlling for this increases the size of estimated multipliers in recession.

The next section of the paper lays out the basic specification of our regime-switching model. Section 3 presents basic results for this model for aggregate spending and taxes. Section

[2] We prefer introducing regime switches in a SVAR rather than in a DSGE model since it is difficult to model slack in the economy and potentially non-clearing markets in a DSGE framework without imposing strong assumptions regarding the behavior of households and firms. In contrast, SVAR models require fewer identifying assumptions and thus are tied more easily to empirical reality.

4 provides results for individual components of spending and Section 5 develops and presents results for our method of controlling for expectations. Section 6 concludes.

2. Econometric specification

To allow for responses differentiated across recessions and expansions, we employ a regime switching vector autoregression where transitions across states (i.e., recession and expansion) are smooth. Our estimation approach, which we will call STVAR, is similar to smooth transition autoregressive (STAR) models developed in Granger and Teravistra (1993). One important difference between STAR and our STVAR, however, is that we allow not only differential dynamic responses but also differential contemporaneous responses to structural shocks.

The key advantage of STVAR relative to estimating SVARs for each regime separately is that with the latter we may have relatively few observations in a particular regime – especially for recessions – which makes estimates unstable and imprecise. In contrast, STVAR effectively utilizes more information by exploiting variation in the degree (which sometimes can be interpreted as the probability) of being in a particular regime so that estimation and inference for each regime is based on a larger set of observations. Note that, to the extent we estimate properties of a given regime using in part dynamics of the system in another regime, we bias our estimates towards not finding differential fiscal multipliers across regimes.

Our basic specification is:

$$X_t = \left(1 - F(z_{t-1})\right)\Pi_E(L)X_{t-1} + F(z_{t-1})\Pi_R(L)X_{t-1} + \Pi_z(L)z_{t-1} + u_t \quad (1)$$

$$u_t \sim N(0, \Omega_t) \quad (2)$$

$$\Omega_t = \Omega_E\left(1 - F(z_{t-1})\right) + \Omega_R F(z_{t-1}) \quad (3)$$

$$F(z_t) = \frac{\exp(-\gamma z_t)}{1+\exp(-\gamma z_t)}, \ \ \gamma > 0 \quad (4)$$

$$var(z_t) = 1, E(z_t) = 0 \quad (5)$$

As in Blanchard and Perotti (2002), we estimate the equation using quarterly data and set $X_t = [G_t \;\; T_t \;\; Y_t]'$ in the basic specification where *G* is log real government (federal, state, and local) purchases (consumption and investment)[3], *T* is log real government receipts of direct and indirect taxes net of transfers to businesses and individuals, and *Y* is log real gross domestic product (GDP) in chained 2000 dollars.[4,5] This ordering of variables in X_t means that shocks in tax revenues and output have no contemporaneous effect on government spending. As argued in Blanchard and Perotti (2002), this identifying minimum-delay assumption may be a sensible description of how government spending operates because in the short run government may be unable to adjust its spending in response to changes in fiscal and macroeconomic conditions.

The model allows two ways for differences in the propagation of structural shocks: a) contemporaneous via differences in covariance matrices for disturbances Ω_R and Ω_E; b) dynamic via differences in lag polynomials $\Pi_R(L)$ and $\Pi_E(L)$.[6] Variable *z* is an index (normalized to have unit variance so that γ is scale invariant) of the business cycle, with positive *z* indicating an expansion. Adopting the convention that $\gamma > 0$, we interpret Ω_R and $\Pi_R(L)$ as describing the behavior of the system in a (sufficiently) deep recession (i.e., $F(z_t) \approx 1$) and Ω_E and $\Pi_E(L)$ as describing the behavior of the system in a (sufficiently) strong expansion (i.e., $1 - F(z_t) \approx 1$).

[3] We use the traditional approach of defining *G* to include direct consumption and investment purchases, which excludes the imputed rent on government capital stocks. While the current U.S. method of constructing the national accounts now includes imputed rent, this was not the case for most of our sample period. Although the historical national accounts have been revised to conform to the new approach, we cannot do this for our series of professional forecasts. Therefore, we utilize the traditional method of measuring *G* in order to have series that are consistent over time.

[4] To compute *G* and *T*, we apply the GDP deflator to nominal counterparts of *G* and *T*. We estimate the equations in log levels in order to preserve the cointegrating relationships among the variables. An alternative but more complex approach would be to estimate the equations in differences and include error correction terms.

[5] We find similar results when we augment this VAR with variables capturing the stance of monetary policy.

[6] The number of lags is chosen by Akaike Information Criterion.

We date the index *z* by *t*-1 to avoid contemporaneous feedbacks from policy actions into whether the economy is in a recession or an expansion.

The choice of index *z* is not trivial because there is no clear-cut theoretical prescription for what this variable should be. We set *z* equal to a seven-quarter moving average of the output growth rate. The key advantages of using this measure of *z* are: *i*) we can use our full sample for estimation, which makes our estimates as precise and robust as possible; *ii*) we can easily consider dynamic feedbacks from policy changes to the state of the regime (i.e., we can incorporate the fact that policy shocks can alter the regime).[7]

Although it is possible, in principle, to estimate $\{\Pi_R(L), \Pi_E(L), \Omega_R, \Omega_E\}$ and γ simultaneously, identification of γ relies on nonlinear moments and hence estimates may be sensitive to a handful of observations in short samples. Granger and Teravistra (1993) suggest imposing fixed values of γ and then using a grid search over γ to ensure that estimates for $\{\Pi_R(L), \Pi_E(L), \Omega_R, \Omega_E\}$ are not sensitive to changes in γ. We calibrate $\gamma = 1.5$ so that the economy spends about 20 percent of time in a recessionary regime (that is, $\Pr(F(z_t) > 0.8) = 0.2$) where we define an economy to be in a recession if $F(z_t) > 0.8$.[8] This calibration is consistent with the duration of recessions in the U.S. according to NBER business cycle dates (21 percent of the time since 1946). Figure 1 compares the dynamics of $F(z_t)$ with recessions identified by the NBER.

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[7] We also considered, as an alternative, the Stock and Watson (1989) coincident index of the business cycle (now maintained by the Federal Reserve Bank of Chicago and called Chicago Fed National Activity Index). This series dates only to the mid-1960s and cannot be used for endogenous-regime multiplier calculations, but a potential benefit is that it incorporates more information than the growth rate of real GDP. However, our alternative estimates using this index (not shown) suggest that the choice between the two definitions of *z* does not have a qualitatively important impact on our empirical results.

[8] When we estimate $\{\Pi_R(L), \Pi_E(L), \Omega_R, \Omega_E\}$ and γ simultaneously, we find point estimates for γ to be above 5 to 10 depending on the definitions of variables and estimation sample. These large parameter estimates suggest that the model is best described as a model switching regimes sharply at certain thresholds. However, we prefer smooth transitions between regimes (which amounts to considering moderate values of γ) because in some samples we have only a handful of recessions and then parameter estimates for $\{\Pi_R(L), \Pi_E(L), \Omega_R, \Omega_E\}$ become very imprecise.

Given the highly non-linear nature of the system described by equations (1)-(5), we use Monte Carlo Markov Chain methods developed in Chernozhukov and Hong (2003) for estimation and inference (see the Appendix for more details). Under standard conditions, this approach finds a global optimum in terms of fit. Furthermore, the parameter estimates as well as their standard errors can be computed directly from the generated chains.

When we construct impulse responses to government spending shocks in a given regime, we initially ignore any feedback from changes in z into the dynamics of macroeconomic variables.[9] In other words, we assume that the system can stay for a long time in a regime. The advantage of this approach is that, once a regime is fixed, the model is linear and hence impulse responses are not functions of history (see Koop et al. (1996) for more details). However, we do consider later the effect of incorporating changes in z as part of the impulse response functions, recomputing z consistently with the predicted changes in output.

Most of the impulse response functions and multipliers we present below are for changes in government purchases, G, and its components. We will also present some results for changes in taxes, but we have several reasons for focusing on G. First, much of the debate in the SVAR and DSGE literatures has been about the effects of government purchases. Second, we are less confident of the SVAR framework as a tool for measuring the effects of tax policy, because (as discussed above) many of the unexpected changes in T may not arise as a result of a policy change, and because we would expect the effects of tax policy to work through the structure of taxation (e.g. marginal tax rates) rather than simply through the level of tax revenues. Finally, our identification of tax shocks depends on our ability to purge innovations in revenues of automatic responses to output. In attempting to do so, we follow Blanchard and Perotti (2002) in

[9] Alternatively, one can interpret this approach as ordering z last in the VAR and setting all z to a fixed value.

using auxiliary information on the elasticity of revenue with respect to output, but it is possible that this elasticity varies over the cycle, thereby introducing a bias of unknown magnitude and direction in our regime-specific estimates.

3. Basic Aggregate Results

We begin by considering the effects of aggregate government purchases in the linear model with no regime shifts or control for expectations, following the basic specification of Blanchard and Perotti (2002), including the same ordering $[G\ T\ Y]$ for the Cholesky decomposition and the control for the automatic tax response to contemporaneous output shocks (an elasticity of 2.08). Our sample period is 1947:1—2009:2. Figure 2 displays, in three panels, the resulting impulse response functions (IRFs) for a government purchase shock. These multipliers demonstrate by how many dollars output, taxes, and government purchases increase over time when government purchases are increased by \$1.[10] In this and all subsequent figures, the shaded bands around the impulse response functions are 90 percent confidence intervals.[11] Consistent with results reported in previous studies (see, for example, the survey by Hall, 2009), the maximum size of the government spending multiplier in the linear VAR model is about 1 and this maximum effect of a government spending shock on output is achieved after a short delay. The response of future government purchases also peaks after a short delay, indicating that the typical government spending shock during the sample period is of relatively short duration. Taxes fall slightly in response to the increase in government purchases. This fall in taxes may contribute to the positive impact on output that persists even as the increase in government purchases dies off over time.

[10] Because government purchases and output enter the estimated equations in logs, we scale the estimated IRFs by the sample average values of *Y/G* to convert percent changes into dollar changes.

[11] The Appendix discusses our method of estimating these confidence intervals.

The next two figures plot the corresponding IRFs in expansions (Figure 3) and recessions (Figure 4). Because of the smaller effective number of observations for each regime, particularly for recessions, the confidence bounds are greater for these IRFs than for those for the linear model in Figure 2. Even with these wide bands, however, the responses in recession and expansion are quite different. In both regimes, the impact output multiplier is about 0.5, slightly below that estimated for the linear model. Over time, though, the IRFs diverge, with the response in expansions never rising higher and soon falling below zero, while the response in recessions rises steadily, reaching a value of over 2.5 after 20 quarters. The strength of this output response in recession is not attributable simply to differences in the permanence of the spending shock or the tax response. Taxes actually rise in recession, while falling in expansion. This difference, which is consistent with the automatic responses of tax collections to changes in output, should weaken the differences in the observed output responses in recession and expansion; and while the government spending shock is more persistent in recession, it is stronger in the short run in expansion.[12]

To put the magnitudes of these multipliers in perspective, consider multipliers in Keynesian models as well as the more recent DSGE literature. Traditional Keynesian (IS-LM-AS) models usually have large multipliers since the size of the multiplier is given by $1/(1-MPC)$ where MPC is the marginal propensity to consume which is typically quite large (about 0.5-0.9).[13] To the extent that the AS curve in the IS-LM-AS model is upward sloping, the multiplier can vary from relatively large (the AS curve is flat and there is a great deal of slack in

[12] Note that the contemporaneous responses of output to a shock in government spending are similar in recessions and expansions. This result suggests that the differences in the magnitudes of the multipliers across regimes are driven by the differences in the dynamics (i.e., $\{\Pi_R(L), \Pi_E(L)\}$) rather than in the covariance of error terms (i.e., $\{\Omega_R, \Omega_E\}$).

[13] For example, Shapiro and Slemrod (2003) and Johnson et al..(2006) report that the marginal propensity to consume out of (small) tax rebates in 2001 EGTRRA was somewhere between in 0.5 and 0.7.

the economy; i.e., in a recession) to relatively small (the AS curve is steeply upward sloping and the economy operates at full capacity; i.e., in an expansion). In contrast, an increase in government spending in modern business cycle models usually leads to a large crowding out of private consumption in recessions and expansions and correspondingly the typical magnitude for the multiplier is less than 0.5 (in many cases much smaller). Recent findings from DSGE models with some Keynesian features (e.g., Christiano et al. 2009, Eggertsson 2008, and Woodford 2010), however, suggest that the government spending multiplier in periods with a binding zero lower bound on nominal interest rates (which are recessionary times) could be somewhere between 3 and 5. Intuitively, with the binding zero lower bound, increases in government spending have no effect on interest rates and thus there is no crowding out of investment or consumption, which leads to large multipliers.

In short, our estimates of the government spending multiplier in recessions and expansions are largely consistent with the theoretical arguments in both (old) Keynesian and (new) modern business cycle models. Table 1 summarizes these output multipliers for the cases just considered, as well as those that follow. The table presents multipliers measured in two ways. The first column gives the maximum impact on output (with standard errors in the second column) and the third column (with standard errors in the fourth column) shows the ratio of the sum of the Y response (to a shock in G) to the sum of G response (to a shock in G). The first measure of the fiscal multiplier has been widely used since Blanchard and Perotti (2002). The second measure has been advocated by Woodford (2010) and others since the size of the multiplier depends on the persistence of fiscal shocks. Regardless of which way we compute the multiplier, it is much larger in recessions than in expansions.

One might guess that the differences between our regime-based multipliers are exaggerated by our assumptions that the regimes themselves don't change. That is, if the multiplier is smaller in expansion than in recession and the economy has a positive probability of shifting from recession to expansion in future periods, then the actual multipliers starting in recession (or expansion) should be a blend of those estimated for the separate regimes. Calculating full dynamic impulse response functions that include internally consistent regime shifts is complicated, because we must compute the index *z* and evaluate the function $F(z)$ at each date along the trajectory. Also, because the IRFs are now nonlinear, they will depend on the initial value of the index *z* and the size of the government policy shock. For example, the more deep the initial recession, and the less positive the spending shock, the less important future regime shifts out of recession will be. Therefore, we must specify the initial conditions and the size of the policy experiment in order to estimate the dynamic IRFs.

Figure 5 presents estimates for the historical effects of shocks to government purchases on output, incorporating regime shifts in response to government spending shocks. For each period, we consider a policy shock equal to one percent increase in *G* and report a dollar increase in output per dollar increase in government spending over 20 quarters (i.e., $\sum_{h=1}^{20} Y_h / \sum_{h=1}^{20} G_h$). The size of the multiplier varies considerably over the business cycle. For example in 1985, an increase in government spending would have barely increased output. In contrast, a dollar increase in government spending in 2009 could raise output by about $1.75. Typically, the multiplier is between 0 and 0.5 in expansions and between 1 and 1.5 in recessions. Note the size of the multiplier tends to change relatively quickly as the economy starts to grow after reaching a trough. Thus, the timing of changes in discretionary government spending is critical for effectiveness of countercyclical fiscal policies.

Bearing in mind caveats we have discussed above, we turn now to the effects of taxes on output. Figures 6-8 are comparable to Figures 2-4 for government purchases, with Figures 6-8 showing the IRFs for output, spending and taxes in response to a tax increase for each of the three regimes, with confidence bands. As with government purchases, the results for taxes in the linear model are consistent with the past results in the SVAR literature. From an initial impact of -0.2, the effect on output grows in strength over time, reaching -1.0 by the end of five years, which is similar to results reported in Blanchard and Perotti (2002).[14] In contrast to the case of spending shocks, however, the IRFs for the expansion and recession regimes do not bracket those for the linear case. In both regimes, the output effects are less negative. They are, in fact, generally positive in the recession regime. However, this response is sensitive to using alternative measures of the elasticity of tax revenue with respect to output and one can obtain negative responses of Y to a shock in T if the elasticity in recessions is larger than the elasticity estimated in Blanchard and Perotti (2002).

The results for the expansion regime may be understood by observing that the responses of government purchases to a tax increase are much more positive in expansions than in the linear model. This increase in G is what can cause a less negative impact on output in expansions. In recessions, the output response is more puzzling; subsequent tax increases are stronger and government spending increases weaker, at least initially, than in expansions, and yet the output effects of an initial tax increase are positive. Presumably, the stronger subsequent tax increases reflect, at least in part, the automatic responses of tax collections to higher output. But

[14] Romer and Romer (2010) report larger multipliers (≈-3) for changes in tax revenue. After a series of methodological refinements (e.g., use changes in tax receipts rather than tax liabilities, formal statistical criteria to choose the length of lag polynomials, more precise timing of the shocks) and using the same approach, Perotti (2010) finds multipliers to be approximately -1.5.

the overall pattern still suggests that the underlying effect on output of the initial tax increase is quite positive, a result for which we can offer no obvious explanation.

4. Results for Components of Spending

Just as output multipliers for government purchases differ according to the regime in which they occur, they also differ for different components of government purchases. As discussed earlier, studies using the narrative approach tend to focus on military build-ups, but how useful are these shocks to defense spending in analyzing the effects of other changes in spending policies, such as those adopted during the recent recession?

