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by

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Abstract

Government spending shocks are frequently identified in quarterly time-series data by ruling out a contemporaneous response of government spending to other macroeconomic aggregates. We provide evidence that this assumption may not be too restrictive for U.S. annual time-series data.

Keywords: Government spending shocks, Annual Data, Identification
JEL-Code: E62

1 Introduction

Vector autoregressions (VAR) are by now frequently employed to study the fiscal transmission mechanism. In order to identify government spending shocks, a number of authors assume that there is no contemporaneous response of government spending to macroeconomic aggregates, i.e. that government spending is predetermined.[1] This requires that government spending does i) neither respond automatically to the economy, ii) nor that it is adjusted in a discretionary manner within the period. The first requirement is likely to be satisfied if government spending does not include transfers, but only government consumption and investment (a commonly used definition of government spending). Whether the second requirement is satisfied depends on the extent of decision lags in the policy process and thus on the data frequency.

Blanchard and Perotti (2002) and several subsequent studies impose the identification assumption on quarterly time-series data for the U.S., thereby ruling out a discretionary policy response to the state of the economy within the quarter. However, as non-interpolated fiscal data are often not available for other countries at quarterly frequency, several authors impose the identification assumption at an annual frequency (see Beetsma, Giuliodori and Klaassen 2006, Beetsma, Giuliodori and Klaasen 2008, Benetrix and Lane 2009). Judged a priori, the identification assumption is more compelling when imposed at quarterly frequency.

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[1] This approach goes back to Blanchard and Perotti (2002). Alternative identification schemes are based on military events or sign restrictions, see, e.g. Ramey (2008) and Mountford and Uhlig (forthcoming).

While there is only one budget legislated before the beginning of the fiscal year, supplements throughout the year are always a possibility (see Perotti 2005).
However, as fiscal data are available at quarterly frequency for the U.S., it is possible to actually test the assumption that U.S. government spending is predetermined within the year. In this paper, we suggest and perform such tests. We spell out and impose restrictions on a quarterly VAR model implied by the assumption that annual government spending is predetermined. We find that these restrictions are not rejected by the data. Also, the identified shocks and the resulting impulse response functions are very similar to those obtained from an unrestricted model.[2] Finally, we compare impulse responses and shocks obtained from the quarterly model with those from the annual model and find a high degree of conformity.

2 A structural VAR model

In this section, we devise a simple test of the assumption that annual government spending is predetermined. We proceed in three steps. First, we specify a data generating process operating at quarterly frequency where government spending is predetermined. Second, we aggregate the quarterly model and, third, we spell out restrictions on the quarterly model under which annual government spending is predetermined.

2.1 Data generating process

Consider a vector of endogenous variables, $y_t = \begin{bmatrix} g_t & x_t' \end{bmatrix}'$, where g_t denotes government spending and x_t denotes a $n \times 1$ vector of additional variables. The data are sampled at quarterly frequency through the structural VAR(4) model:

$$A^{(0)} y_t = A^{(1)} y_{t-1} + A^{(2)} y_{t-2} + A^{(3)} y_{t-3} + A^{(4)} y_{t-4} + \varepsilon_t, \tag{1}$$

where $\varepsilon_t = \begin{bmatrix} \varepsilon_t^g & \varepsilon_t^{x\prime} \end{bmatrix}'$ is a vector of mutually uncorrelated structural shocks.
We assume that government spending is predetermined, i.e. that the non-fiscal entries of the first row of $A^{(0)}$ are zero. Further assuming that $A^{(0)}$ is lower triangular allows recursive estimation of model (1) by OLS without loss of generality, as long as the interest is in identifying government spending shocks and no structural interpretation is given to ε_t^x (see Christiano, Eichenbaum and Evans 1999). For future reference, it is convenient to partition the $A^{(i)}, i = 0 \ldots 4$, while appropriately restricting the impact matrix $A^{(0)}$:

$$A^{(0)} = \begin{bmatrix} 1 & \underset{1\times n}{0} \\ \underset{n\times 1}{a_{xg}^{(0)}} & \underset{n\times n}{Q} \end{bmatrix}, -A^{(i)} = \begin{bmatrix} a_{gg}^{(i)} & \underset{1\times n}{a_{gx}^{(i)}} \\ \underset{n\times 1}{a_{xg}^{(i)}} & \underset{n\times n}{a_{xx}^{(i)}} \end{bmatrix}, \qquad i = 1 \ldots 4, \tag{2}$$

where Q is a lower-triangular matrix with 1's on its main diagonal.