Figure 9 shows that IRFs for output in response to defense and non-defense spending shocks, based on a four-variable VAR including defense and non-defense purchases, as well as output and taxes. We order the Cholesky decomposition with defense spending first and non-defense spending second, although this does not have an important effect on the results.[15] Clearly, the IRFs have different shapes for the linear model. For a unit shock to defense spending, output rises immediately by just over 1, which is consistent with Ramey (2009), and then gradually falls, becoming negative after several quarters. For non-defense spending, the output effect starts smaller but eventually exceeds 1 and remains above 0.6 for the entire period shown. Once the results are broken down by regime, however, we can see a much stronger dependence on the regime of the defense spending IRFs, which are similar to the linear-model results for the case of expansion but much more positive in recession, peaking at nearly 4 in the fifth quarter after the shock. For non-defense spending, on the other hand, the differences

[15] Further details regarding confidence intervals and the effects on taxes and spending components are provided in the Appendix in Figures A1-A6.

between regimes are primarily with respect to timing rather than size, with the most positive responses occurring rapidly in expansions but with several quarters' delay in recessions.

Figure 10 shows the results of an experiment that breaks government purchases down in a different way, into consumption and investment spending, with consumption ordered first.[16] Once again, the results differ considerably by regime and by spending component. In this decomposition, both components of spending have positive effects on output in the linear model, although the effects of investment spending are much stronger, particularly during the first few quarters when the impact on output exceeds 2 for investment but is around 0.5 for consumption. Estimating the IRFs separately for recession and expansion leads in general to the expected result of more positive multipliers in recession than in expansion. The IRFs are also noisier for the separate regimes, indicating an imprecision of these point estimates that is consistent with the larger confidence intervals (see Appendix figures).

5. Controlling for Expectations

As emphasized by Ramey (2009) and others, the timing of fiscal shocks plays a critical role in identifying the effect of fiscal shocks. In spirit of Ramey (2009), we control for expectations not already absorbed by the VAR using real-time professional forecasts from three sources. First, we draw forecasts for output and government spending variables from the Survey of Professional Forecasters (SPF), an average of forecasts (with the number of individual forecasters ranging from 9 to 50) available since 1968 for GDP and since 1982 for government spending and its components. Second, for government revenues, we use the University of Michigan RSQE

[16] Appendix Figures A7-A12 provide further details of this experiment.

econometric model, for which forecasts are available for the period beginning in 1982.[17] Third, we use government spending (Greenbook) forecasts prepared by the FRB staff for FOMC meetings. The Greenbook forecasts for government spending are available from 1966 to 2004. Since the FOMC meets 8 or 12 times a year in our sample, we take Greenbook forecasts prepared for the meeting which is the closest to the middle of the quarter to make it comparable to SPF forecasts. Since the properties of the Greenbook and SPF forecasts are similar, we splice the Greenbook and SPF government spending forecasts and construct a continuous forecast series running from 1966 to present. For each variable, we use the forecast made in period t-1 for the period-t value. Because there have been numerous data revisions in the National Income and Product Accounts since the dates of these forecasts, we use forecast growth rates rather than levels.

The importance of controlling for expectations is illustrated in Figure 11, which plots the residuals from projecting forecasted and actual growth rates of government spending on lags of the variables in our baseline VAR.[18] If the VAR innovations were truly unexpected, then these two residuals would be unrelated, but the correlation between forecasted and actual growth rates of government spending (net of the information contained in the VAR lags) is about 0.3-0.4 which points to conclusion that a sizable fraction of VAR innovations is predictable. Therefore, one should be interested in using refined measures of unanticipated shocks to government spending.

The simplest way to account for these forecastable components of VAR residuals is to expand the vector X to include professional forecasts. That is, if we let the

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[17] The University of Michigan data are coded from hard copies. Hard copies of forecasts prior to 1982 were lost that year in the fire that destroyed that university's Economics Department building.

[18] The figure presents two versions of this plot, with similar results, one relating forecast residuals to VAR residuals based on real-time data, the other to VAR residuals based on final-vintage data.

SPF/Greenbook/RSQE forecasts made at time t-1 for the growth rate of real government purchases for time t be denoted $\Delta G^F_{t|t-1}$ (where $\Delta G^F_{s|t}$ is the growth rate of government spending G at time s forecasted at time t) and define the professional forecasts for output and taxes the same way, we would use the expanded vector in equation (1) $[\Delta G^F_{t|t-1}\ \Delta T^F_{t|t-1}\ \Delta Y^F_{t|t-1}\ G_t\ \ T_t\ \ Y_t]'$, stacking the forecasts first because by the timing there is no contemporaneous feedback from unanticipated shocks at time t to forecasts made at time t-1.[19] This direct approach is attractive because it accounts automatically for any effects that expectations might have on the aggregate variables and for the determinants of the expectations themselves. In practice, however, we have found this approach to be too demanding given our data limitations, for it doubles the number of variables in the VAR while eliminating more than half of the observations in our sample (i.e., those before 1982); the resulting confidence intervals are very large, particularly for the recession regime for which we have effectively fewer observations.[20,21]

We consider two alternative approaches. The first alternative is a two-step process. The first step of this process is to create "true" innovations by subtracting forecasts of the vector X_t from X_t itself. We then fit $\Omega_t = \Omega_E\big(1 - F(z_{t-1})\big) + \Omega_R F(z_{t-1})$ (i.e., equation (3)) using these forecast errors (rather than the residuals from the VAR itself). From this step, we use estimated Ω_E and Ω_R to construct contemporaneous responses to shocks in expansions and recessions. The second step involves using the previously-estimated baseline VAR with regime switches. In this step, we use the estimated coefficients $\Pi_E(L)$ and $\Pi_R(L)$ to map the propagation of

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[19] See Leduc et al. (2007) for a more detailed discussion on the ordering.

[20] We do consider a more restricted version of this approach shortly, in which we add a series on defense spending innovations available for our full sample directly to the VAR.

[21] Mertens and Ravn (2010) distinguish anticipated and unanticipated shocks in a VAR by using long-run restrictions combined with calibration. We do not use this strategy in part because with regime switches we cannot distinguish long-run responses in expansions and recessions.

contemporaneous responses created in the first step. This two-step approach has the advantage of allowing us to base the VAR on our full sample and the original number of variables. Its main disadvantage is that the IRF dynamics will not necessarily be correct, given that the VAR is estimated under the assumption that the innovations to X are fully unanticipated.

The second alternative approach is to augment the baseline VAR directly, but with only one variable, pertaining to the forecast of government spending. For example, the vector of variables in the VAR could be $\tilde{X}_t = [\Delta G^F_{t|t-1}\ G_t\ \ T_t\ \ Y_t]'$ or $\hat{X}_t = [FE^G_t\ G_t\ \ T_t\ \ Y_t]'$ where FE^G_t is the forecast error for the growth rate of government spending or some other measure of news about government spending. In the former specification, an innovation in G_t orthogonal to $\Delta G^F_{t|t-1}$ is interpreted as an unanticipated shock. In the latter specification, an innovation in the forecast error or news about government spending is interpreted as an unanticipated shock. The key advantage of this approach is that, with sufficiently long series, we can have a VAR of a manageable size and yet we can remove directly a predictable component from government spending innovations.

With these alternative approaches and specifications, unanticipated shocks to government spending of a given initial size will lead to differing government spending responses over time. To make IRFs comparable, we normalize the size of the unanticipated government spending shock so that the integral of a government spending response over 20 quarters is equal to one. Therefore the interpretation of the fiscal multipliers is similar to the second column in Table 1. Figure 12 shows the IRFs for different approaches and specifications and contrasts these results with the results for the baseline specification (1)-(5) that does not control for the predictable component in government spending innovations. Table 1 reports the maximum and average multipliers along with associated standard errors.

Panel A (Figure 12) presents IRFs for the first approach. The results suggest that controlling for expectations increases the absolute magnitudes of the government spending multipliers, making them more positive in recessions and more negative in expansions. Panel B (Figure 12) shows results for the second approach with $\tilde{X}_t = [\Delta G^F_{t|t-1}\ G_t\ \ T_t\ \ Y_t]'$ where $\Delta G^F_{t|t-1}$ is the spliced Greenbook/SPF forecast series for the growth rate of government spending. In this specification, which is estimated on the 1966-2009 sample, the multiplier in the recession regime is a notch larger than in the baseline model while the multiplier in the expansion regime stays positive but small which contrasts with the baseline model where the multiplier turns negative at long horizons. Panel C (Figure 12) shows results for the second approach with $\hat{X}_t = [FE^G_t\ G_t\ \ T_t\ \ Y_t]'$ where FE^G_t is the forecast error computed as the difference between spliced Greenbook/SPF forecast series and actual, first-release series of the government spending growth rate.[22] In this specification, an unanticipated shock to government spending in an expansion has an effect on output similar to the effect we find in the baseline model. In a recession, however, the multiplier could be larger than in the baseline model, especially at short horizons. By and large, these results suggest that the government spending multiplier in recessions increases and the multiplier in expansions does stay close to zero when we purify government spending shocks from predictable movements.

Finally, we use spending news constructed in Ramey (2009) to control for the timing of fiscal shocks (Panel D, Figure 12). Specifically, we augment the baseline VAR with Ramey's spending news series, which is ordered first in this new VAR. The key advantage of using Ramey's series is that, in contrast to forecast series, it covers the whole post-WWII sample and thus our estimates are more precise. A limitation of Ramey's unanticipated shocks is that these

[22] An advantage of using real-time data to compute forecast errors is that it makes forecasts and actual series refer to the same concept of government spending.

shocks refer only to military spending. However, since changes in military spending account for a large share of variation in total government spending, Ramey's shocks are informative for our analysis. Panel D shows that although controlling for spending news does not materially affect output responses during expansions, there are some important differences during recessions. In particular, the multiplier on impact is about 2 in response to an unanticipated shock and the average multiplier over 20 quarters is 3.7. In contrast, the baseline VAR specification reports the impact multiplier of 0.8 and the average multiplier of 2.2. We view these findings as corroborating our other evidence on the importance of constructing unanticipated fiscal shocks, which tend to have larger effects on output in recessions.

6. Concluding remarks

Our findings suggest that all of the extensions we developed in this paper – controlling for expectations, allowing responses to vary in recession and expansion, and allowing for different multipliers for different components of government purchases – all have important effects on the resulting estimates. In particular, policies that increase government purchases have a much larger impact in recession than is implied by the standard linear model, even more so when one controls for expectations, which is clearly called for given the extent to which independent forecasts help predict VAR policy "shocks."

While we have extended the SVAR approach, our analysis still shares some of the limitations of the previous literature. We have allowed for different economic environments, but there may be still other important differences among historical episodes that we lump together, for example recessions, such as the recent one, associated with financial market disruptions and very low nominal government interest rates, and other recessions induced by monetary contractions (such as the one in the early 1980s). Our predictions are also tied to historical experience concerning the persistence of policy shocks, and therefore may not apply to policies either less or more permanent. The effects of taxes, even if purged of expected changes, are still probably too simple as they fail to take account of the complex ways in which structural tax policy changes can influence the economy. And, finally, as we enter a period of unprecedented long-run budget stress, the U.S. postwar experience, or even the experience of other countries that have dealt with more acute budget stress[23], may not provide very accurate forecasts of future responses.

These limitations of our analysis should motivate future theoretical work to develop realistic DSGE models with potentially nonlinear features to understand more deeply the forces driving differences in the size of fiscal multipliers over the business cycle, the role of (un)anticipated shocks for fiscal multipliers in these environments, and implications of levels of government debt for the potency of discretionary fiscal policy to stabilize the economy.

[23] See, for example, Perotti (1999) and Ardagna (2004).

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Appendix: Estimation procedure

The model is estimated using maximum likelihood methods. The log-likelihood for model (1)-(5) is given by:

$$log\, L = const - \frac{1}{2}\sum_{t=1}^{T} log|\Omega_t| - \frac{1}{2}\sum_{t=1}^{T} u_t'\Omega_t^{-1}u_t \qquad \text{(A1)}$$

where $u_t = X_t - (1 - F(z_{t-1}))\Pi_E(L)\, X_{t-1} - F(z_{t-1})\Pi_R(L)X_{t-1}$.[24] Since the model is highly nonlinear and has many parameters $\Psi = \{\gamma, \Omega_R, \Omega_E, \Pi_R(L), \Pi_E(L)\}$, using standard optimization routines is problematic and, thus, we employ the following procedure.

Note that conditional on $\{\gamma, \Omega_R, \Omega_E\}$ the model is linear in lag polynomials $\{\Pi_R(L), \Pi_E(L)\}$. Thus, for a given guess of $\{\gamma, \Omega_R, \Omega_E\}$, we can estimate $\{\Pi_R(L), \Pi_E(L)\}$ with weighted least squares where weights are given by Ω_t^{-1} and estimates of $\{\Pi_R(L), \Pi_E(L)\}$ must minimize $\frac{1}{2}\sum_{t=1}^{T} u'_t\Omega_t^{-1}u_t$. Let

$$W_t = \left[\left(1 - F(z_{t-1})\right)X_{t-1} \quad F(z_{t-1})X_{t-1} \ldots \left(1 - F(z_{t-1})\right)X_{t-p} \quad F(z_{t-1})X_{t-p}\right]$$

be the extended vector of regressors and $\Pi = [\Pi_R\ \ \Pi_E]$ so that $u_t = X_t - \Pi W_t'$ and the objective function is

$$\frac{1}{2}\sum_{t=1}^{T}\left(X_t - \Pi W_t'\right)'\Omega_t^{-1}\left(X_t - \Pi W_t'\right). \qquad \text{(A2)}$$

Note that we can rewrite (A2) as

$$\begin{aligned}\frac{1}{2}\sum_{t=1}^{T}\left(X_t - \Pi W_t'\right)'\Omega_t^{-1}\left(X_t - \Pi W_t'\right) &= trace\left[\frac{1}{2}\sum_{t=1}^{T}\left(X_t - \Pi W_t'\right)'\Omega_t^{-1}\left(X_t - \Pi W_t'\right)\right] \\ &= \frac{1}{2}\sum_{t=1}^{T} trace\left[\left(X_t - \Pi W_t'\right)\left(X_t - \Pi W_t'\right)'\Omega_t^{-1}\right].\end{aligned}$$

The first order condition with respect to Π is $\sum_{t=1}^{T}\left(W_t'X_t\Omega_t^{-1} - W_t'W_t\Pi'\Omega_t^{-1}\right) = 0$.

Now using the *vec* operator, we get

$$\begin{aligned} vec\left(\sum_{t=1}^{T} W_t'X_t\Omega_t^{-1}\right) &= vec\left[\sum_{t=1}^{T} W_t'W_t\Pi'\Omega_t^{-1}\right] = \sum_{t=1}^{T} vec\left[W_t'W_t\Pi'\Omega_t^{-1}\right] \\ &= \sum_{t=1}^{T}[vec\, \Pi']\left[\Omega_t^{-1} \otimes W_t'W_t\right] = vec\Pi' \sum_{t=1}^{T}\left[\Omega_t^{-1} \otimes W_t'W_t\right]\end{aligned}$$

which gives

$$vec\Pi' = \left(\sum_{t=1}^{T}\left[\Omega_t^{-1} \otimes W_t'W_t\right]\right)^{-1} vec\left(\sum_{t=1}^{T} W_t'X_t\,\Omega_t^{-1}\right). \qquad \text{(A3)}$$

The procedure iterates on $\{\gamma, \Omega_R, \Omega_E\}$ (which yields Π and the likelihood) until an optimum is reached. Note that with a homoscedastic error term (i.e. $\Omega_t = const$), we recover standard VAR estimates.

[24] To simplify notation, we omit other controls in equation (1).

Since the model is highly non-linear in parameters, it is possible to have several local optima and one must try different starting values for $\{\gamma, \Omega_R, \Omega_E\}$. To ensure that Ω_R and Ω_E are positive definite, we use $\Psi = \{\gamma, chol(\Omega_R), chol(\Omega_E), \Pi_R(L), \Pi_E(L)\}$, where *chol* is the operator for Cholesky decomposition. Furthermore, given the non-linearity of the problem, it may be difficult to construct confidence intervals for parameter estimates as well as impulse responses. To address these issues, we use a Markov Chain Monte Carlo (MCMC) method developed in Chernozhukov and Hong (2003; henceforth CH). This method delivers not only a global optimum but also distributions of parameter estimates.

We employ the Hastings-Metropolis algorithm to implement CH's estimation method. Specifically our procedure to construct chains of length N can be summarized as follows:

Step 1: Draw $\Theta^{(n)}$, a candidate vector of parameter values for the chain's n+1 state, as $\Theta^{(n)} = \Psi^{(n)} + \psi^{(n)}$ where $\Psi^{(n)}$ is the current n state of the vector of parameter values in the chain, $\psi^{(n)}$ is a vector of i.i.d. shocks taken from $N(0,\Omega_\psi)$, and Ω_ψ is a diagonal matrix.

Step 2: Take the n+1 state of the chain as

$$\Psi^{(n+1)} = \begin{cases} \Theta^{(n)} & \text{with probability } \min\{1, \exp[L(\Theta^{(n)}) - L(\Psi^{(n)})]\} \\ \Psi^{(n)} & \text{otherwise} \end{cases}$$

where $L(\Psi^{(n)})$ is the value of the objective function at the current state of the chain and $L(\Theta^{(n)})$ is the value of the objective function using the candidate vector of parameter values.

The starting value $\Psi^{(0)}$ is computed as follows. We approximate the model in (1)-(5) so that the model can be written as regressing X_t on lags of $X_t, X_t z_t, X_t z_t^2$. We take the residual from this regression and fit equation (3) using MLE to estimate Ω_R and Ω_E. These estimates are used as staring values. Given Ω_R and Ω_E and the fact that the model is linear conditional on Ω_R and Ω_E, we construct starting values for lag polynomials $\{\Pi_R(L), \Pi_E(L)\}$ using equation (A3).

The initial Ω_ψ is calibrated to about one percent of the parameter value and then adjusted on the fly for the first 20,000 draws to generate 0.3 acceptance rates of candidate draws, as proposed in Gelman et al (2004). We use 100,000 draws for our baseline and robustness estimates, and drop the first 20,000 draws ("burn-in" period). We run a series of diagnostics to check the properties of the resulting distributions from the generated chains. We find that the simulated chains converge to stationary distributions and that simulated parameter values are consistent with good identification of parameters.

CH show that $\bar{\Psi} = \frac{1}{N}\sum_{n=1}^{N}\Psi^{(n)}$ is a consistent estimate of Ψ under standard regularity assumptions of maximum likelihood estimators. CH also prove that the covariance matrix of the estimate of Ψ is given by $V = \frac{1}{N}\sum_{n=1}^{N}\left(\Psi^{(n)} - \bar{\Psi}\right)^2 = \mathrm{var}\left(\Psi^{(n)}\right)$, that is the variance of the estimates in the generated chain.

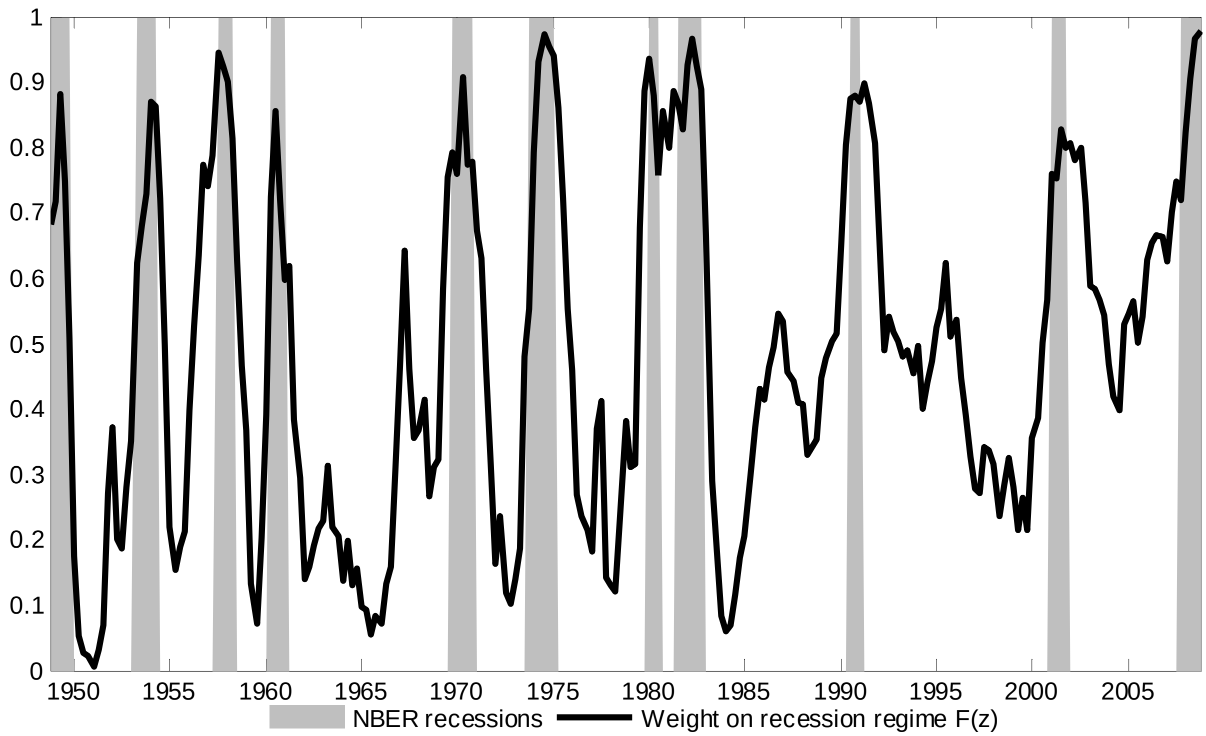
Furthermore, we can use the generated chain of parameter values $\left\{\Psi^{(n)}\right\}_{n=1}^{N}$ to construct confidence intervals for the impulse responses. Specifically, we make 1,000 draws (with replacement) from $\left\{\Psi^{(n)}\right\}_{n=1}^{N}$ and for each draw we calculate an impulse response. Since columns of $chol(\Omega_R)$ and $chol(\Omega_E)$ in $\left\{\Psi^{(n)}\right\}_{n=1}^{N}$ are identified up to sign, the generated chains for $chol(\Omega_R)$ and $chol(\Omega_E)$ can change signs. Although this change of signs is not a problem for estimation, it can sometimes pose a problem for the analysis of impulse responses. In particular, when there is a change of signs for the entries of $chol(\Omega_R)$ and $chol(\Omega_E)$ that correspond to the variance of government spending shocks, these entries can be very close to zero. Given that we compute responses to a unit shock in government spending and thus have to divide entries of chol(Ω_R) and chol(Ω_E) that correspond to the government spending shock by the standard deviation of the government spending shock, confidence bands may be too wide. To address this numerical issue, when constructing impulse responses, we draw $\{\Pi_R(L), \Pi_E(L)\}$ directly from $\left\{\Psi^{(n)}\right\}_{n=1}^{N}$ while the covariance matrix of residuals in regime *s* is drawn from $N(\mathrm{vec}(\Omega_\mathrm{s}), \Sigma_\mathrm{s})$ where $\Sigma_\mathrm{s} = 2[(D_n'D_n)^{-1}D_n]\left\{\mathrm{var}\left(\mathrm{vec}(\Omega_\mathrm{s})\right) \otimes \mathrm{var}\left(\mathrm{vec}(\Omega_\mathrm{s})\right)\right\}[(D_n'D_n)^{-1}D_n])'$, D_n is the duplication matrix, and $\mathrm{var}\left(\mathrm{vec}(\Omega_\mathrm{s})\right)$ is computed from $\left\{\Psi^{(n)}\right\}_{n=1}^{N}$ (see Hamilton (1994) for more details). The 90 percent confidence bands are computed as the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of the generated impulse responses.

Table 1: Multipliers

	$\max_{h=1,\ldots,20}\{Y_h\}$		$\sum_{h=1}^{20} Y_h / \sum_{h=1}^{20} G_h$	
	Point estimate	Standard error	Point estimate	Standard error
Total spending				
Linear	1.00	0.32	0.57	0.25
Expansion	0.57	0.12	-0.33	0.20
Recession	2.48	0.28	2.24	0.24
Total taxes*				
Linear	-0.99	0.10	-6.71	0.11
Expansion	-0.50	0.10	-2.03	0.11
Recession	-0.08	0.12	0.30	0.10
Defense spending				
Linear	1.16	0.52	-0.21	0.27
Expansion	0.80	0.22	-0.43	0.24
Recession	3.56	0.74	1.67	0.72
Non-defense spending				
Linear	1.17	0.19	1.58	0.18
Expansion	1.26	0.14	1.03	0.15
Recession	1.12	0.27	1.09	0.31
Consumption spending				
Linear	1.21	0.27	1.20	0.31
Expansion	0.17	0.13	-0.25	0.10
Recession	2.11	0.54	1.47	0.31
Investment spending				
Linear	2.12	0.68	2.39	0.67
Expansion	3.02	0.25	2.27	0.15
Recession	2.85	0.36	3.42	0.38
Total spending; multipliers for alternative measures of normalized unanticipated shocks to government spending				
Baseline model, normalized shocks to government				
Expansion	0.63	0.13	-0.33	0.20
Recession	3.06	0.35	2.24	0.24
SPF/RSQE forecast errors as contemporaneous shocks (Panel A in Figure 12)				
Expansion	1.13	0.20	-1.23	0.65
Recession	3.85	0.29	2.99	0.27
Control for SPF/Greenbook forecast of government spending (Panel B in Figure 12)				
Expansion	0.82	0.12	0.40	0.15
Recession	3.27	0.73	2.58	0.59
Real-time SPF/Greenbook forecast error for ΔG as an unanticipated shock (Panel C in Figure 12)				
Expansion	0.46	0.27	-0.25	0.23
Recession	7.14	1.45	2.09	1.35
Ramey (2009) news shocks (Panel D in Figure 12)				
Expansion	0.66	0.12	-0.49	0.24
Recession	4.88	0.67	3.76	0.52

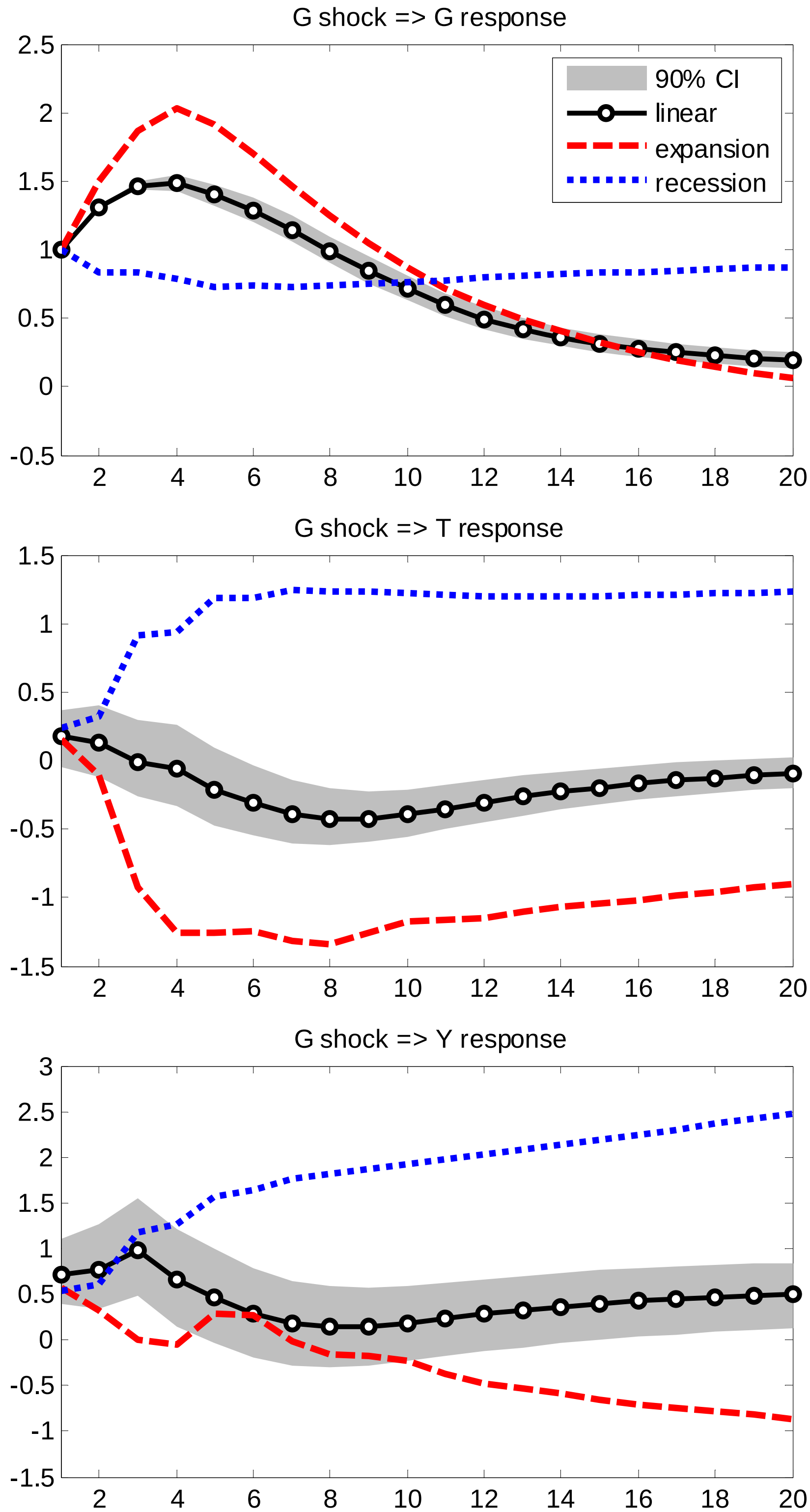
* Note: the first column for total taxes is the minimal response to a positive shock in taxes.

Figure 1. NBER dates and weight on recession regime *F*(*z*)



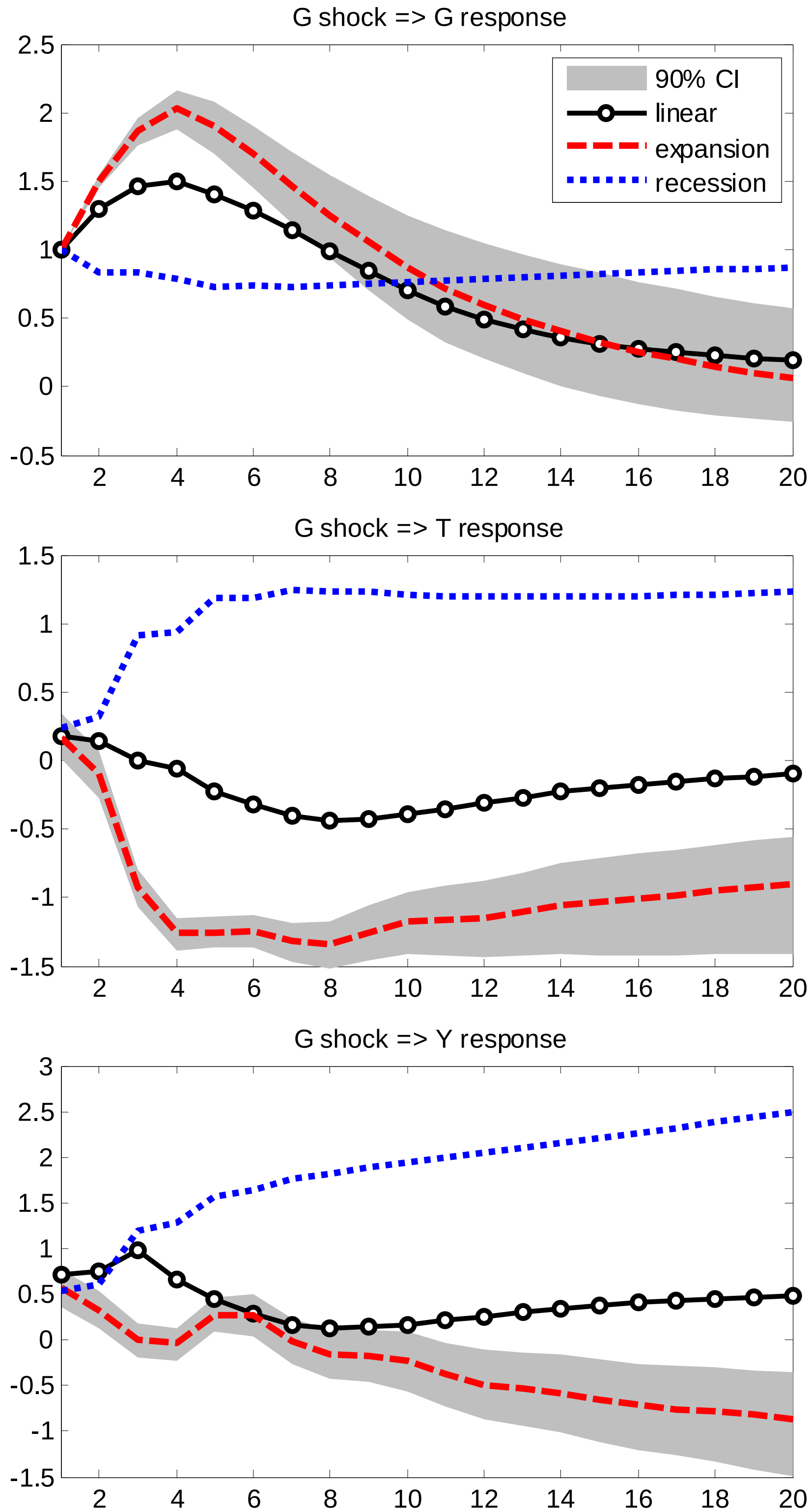
Notes: The shaded region shows recessions as defined by the NBER. The solid black line shows the weight on recession regime $F(z)$.