[2]In a similar experiment, Beetsma et al. (2006) consider German data and transform estimates from a quarterly model into the corresponding coefficients of an annual model. They find evidence supporting the assumption that annual government spending is predetermined.

2.2 Aggregation

We are now interested in how data generated by the process (1) aggregates into data sampled at annual frequency. Following Lütkepohl (2006, p. 441), we obtain the system:

$$\underbrace{\begin{bmatrix} A^{(0)} & 0 & 0 & 0 \\ -A^{(1)} & A^{(0)} & 0 & 0 \\ -A^{(2)} & -A^{(1)} & A^{(0)} & 0 \\ -A^{(3)} & -A^{(2)} & -A^{(1)} & A^{(0)} \end{bmatrix}}_{\equiv B^{(0)}} \underbrace{\begin{bmatrix} y_{4(\tau-1)+1} \\ y_{4(\tau-1)+2} \\ y_{4(\tau-1)+3} \\ y_{4\tau} \end{bmatrix}}_{\equiv \eta_\tau} \tag{3}$$

$$= \underbrace{\begin{bmatrix} A^{(4)} & A^{(3)} & A^{(2)} & A^{(1)} \\ 0 & A^{(4)} & A^{(3)} & A^{(2)} \\ 0 & 0 & A^{(4)} & A^{(3)} \\ 0 & 0 & 0 & A^{(4)} \end{bmatrix}}_{\equiv B^{(1)}} \underbrace{\begin{bmatrix} y_{4(\tau-2)+1} \\ y_{4(\tau-2)+2} \\ y_{4(\tau-2)+3} \\ y_{4(\tau-1)} \end{bmatrix}}_{\equiv \eta_{\tau-1}} + \underbrace{\begin{bmatrix} \varepsilon_{4(\tau-1)+1} \\ \varepsilon_{4(\tau-1)+2} \\ \varepsilon_{4(\tau-1)+3} \\ \varepsilon_{4\tau} \end{bmatrix}}_{\equiv u_\tau}.$$

It is convenient to reshuffle the variables in η_τ. Let

$$\widetilde{\eta}_\tau = \begin{bmatrix} g_{4(\tau-1)+1} & g_{4(\tau-1)+2} & g_{4(\tau-1)+3} & g_{4\tau} & x'_{4(\tau-1)+1} & x'_{4(\tau-1)+2} & x'_{4(\tau-1)+3} & x'_{4\tau} \end{bmatrix}'$$

and use a 'tilde' to denote the appropriately reshuffled counterparts of the matrices $B^{(i)}, i = 0, 1$, and the shock vector u_τ. One may then write (3) as follows:

$$\widetilde{B}^{(0)}\widetilde{\eta}_\tau = \widetilde{B}^{(1)}\widetilde{\eta}_{\tau-1} + \widetilde{u}_\tau. \tag{4}$$

Aggregating a quarterly time series into an annual time series, denoted by an 'a'-superscript, corresponds to the following linear transformation

$$y^a_\tau = \begin{bmatrix} g^a_\tau \\ x^a_\tau \end{bmatrix} = F\widetilde{\eta}_\tau, \text{ where } F = \begin{bmatrix} \underset{1\times 4}{\iota} & \underset{1\times 4n}{0} \\ \underset{n\times 4}{0} & \underset{n\times 4n}{K} \end{bmatrix}.$$

Here, ι is a row vector of ones and K an appropriately defined matrix. Applying F to the reduced form system of (4) gives

$$y^a_\tau = FC\widetilde{B}^{(1)}\widetilde{\eta}_{\tau-1} + FC\widetilde{u}_\tau, \tag{5}$$

where $C^{-1} = \widetilde{B}^{(0)}$.

2.3 When is annual spending predetermined?

Relationship (5) maps quarterly data into annual observations. We spell out sufficient conditions on the underlying quarterly model such that annual government spending is predetermined, i.e. we require that the linear mapping FC in (5) excludes non-fiscal innovations to have an impact on g^a_t. We can then state the following proposition.

Proposition 1. *Annual government spending is predetermined with respect to x^a_t if the following linear restrictions are satisfied:*

$$\underset{1\times n}{a^{(1)}_{gx}}, \underset{1\times n}{a^{(2)}_{gx}}, \underset{1\times n}{a^{(3)}_{gx}} = 0, \tag{6}$$

where $a^{(i)}_{gx}$, $i = 1, 2, 3$, is defined in (2).

Proof. See appendix A. □

These restrictions only concern the first equation of our quarterly model (1), allowing us to test the joint null hypothesis

$$H_0: \qquad a_{gx}^{(1)} = a_{gx}^{(2)} = a_{gx}^{(3)} = 0 \tag{7}$$

in the single OLS regression

$$g_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-3} + \beta_4 y_{t-4} + \varepsilon_t^g, \tag{8}$$

where $\beta_i = \begin{bmatrix} a_{gg}^{(i)} & a_{gx}^{(i)} \end{bmatrix}, \quad i = 1, \ldots, 4.$

We use two approaches to test the null hypothesis. A likelihood ratio test is given by

$$LR = T(\ln \sigma_r^2 - \ln \sigma_u^2), \tag{9}$$

where σ_r^2 is the residual variance of regression (8) when the restrictions are imposed, σ_u^2 is the residual variance of the unrestricted regression, and T is the number of observations. For the likelihood ratio statistic, we assume joint normality of the disturbances. As an alternative approach, which is robust to variations in the underlying distribution, we consider the Wald statistic. Let $\beta = \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 \end{bmatrix}'$ and $\widehat{\beta}$ its corresponding sample estimator. The null hypothesis that a subvector β_0 of β is equal to zero can then be tested by the Wald statistic

$$W = \widehat{\beta}_0' V_0^{-1} \widehat{\beta}_0 \tag{10}$$

where V_0 denotes the submatrix of the estimated covariance matrix V corresponding to $\widehat{\beta}_0$. Both the likelihood ratio and the Wald statistic have a limiting $\chi^2(j)$-distribution where j is the number of zero restrictions imposed on β.

3 Evidence from U.S. time-series data

In this section, we proceed in three steps. First, we briefly discuss our data and empirical specification. Second, we use quarterly data to test whether annual government spending is predetermined. Third, we compare results obtained on the basis of annual and quarterly data.

3.1 Data and specification

In the following, we estimate a VAR model on U.S. time-series data covering the period 1954–2007. We use quarterly data to estimate equation (1), where the model also contains a constant and a linear time trend. In the baseline case, the vector of endogenous variables contains government spending, GDP, and private consumption.[3] Given the limited number of annual observations, this parsimonious specification allows a comparison with the results obtained from a VAR model estimated on annual data for the same sample period. To explore the robustness of our results, we also consider a 7-variable VAR model for quarterly data, augmenting the baseline VAR with net tax revenues, private investment, inflation, and the 3-month T-bill rate, thereby following Perotti's (2007) specification closely.[4]

[3]Data series are obtained from the National Income and Product Accounts (NIPA) provided by the U.S. Bureau of Economic Analysis, deflated with the GDP deflator, and divided by population. Government spending consists of consumption expenditure and gross investment; private consumption is personal consumption expenditure on non-durable goods and services.

[4]In the small VAR, identification is achieved by excluding a response of government spending within the quarter. In the large VAR, we follow Perotti (2005) and assume that the price elasticity of real government

3.2 Is annual spending predetermined?

In estimating the VAR model on quarterly data, we test restrictions (6). Results reported in table 1 show that we cannot reject the null hypothesis (7) and, hence, that annual government spending is predetermined.

Table 1: TEST STATISTICS

	LR-statistic	Wald-statistic
Baseline VAR	3.13 (0.79)	3.15 (0.79)
7-Variable VAR	18.75 (0.41)	19.59 (0.36)

Note: Under the null, the tests are both distributed as $\chi^2(18)$ in the large and $\chi^2(6)$ in the small VAR. Values are test statistics, p-values are given in parentheses.

Figure (1) presents the impulse response functions of the quarterly models to an increase in government spending by one percent of GDP. The upper row shows results for the baseline 3-variable VAR model, the lower row shows the results for government spending, output and consumption obtained from the 7-variable VAR model. Importantly, in all panels we show impulse responses of the restricted (dashed line) and the unrestricted model (solid line). There is, however, hardly any difference across these responses—suggesting, in line with the results reported in table 1, that the restrictions (6) are easily tolerated by the data. Finally, we note that results for the baseline VAR and the 7-Variable specification are fairly similar (see also Perotti 2007). In the following, we focus on the results from the baseline VAR.