Figure 2. Impulse responses in the linear model



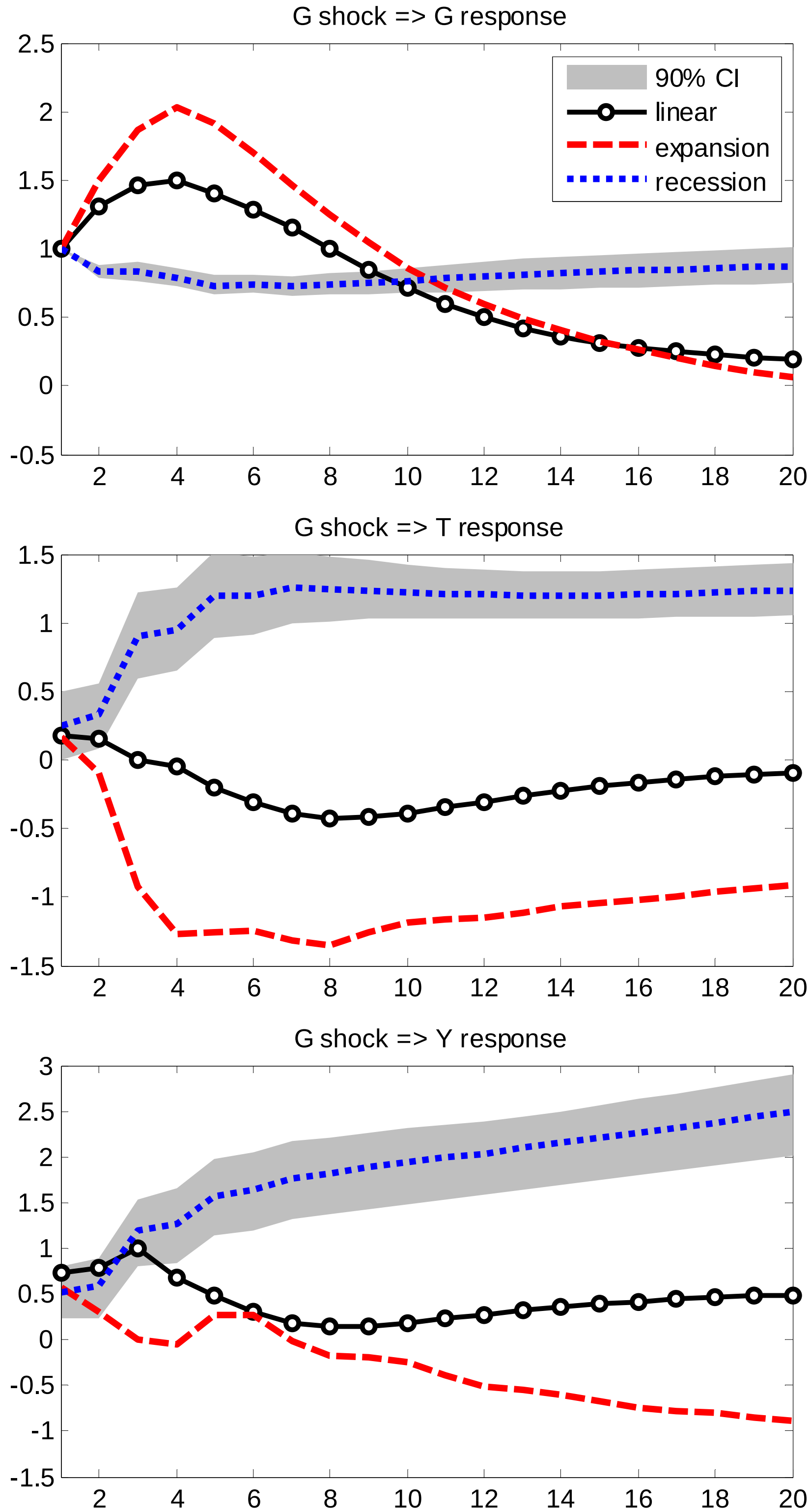
Notes: The figures show impulse responses to a $1 increase in government spending. Shaded region is the 90% confidence interval. Dashed lines show the responses in expansionary (red, long dash) and recessionary (blue, short dash) regimes. Solid line with circles shows the response in the linear model.

Figure 3. Impulse responses in expansions



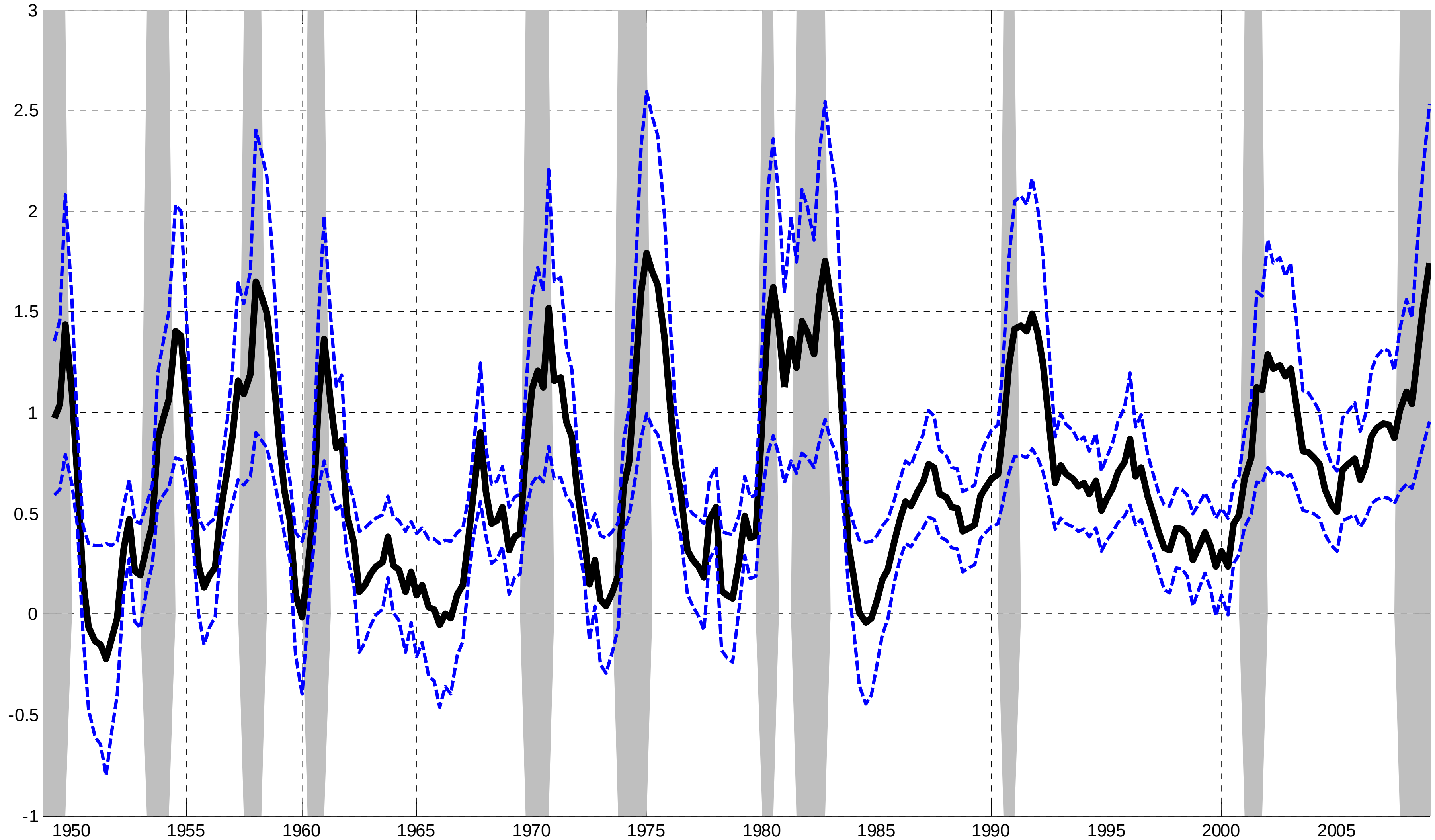
Notes: The figures show impulse responses to a $1 increase in government spending. Shaded region is the 90% confidence interval. Dashed lines show the responses in expansionary (red, long dash) and recessionary (blue, short dash) regimes. Solid line with circles shows the response in the linear model.

Figure 4. Impulse responses in recessions



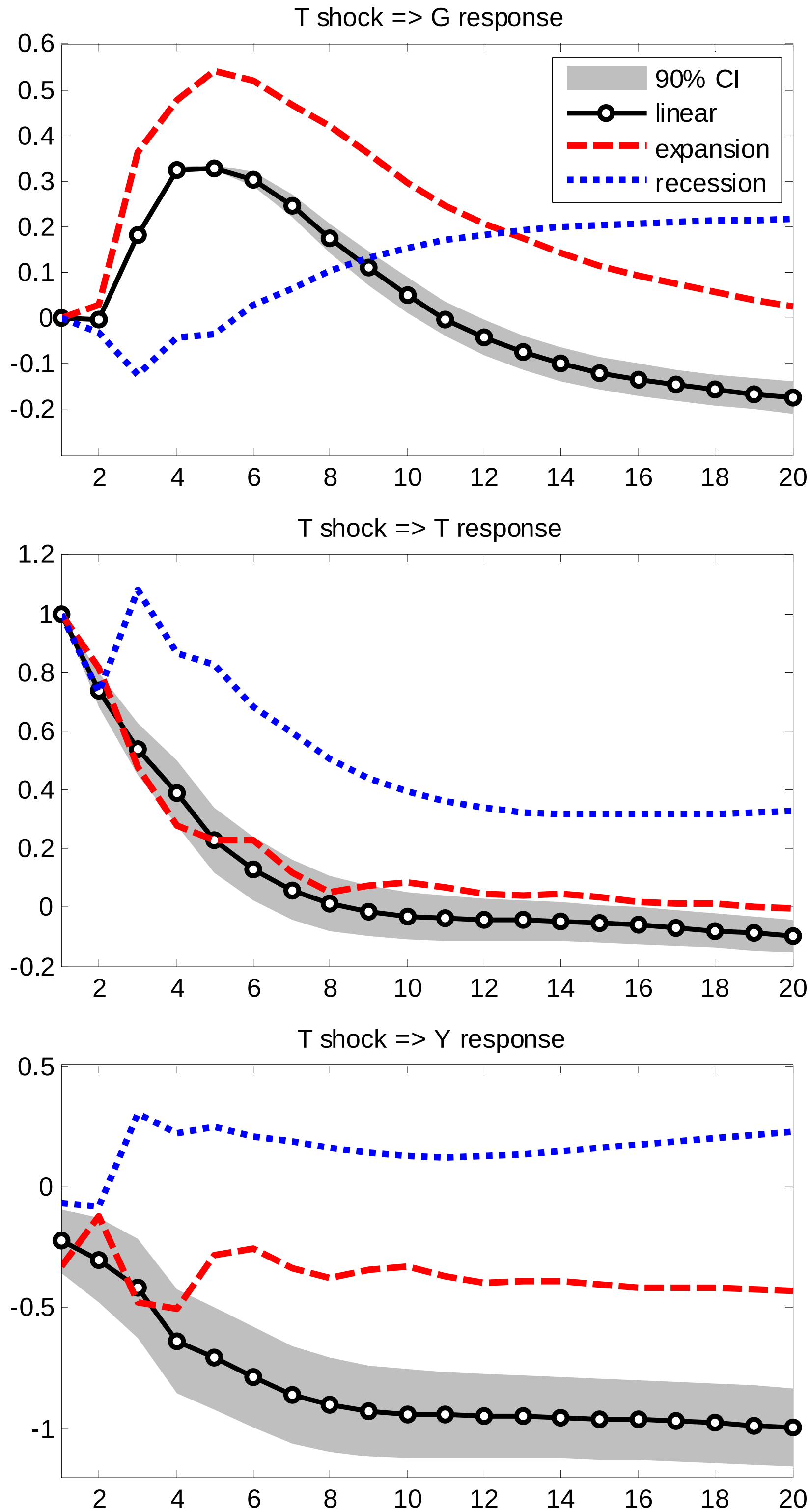
Notes: The figures show impulse responses to a $1 increase in government spending. Shaded region is the 90% confidence interval. Dashed lines show the responses in expansionary (red, long dash) and recessionary (blue, short dash) regimes. Solid line with circles shows the response in the linear model.

Figure 5. Historical multiplier for total government spending



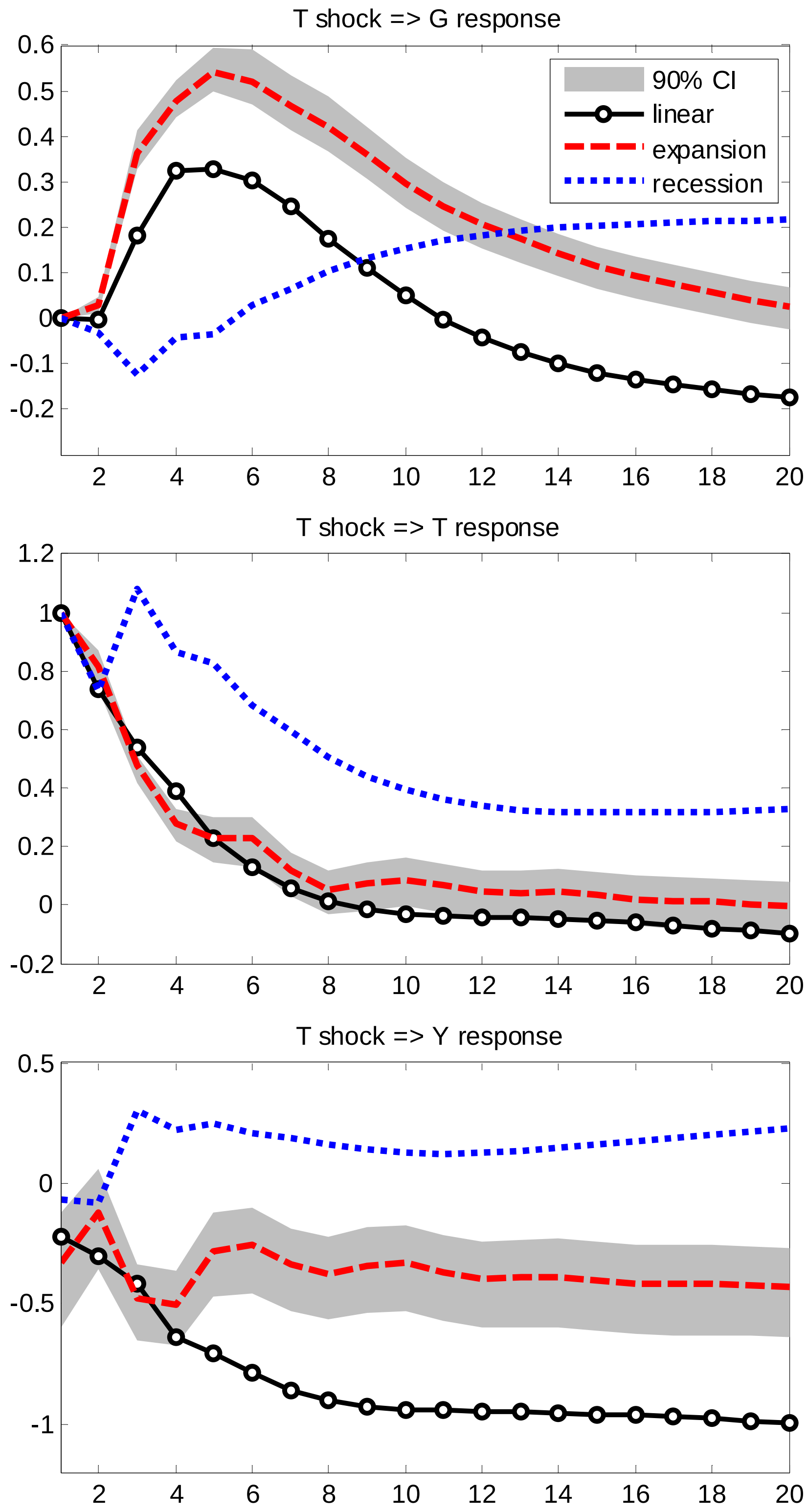
Notes: shaded regions are recessions defined by the NBER. The solid black line is the cumulative multiplier computed as $\sum_{h=1}^{20} Y_h / \sum_{h=1}^{20} G_h$, where time index h is in quarters. Blue dashed lines are 90% confidence interval. The multiplier incorporates the feedback from G shock to the business cycle indicator z. In each instance, the shock is one percent increase in government spending.