3.3 Spending shocks in quarterly and annual time-series

We turn to estimating the baseline VAR model on annual data. We allow for two lags.[5] Given the results of the previous section, we impose the restriction that annual government spending is predetermined to identify government spending shocks.

Figure 2 reports the responses of government spending, output, and private consumption to an exogenous increase in government spending by one percent of GDP obtained from the VAR model estimated on annual data (solid line with squares). Qualitatively, results are similar to those obtained unter the quarterly model. For a systematic comparison, we annualize the responses of the unrestricted quarterly baseline model and plot them in the panels of figure 2 (dashed-dotted line with circles). Clearly, while some differences can be observed,

spending is -0.5. In this case, we use an inflation adjusted measure of government spending when estimating the equation for spending and also in the testing equation (8). In addition, we use instrumental variables when estimating the VAR recursively.

[5] The Schwarz Information Criterion proposes two lags while Akaike and a recursive LR test propose three lags. We use the more parsimonious specification as it is closer to the quarterly VAR(4) model.

the annualized responses obtained from the quarterly model are fairly close to those obtained from the annual model.[6]

Finally, we also compare the identified government spending shocks obtained from the annual model with the annualized shocks obtained from the unrestricted quarterly model. The shock series are plotted in figure 3, showing a high degree of correlation.

4 Conclusion

Several authors have turned to VAR models to investigate the fiscal transmission mechanism and identified government spending shocks by ruling out a contemporaneous response of government spending to the state of the economy. This assumption is fairly plausible at quarterly frequency, because decision lags make it difficult for policy makers to engineer discretionary fiscal measures within the quarter.

For lack of quarterly data, several studies on non-U.S. time-series data employ the assumption that annual government spending is predetermined as well. This assumption is more restrictive, given that supplements to the annual budget may be legislated throughout the year. However, as annual and quarterly fiscal data are available for the U.S., we may actually test whether annual government spending is predetermined.

We perform several tests and provide evidence that annual government spending is indeed predetermined. As a caveat, we note that our experiments are confined to the U.S. and that institutional differences across countries limit the extent to which our results can be generalized. Nevertheless, in case fiscal data are not available at quarterly frequency, our results may provide some support for the identification assumption that annual government spending is predetermined.

[6]The annualized responses of the quarterly model tend to peak earlier than the annual responses. This shift to the left disappears, once eight lags are included in the quarterly model.

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A Proof of Proposition 1

Proof. Given the process defined by (5), g_t^a is predetermined relative to x_t^a if FC is lower-triangular. Assuming for simplicity that $n = 1$, we have

$$FC = \begin{bmatrix} \sum_{j=1}^4 c_{j1} & \sum_{j=1}^4 c_{j2} & \sum_{j=1}^4 c_{j3} & \sum_{j=1}^4 c_{j4} & \sum_{j=1}^4 c_{j5} & \sum_{j=1}^4 c_{j6} & \sum_{j=1}^4 c_{j7} & \sum_{j=1}^4 c_{j8} \\ \sum_{j=5}^8 c_{j1} & \sum_{j=5}^8 c_{j2} & \sum_{j=5}^8 c_{j3} & \sum_{j=5}^8 c_{j4} & \sum_{j=5}^8 c_{j5} & \sum_{j=5}^8 c_{j6} & \sum_{j=5}^8 c_{j7} & \sum_{j=5}^8 c_{j8} \end{bmatrix}.$$

A sufficient condition for FC to be lower is that C is lower triangular:

$$FC = \begin{bmatrix} \sum_{j=1}^4 c_{j1} & \sum_{j=1}^4 c_{j2} & \sum_{j=1}^4 c_{j3} & \sum_{j=1}^4 c_{j4} & 0 & 0 & 0 & 0 \\ \sum_{j=5}^8 c_{j1} & \sum_{j=5}^8 c_{j2} & \sum_{j=5}^8 c_{j3} & \sum_{j=5}^8 c_{j4} & \sum_{j=5}^8 c_{j5} & \sum_{j=5}^8 c_{j6} & \sum_{j=5}^8 c_{j7} & \sum_{j=5}^8 c_{j8} \end{bmatrix}.$$