Figure 6. Impulse responses in the linear model: tax shocks



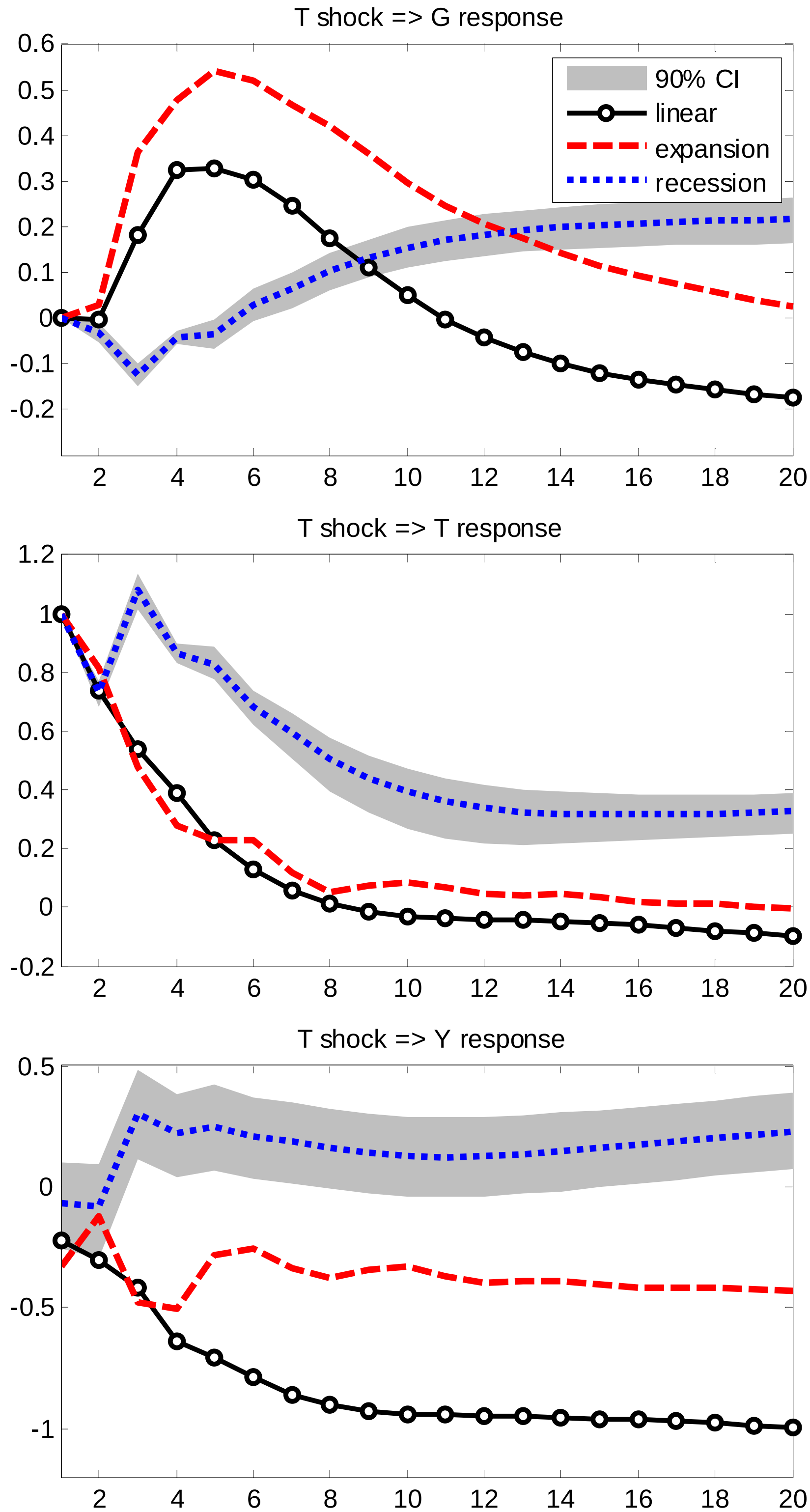
Notes: The figures show impulse responses to a $1 increase in taxes. Shaded region is the 90% confidence interval. Dashed lines show the responses in expansionary (red, long dash) and recessionary (blue, short dash) regimes. Solid line with circles shows the response in the linear model.

Figure 7. Impulse responses in expansions: tax shocks



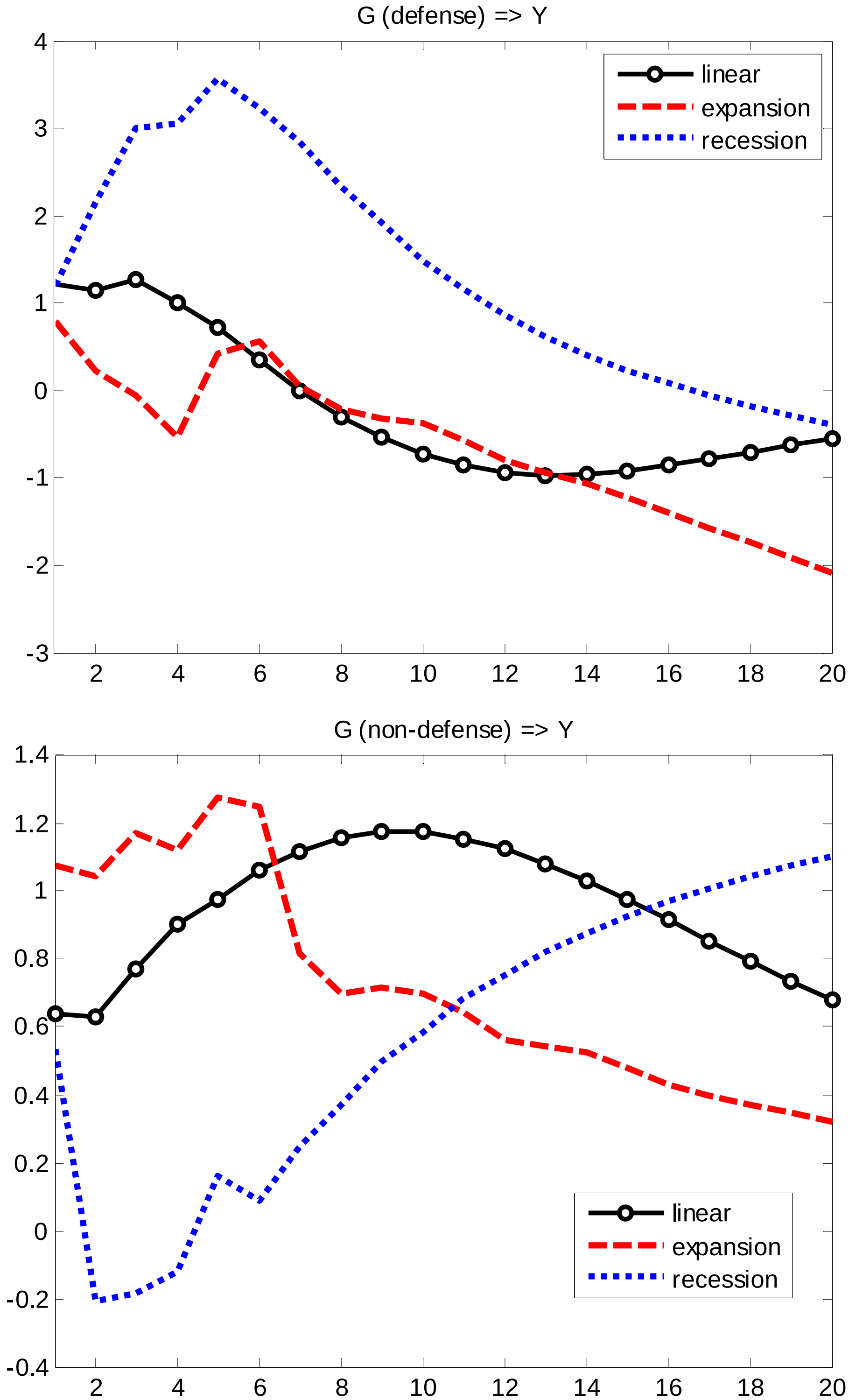
Notes: The figures show impulse responses to a $1 increase in taxes. Shaded region is the 90% confidence interval. Dashed lines show the responses in expansionary (red, long dash) and recessionary (blue, short dash) regimes. Solid line with circles shows the response in the linear model.

Figure 8. Impulse responses in recessions: tax shocks



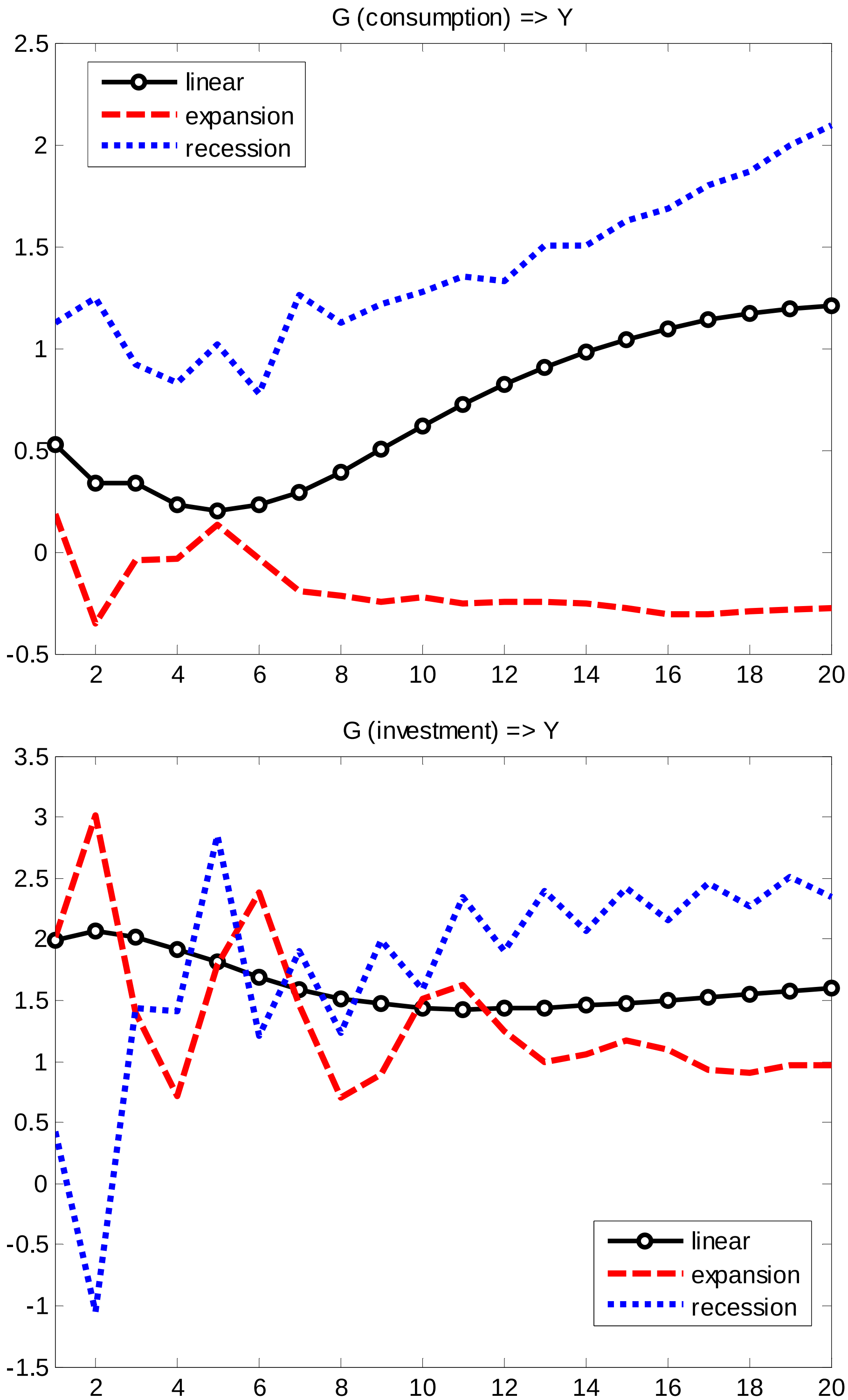
Notes: The figures show impulse responses to a $1 increase in taxes. Shaded region is the 90% confidence interval. Dashed lines show the responses in expansionary (red, long dash) and recessionary (blue, short dash) regimes. Solid line with circles shows the response in the linear model.

Figure 9. Defense and nondefense government spending



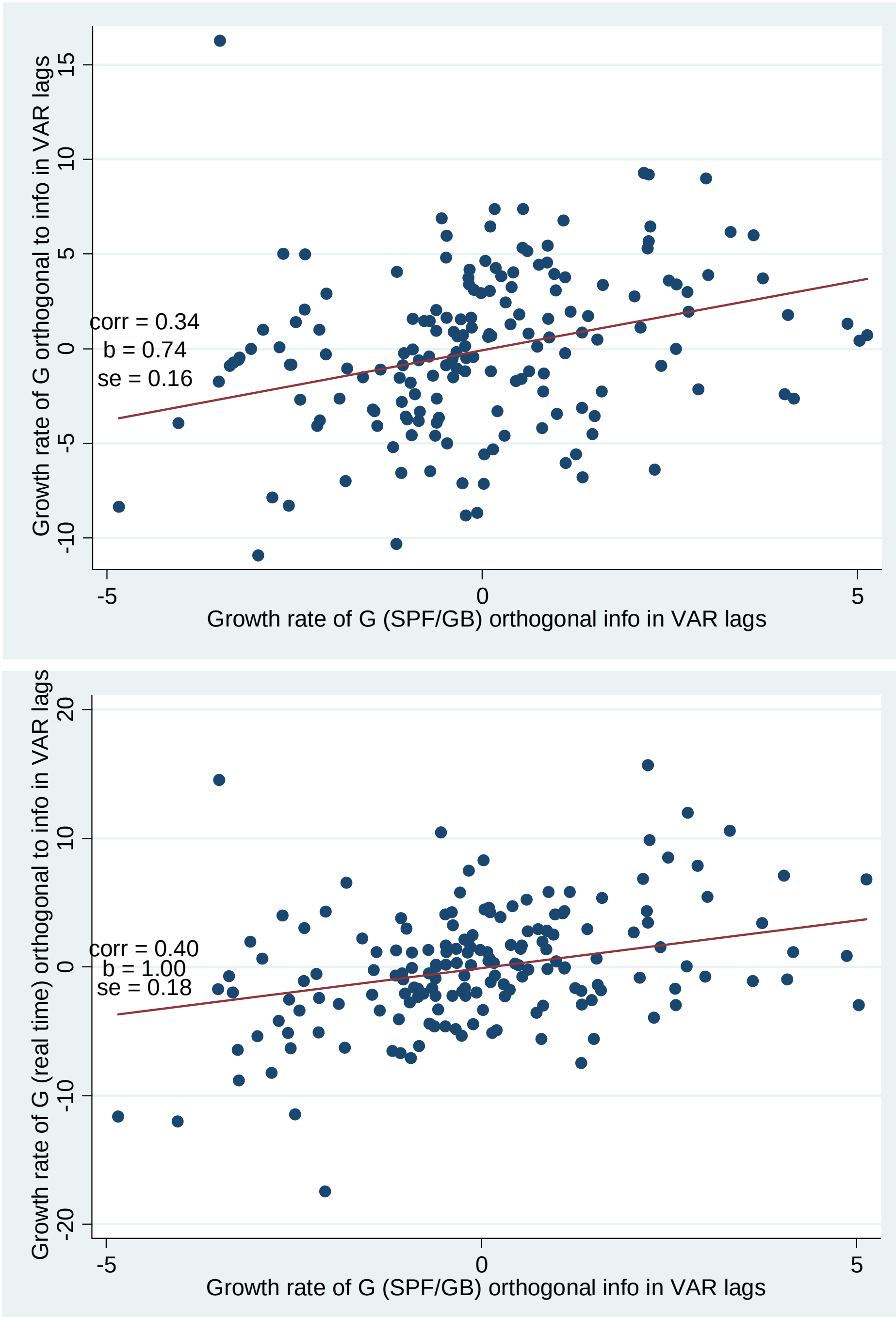
Notes: The figures show impulse responses to a $1 increase in government spending: defense spending in the top panel and non-defense spending in the bottom panel. Dashed lines show the responses in expansionary (red, long dash) and recessionary (blue, short dash) regimes. Solid line with circles shows the response in the linear model.

Figure 10. Consumption and investment government spending



Notes: The figures show impulse responses to a $1 increase in government spending: consumption spending in the top panel and investment spending in the bottom panel. Dashed lines show the responses in expansionary (red, long dash) and recessionary (blue, short dash) regimes. Solid line with circles shows the response in the linear model.

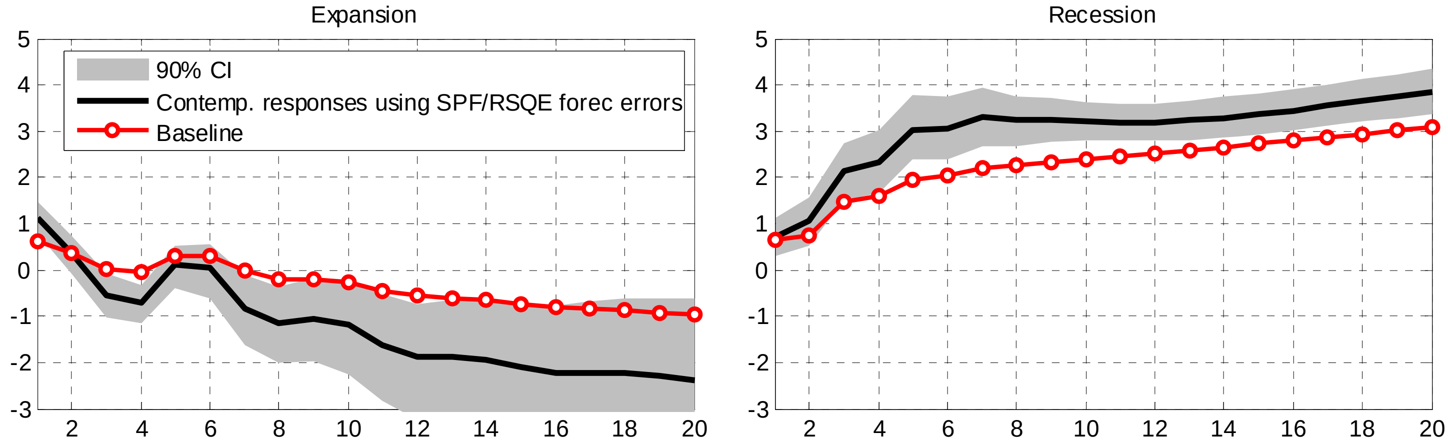
Figure 11. Forecastability of VAR shocks to government spending



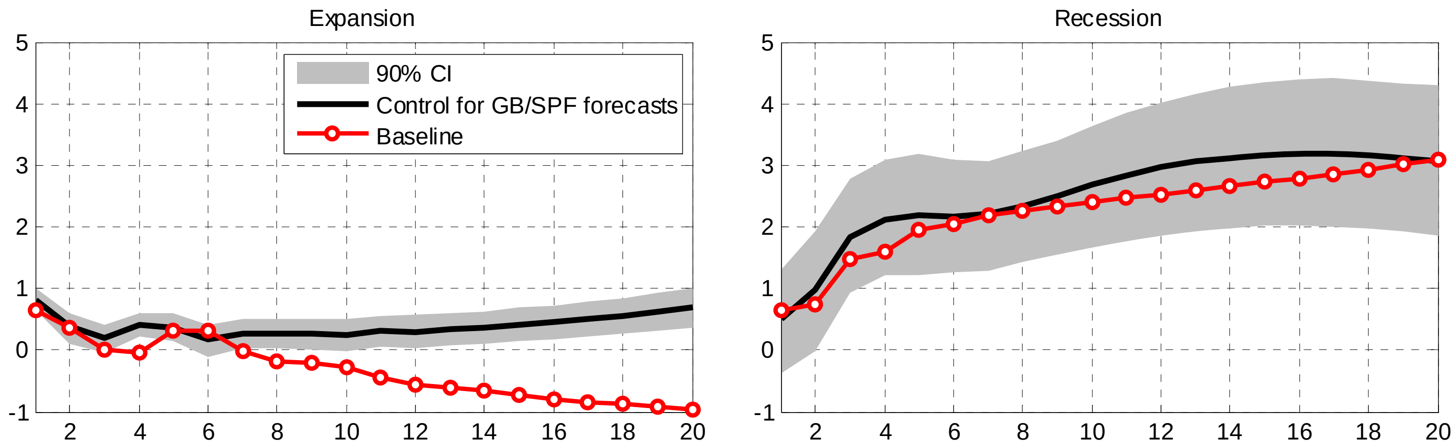
Notes: The figure plots residuals from projections of the growth rate of government spending predicted in SPF/Greenbook [horizontal axis] and actual growth rate of government spending (final vintage of data = top panel; real-time/first-release data = bottom panel) [vertical axis] on the information contained in the lags of the our baseline VAR. *corr* stands for the correlation between series. *b* and *se* show the estimated slope and associated standard error from regressing the residual for the actual growth rate of government spending on the residual for the predicted growth rate of government spending

Figure 12. Government spending multipliers for purified unanticipated shocks.

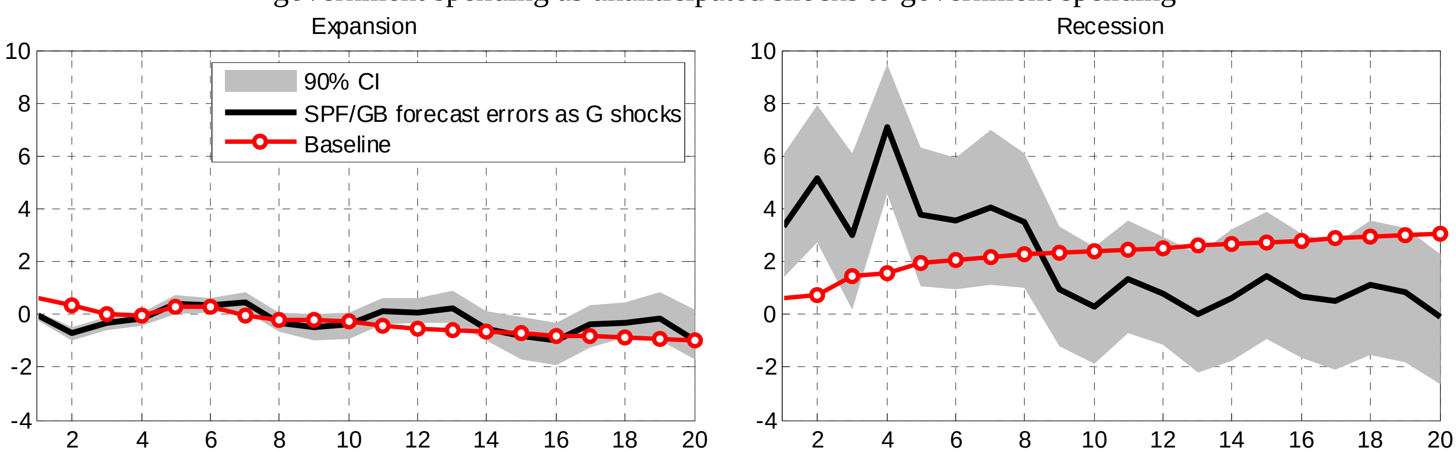
Panel A: Contemporaneous responses based on forecast errors from SPF/RSQE



Panel B: Purify innovations in government spending using SPF/Greenbook forecasts



Panel C: Interpret forecast errors (real time data) of SPF/Greenbook forecasts for the growth rate of government spending as unanticipated shocks to government spending



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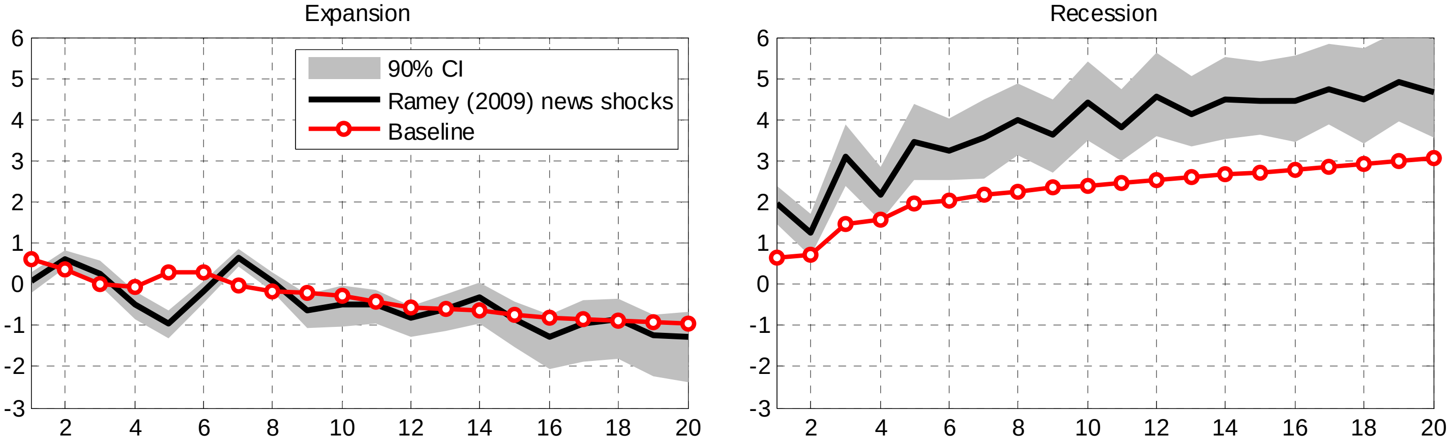
Panel D: Government spending innovations are Ramey (2009) news shocks to military spending.



Notes: Note: The figure plots impulse response of output to an unanticipated government spending shock which is normalized to have the sum of government spending over 20 quarters equal to one. The red lines with circles correspond to the responses in the baseline VAR specification. The shaded region is the 90% confidence interval.