As $C^{-1} = \widetilde{B}^{(0)}$, C is lower triangular if $\widetilde{B}^{(0)}$ is lower triangular. Given the definition of $\widetilde{B}^{(0)}$,

$$\widetilde{B}^{(0)} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \underset{1\times1}{a_{gg}^{(1)}} & 1 & 0 & 0 & \underset{1\times n}{a_{gx}^{(1)}} & 0 & 0 & 0 \\ \underset{1\times1}{a_{gg}^{(2)}} & \underset{1\times1}{a_{gg}^{(1)}} & 1 & 0 & \underset{1\times n}{a_{gx}^{(2)}} & \underset{1\times n}{a_{gx}^{(1)}} & 0 & 0 \\ \underset{1\times1}{a_{gg}^{(3)}} & \underset{1\times1}{a_{gg}^{(2)}} & \underset{1\times1}{a_{gg}^{(1)}} & 1 & \underset{1\times n}{a_{gx}^{(3)}} & \underset{1\times n}{a_{gx}^{(2)}} & \underset{1\times n}{a_{gx}^{(1)}} & 0 \\ \underset{n\times1}{a_{xg}^{(0)}} & 0 & 0 & 0 & \underset{n\times n}{Q} & 0 & 0 & 0 \\ \underset{n\times1}{a_{xg}^{(1)}} & \underset{n\times1}{a_{xg}^{(0)}} & 0 & 0 & \underset{n\times n}{a_{xx}^{(1)}} & \underset{n\times n}{Q} & 0 & 0 \\ \underset{n\times1}{a_{xg}^{(2)}} & \underset{n\times1}{a_{xg}^{(1)}} & \underset{n\times1}{a_{xg}^{(0)}} & 0 & \underset{n\times n}{a_{xx}^{(2)}} & \underset{n\times n}{a_{xx}^{(1)}} & \underset{n\times n}{Q} & 0 \\ \underset{n\times1}{a_{xg}^{(3)}} & \underset{n\times1}{a_{xg}^{(2)}} & \underset{n\times1}{a_{xg}^{(1)}} & \underset{n\times1}{a_{xg}^{(0)}} & \underset{n\times n}{a_{xx}^{(3)}} & \underset{n\times n}{a_{xx}^{(2)}} & \underset{n\times n}{a_{xx}^{(1)}} & \underset{n\times n}{Q} \end{bmatrix},$$

the latter is true if $a_{gx}^{(1)}$, $a_{gx}^{(2)}$, $a_{gx}^{(3)} = 0$.