Figure A1. Defense spending: linear model

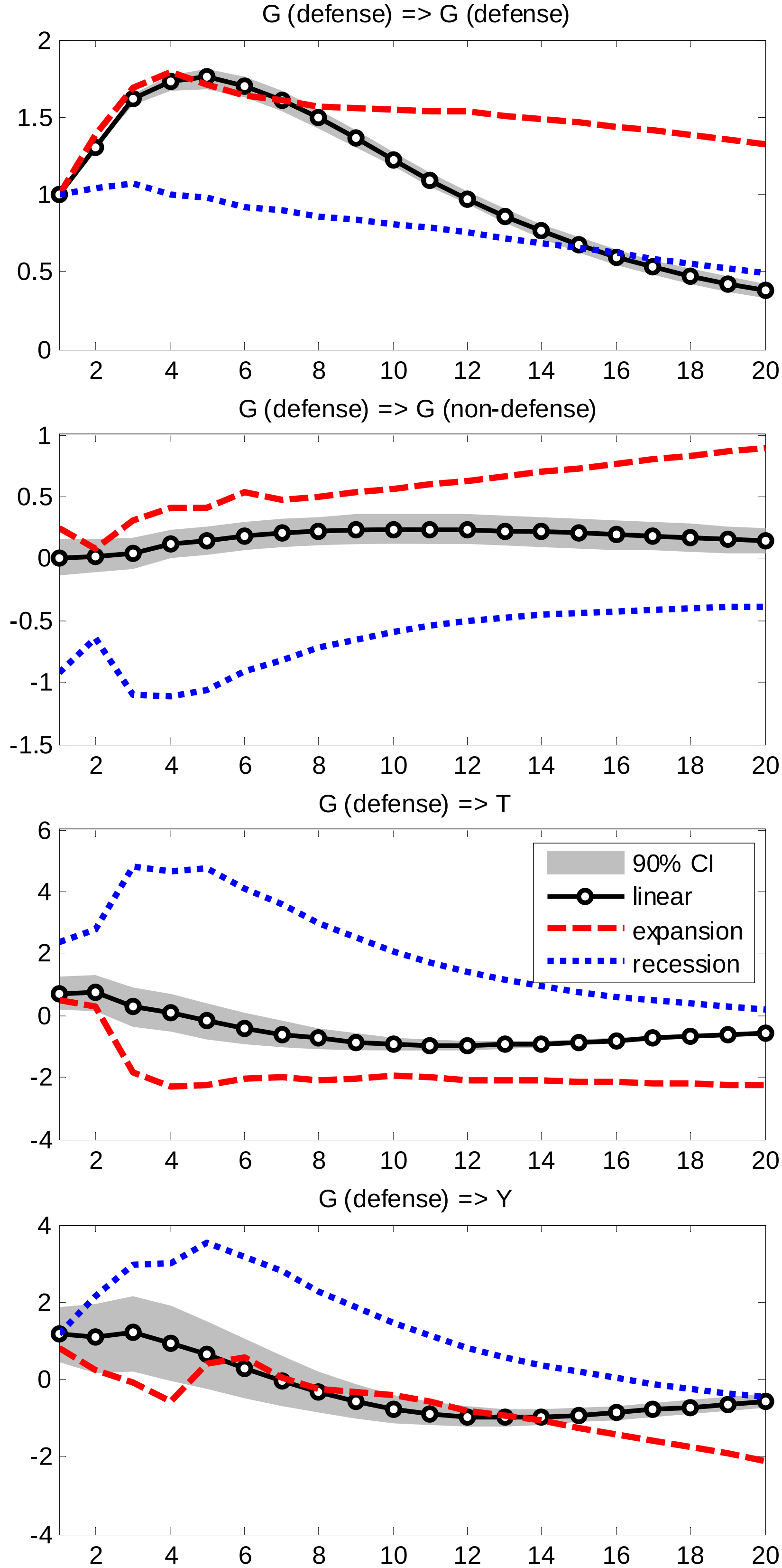


Figure A2. Non-defense spending: linear model

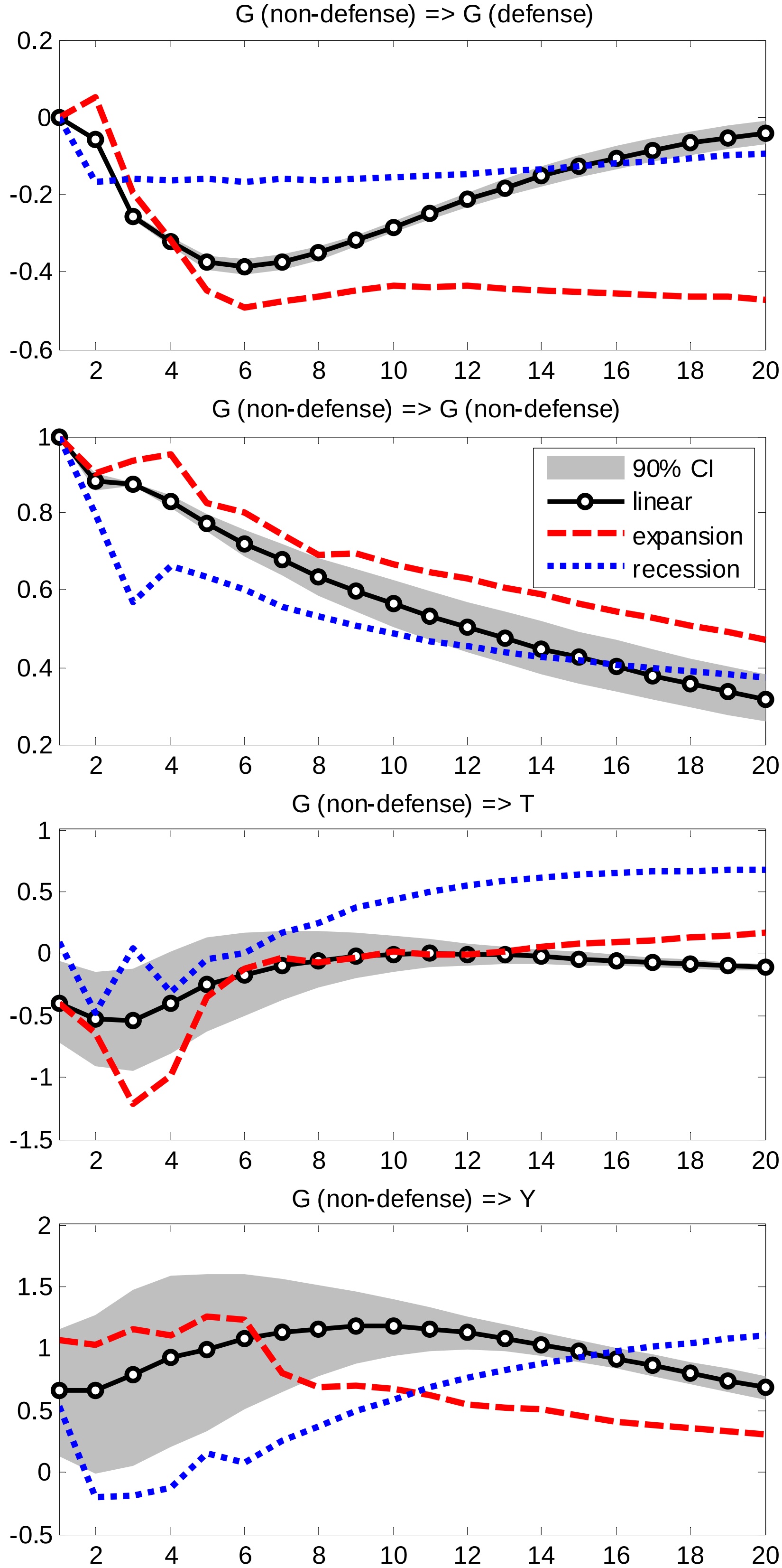


Figure A3. Defense spending: Recession

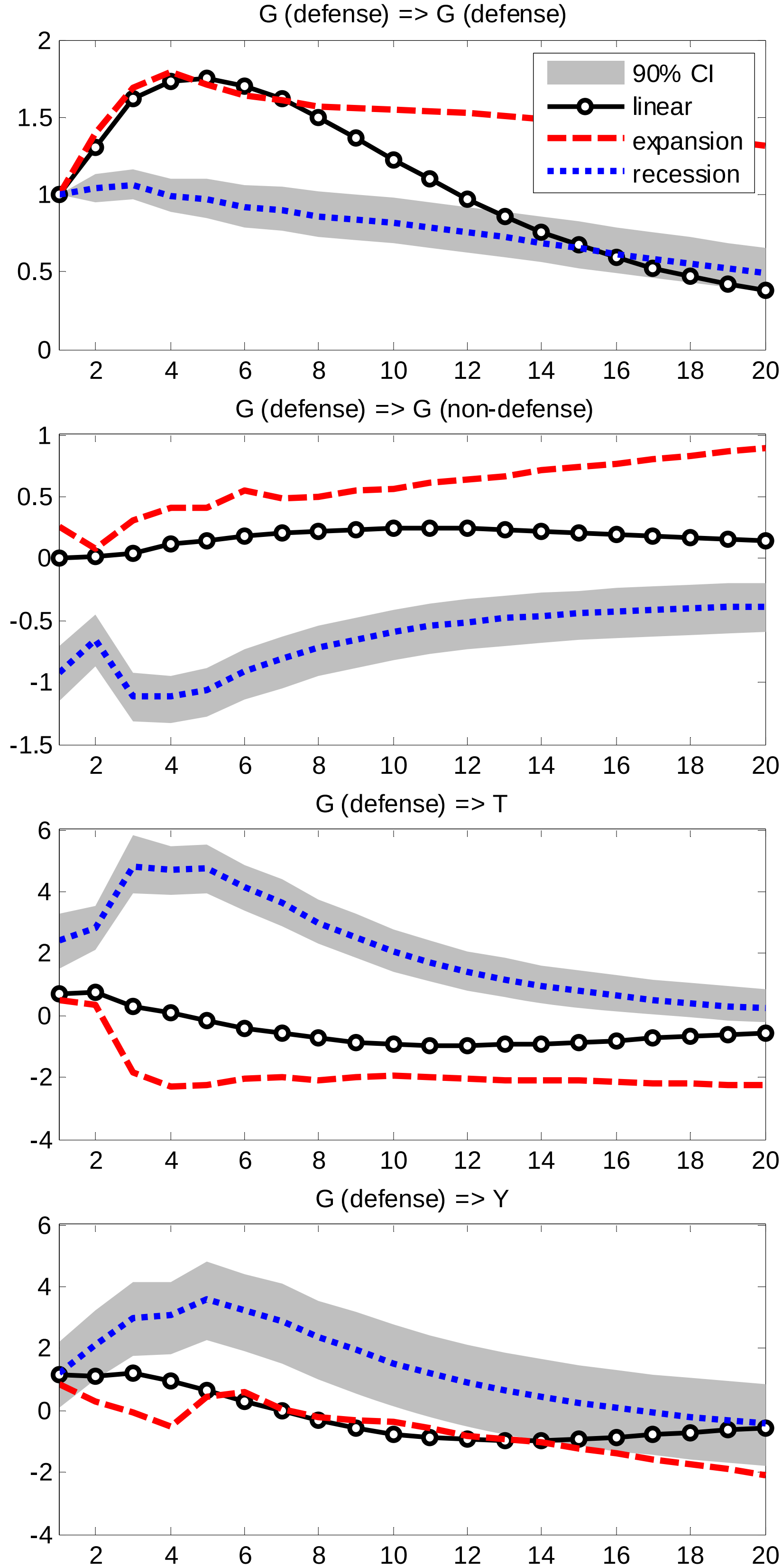


Figure A4. Non-defense spending: recessions

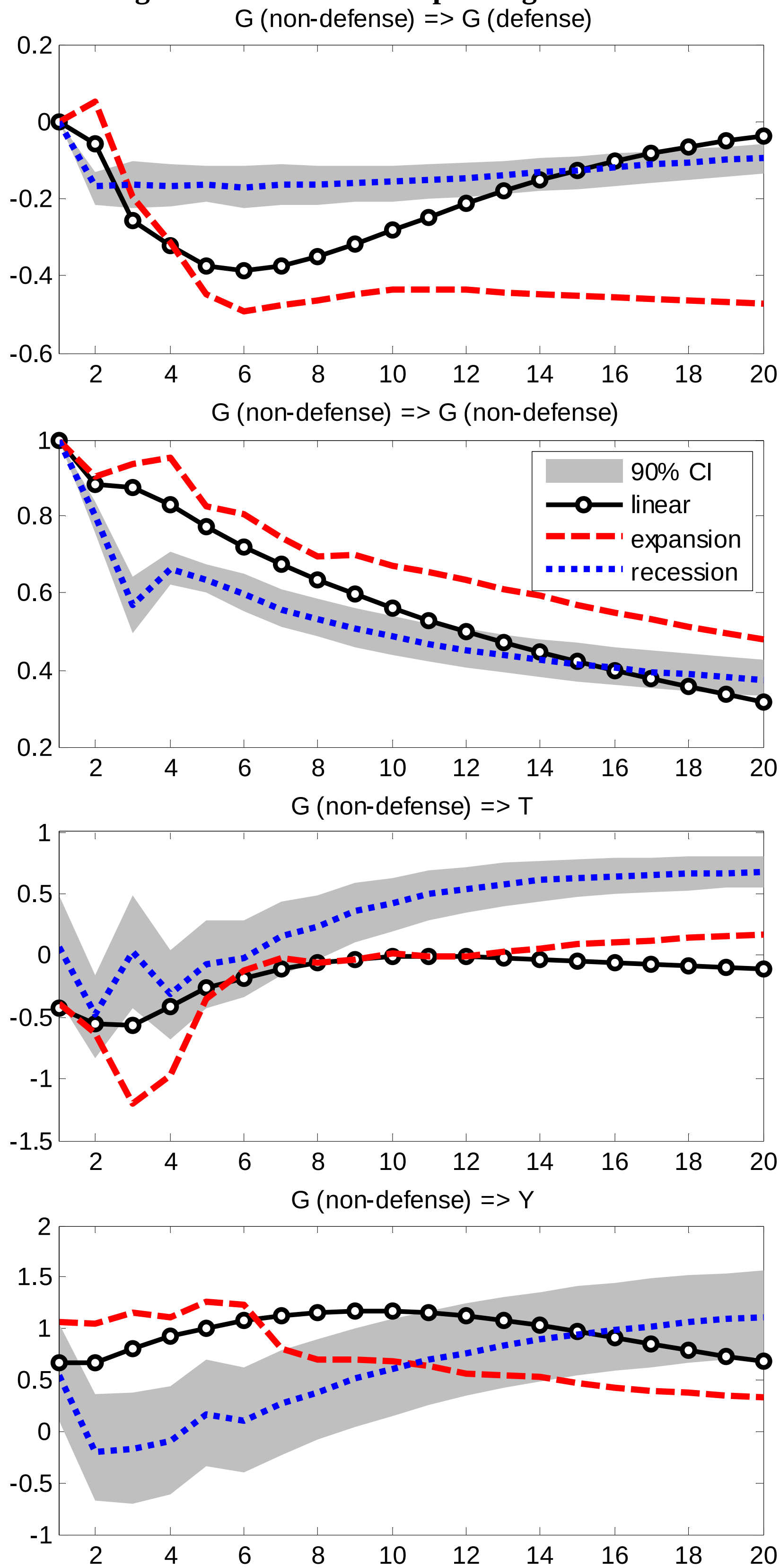


Figure A5. Defense spending: expansions

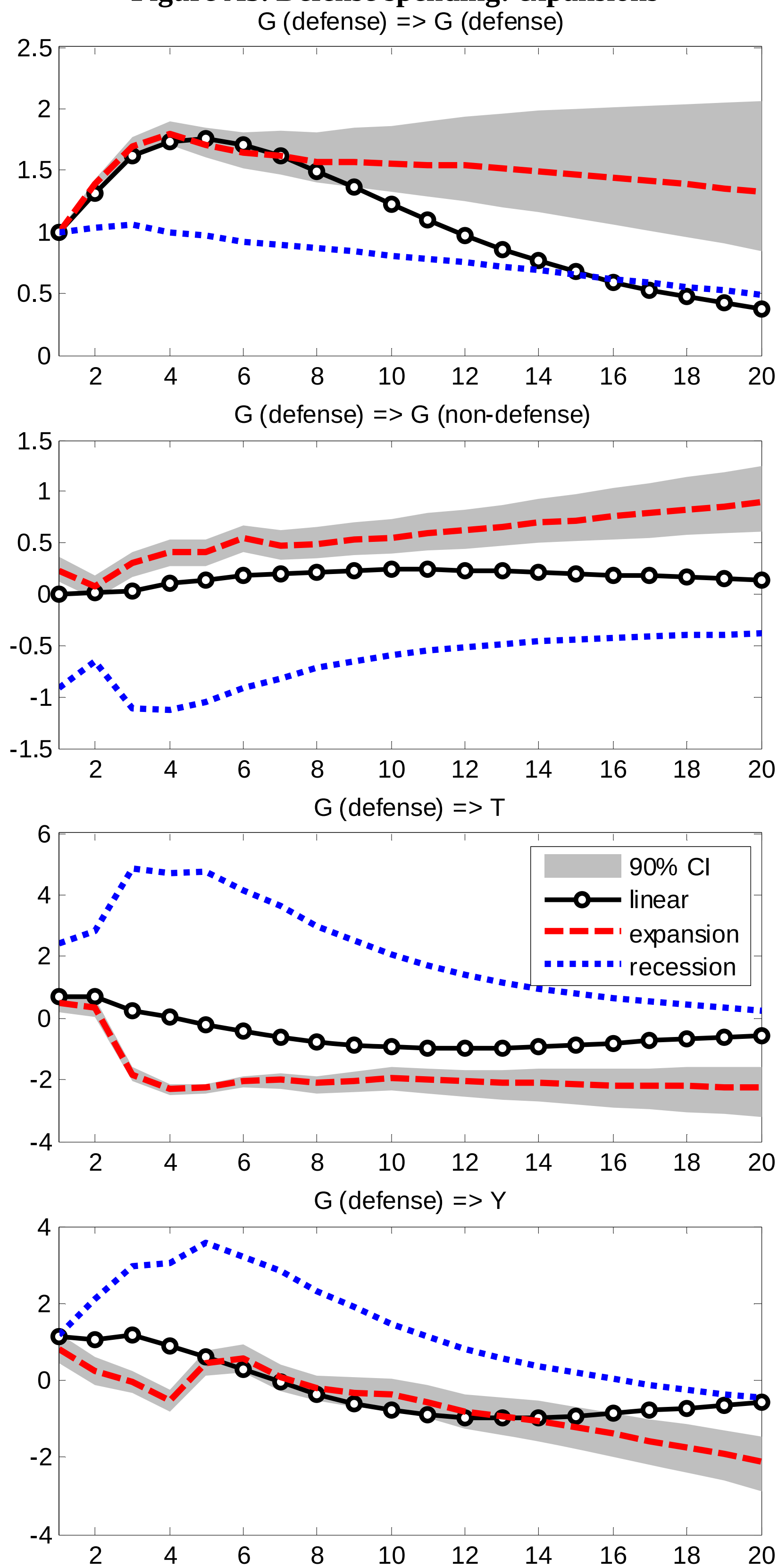


Figure A6. Non-defense spending: expansion

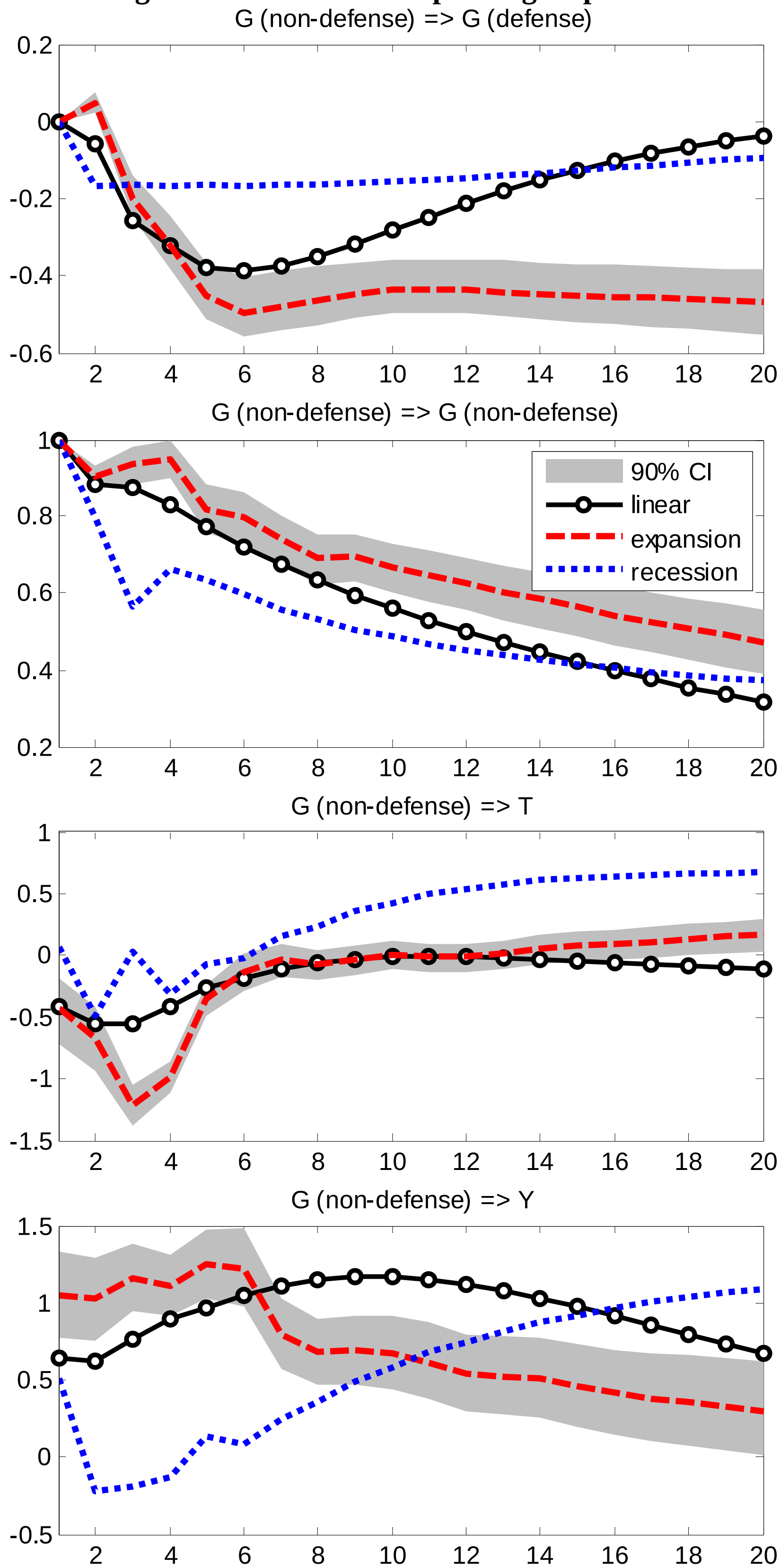


Figure A7. Consumption spending: linear model

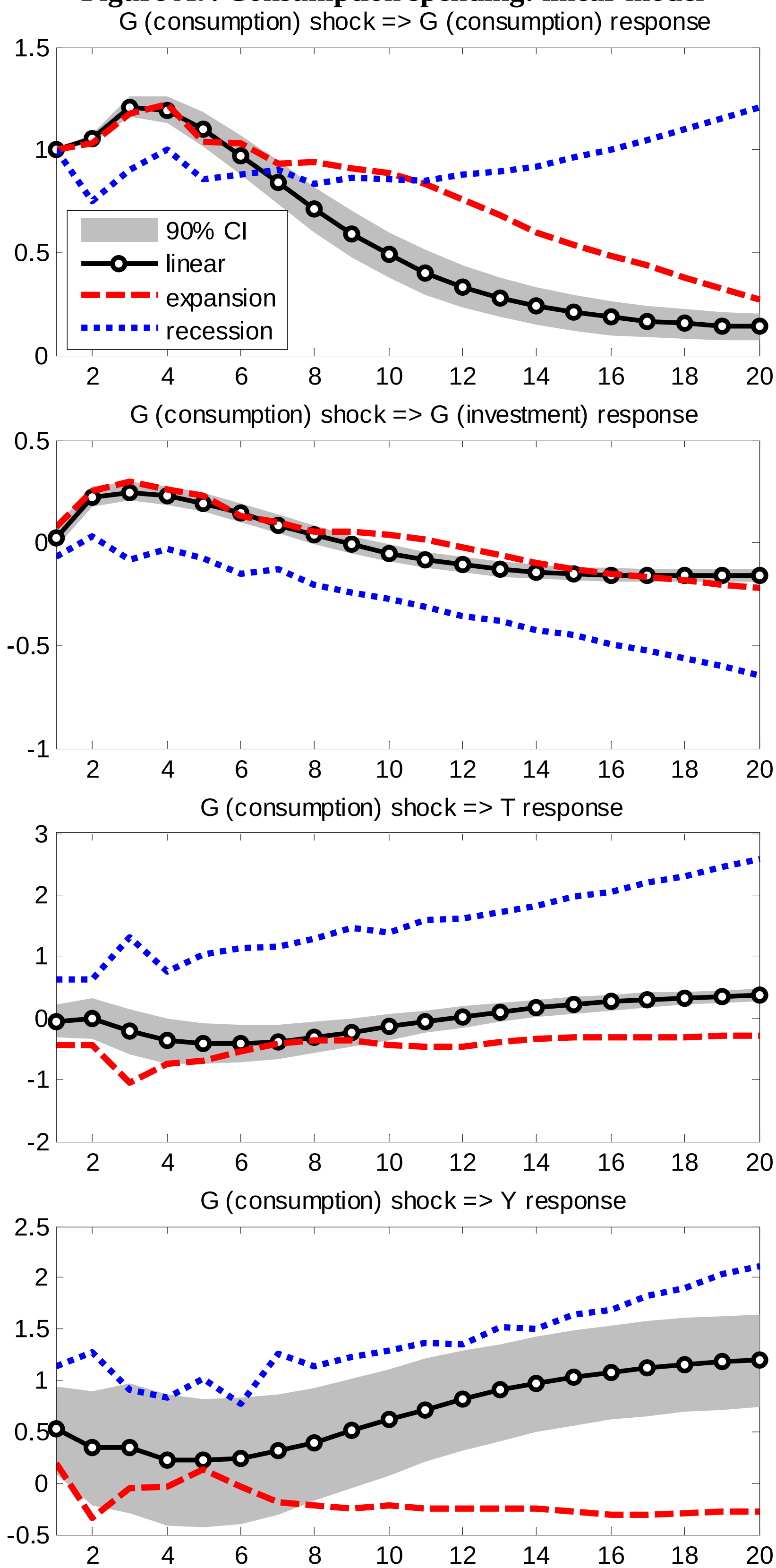


Figure A8. Investment spending: linear model

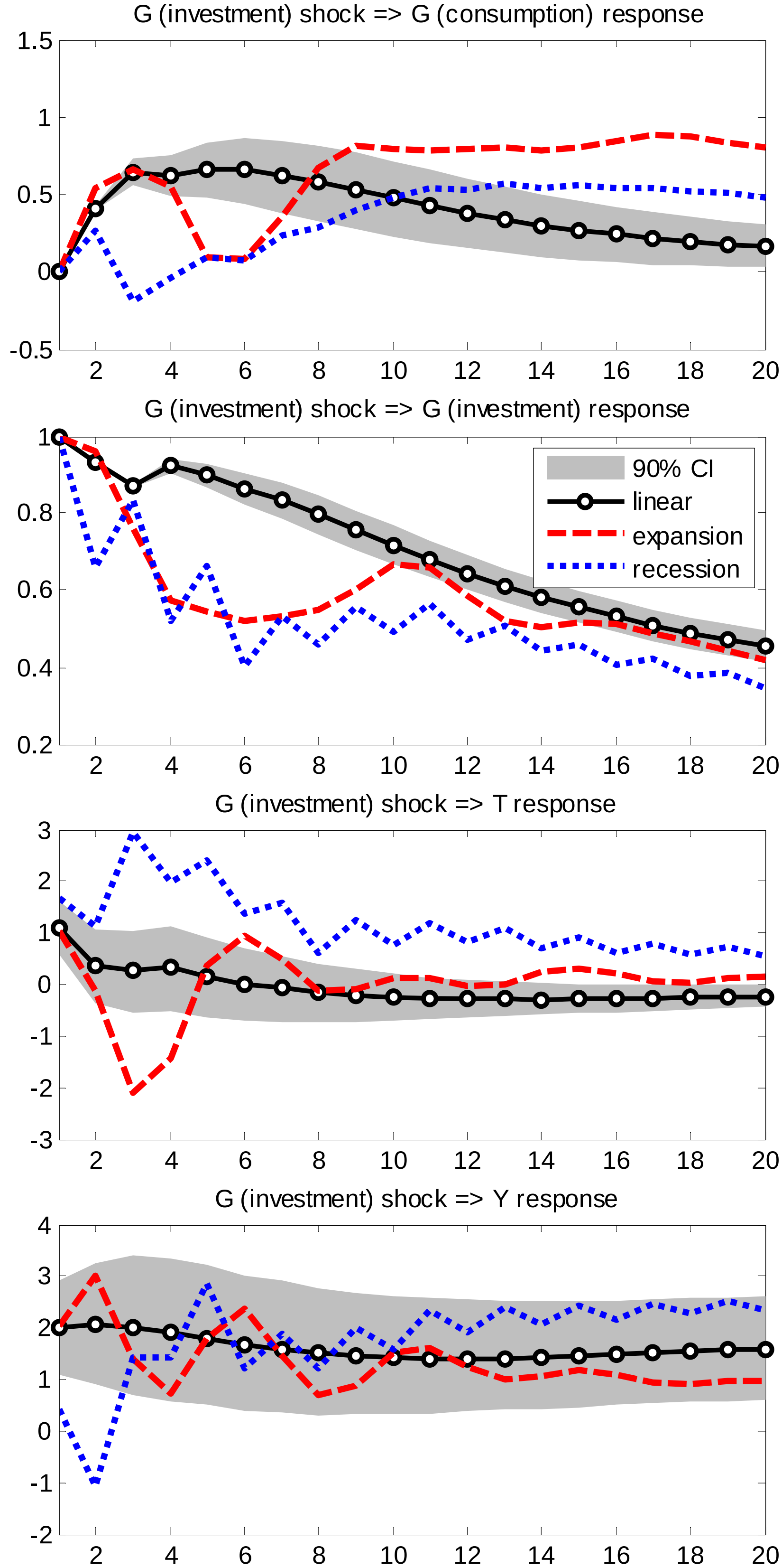


Figure A9. Consumption spending: recessions

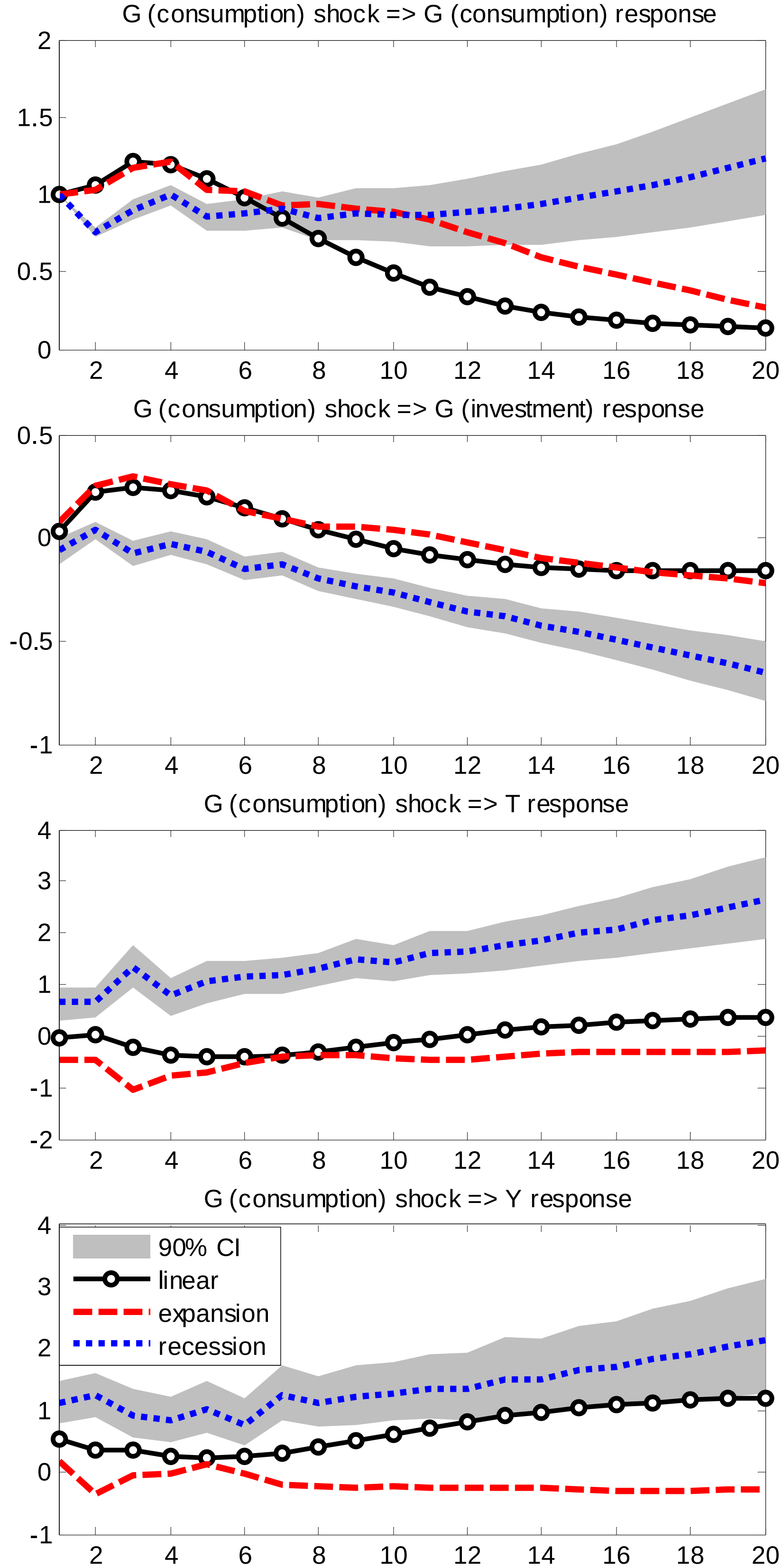


Figure A10. Investment spending: recessions

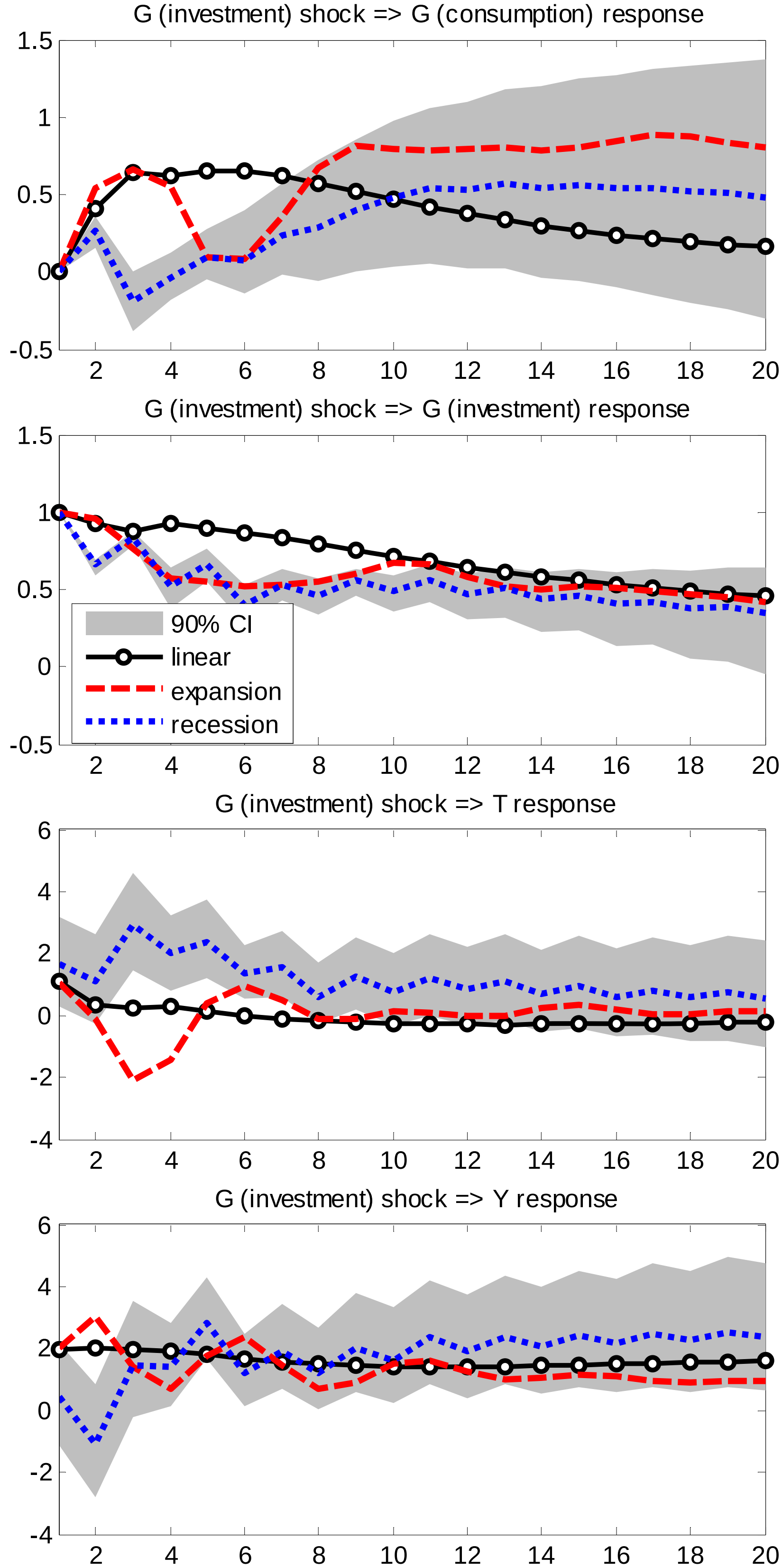


Figure A11. Consumption spending: expansions

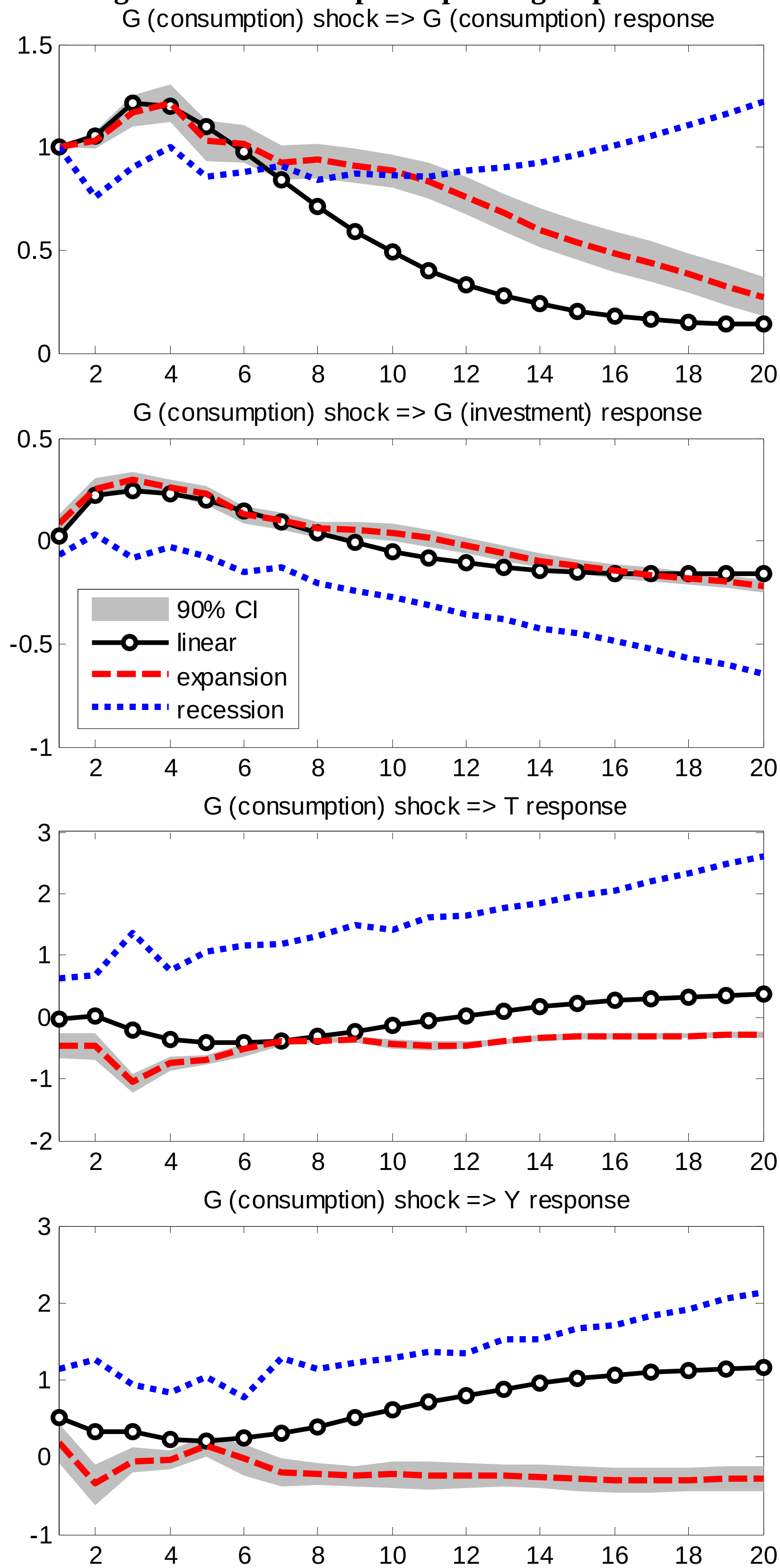


Figure A12. Investment spending: expansions