□

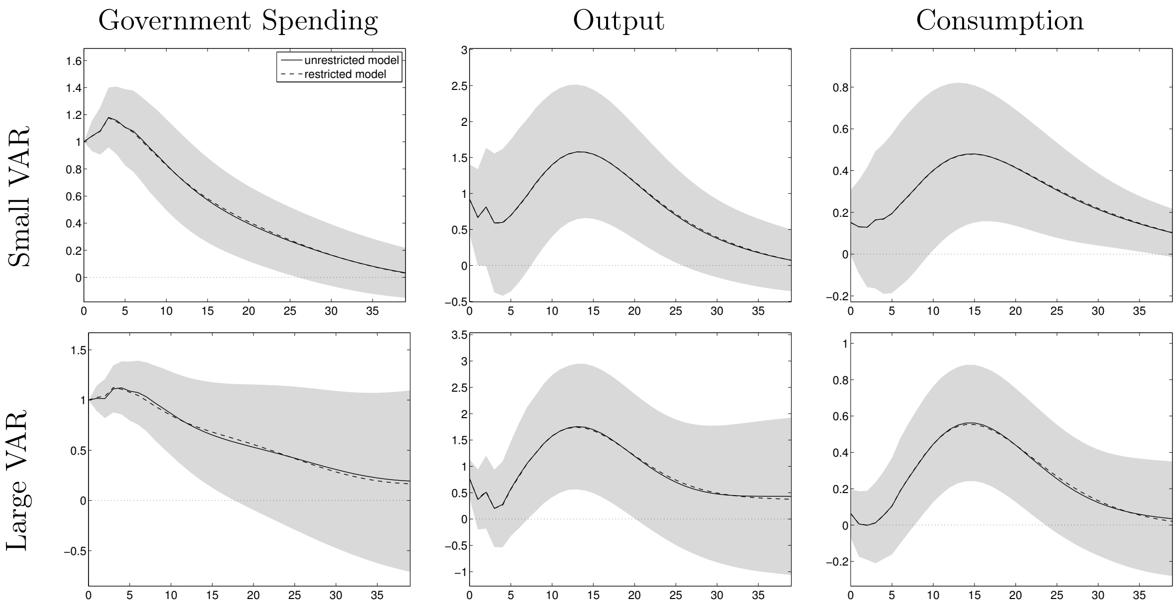

Figure 1: Effect of government spending shock (quarterly data). *Notes*: Impulse responses to exogenous increase in real government spending by one percent of GDP. Solid line: unrestricted baseline model; shaded areas: bootstrapped 90 percent confidence intervals; dashed line: restricted baseline model. Vertical axes indicate deviations from unshocked path in percent of GDP. Horizontal axes indicate quarters.

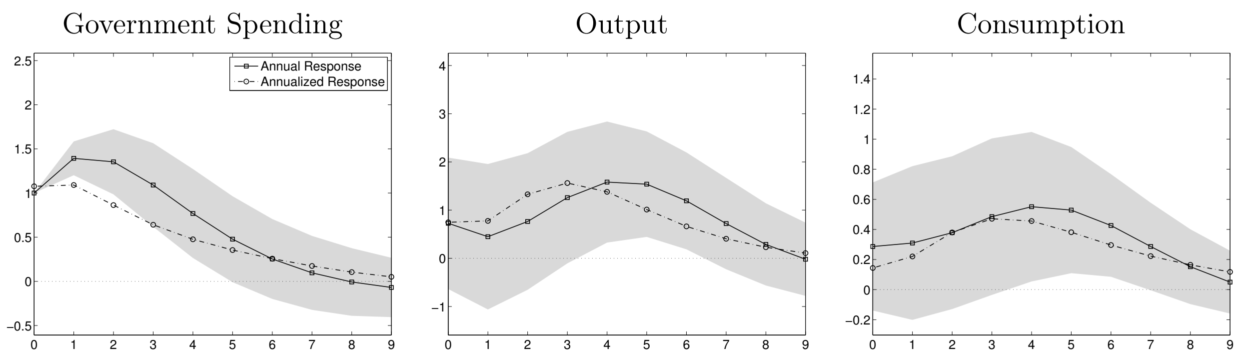

Figure 2: Effect of government spending shock (annual vs. annualized responses). *Notes:* Impulse responses to exogenous increase in real government spending by one percent of GDP. Solid line with squares: annual baseline model; shaded areas: bootstrapped 90 percent confidence intervals; dashed-dotted line with circles: annualized impulse responses from unrestricted quarterly baseline model. Vertical axes indicate deviations from unshocked path in percent of GDP. Horizontal axes indicate years.

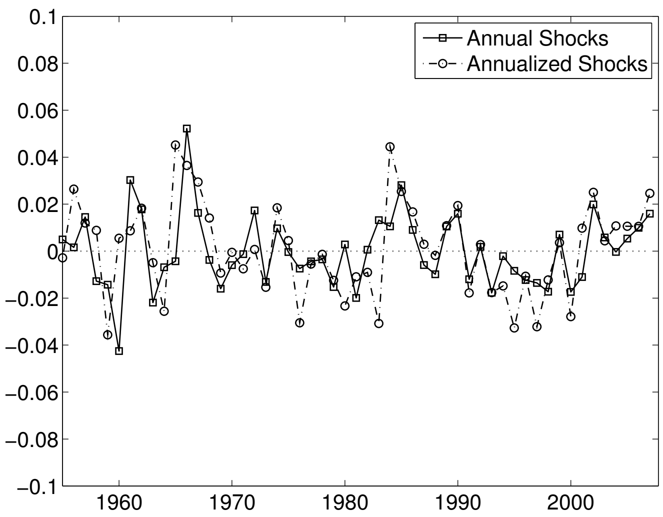

Figure 3: Annual vs. annualized shocks. *Notes:* Solid line with squares: annual shocks in baseline VAR; dashed-dotted line with circles: annualized shocks in baseline VAR.