Macroeconomic Shocks and Their Propagation

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1. Introduction

At the beginning of the 20th Century, economists seeking to explain business cycle fluctuations recognized the importance of both impulses and propagations as components of the explanations. A key question was how to explain regular fluctuations in a model with dampened oscillations. In 1927, the Russian statistician Eugen Slutsky published a paper titled “The Summation of Random Causes as a Source of Cyclic Processes.” In this paper, Slutsky demonstrated the (then) surprising result that moving sums of random variables could produce time series that looked very much like the movements of economic time series – “sequences of rising and falling movements, like waves...with marks of certain approximate uniformities and regularities.”¹ This insight, developed independently by British mathematician Yule in 1926 and extended by Frisch (1933) in his paper “Propagation Problems and Impulse Problems in Dynamic Economics,” revolutionized the study of business cycles. Their insights shifted the focus of research from developing mechanisms to support a metronomic view of business cycles, in which each boom created conditions leading to the next bust, to a search for the sources of the random shocks. Since then economists have offered numerous candidates for these “random causes,” such as crop failures, wars, technological innovation, animal spirits, government actions, and commodity shocks.

Research from the 1940s through the 1970s emphasized fiscal and monetary policy shocks, identified from large-scale econometric models or single equation analyses. The 1980s witnessed two important innovations that fundamentally changed the direction of the research. First, Sims’ (1980) paper “Macroeconomics and Reality” revolutionized the identification of shocks and the analysis of their effects by introducing vector autoregressions (VARs). Sims’

¹ Page 105 of the 1937 English version of the article published in *Econometrica.*
VARs made the link between exogenous shocks and forecast errors, and used Cholesky decompositions to identify the economic shocks from the reduced form residuals. Using his method, it became easier to talk about identification assumptions, impulse response functions, and to do innovation accounting using forecast error decompositions. The second important innovation was the expansion of the inquiry beyond policy shocks to consider important non-policy shocks, such as technology shocks (Kydland and Prescott (1982) and oil shocks (Hamilton (1983).

These innovations led to a flurry of research on shocks and their effects. In his 1994 paper “Shocks,” John Cochrane took stock of the state of knowledge at that time by using the by-then standard VAR techniques to conduct a fairly comprehensive search for the shocks that drove economic fluctuations. Surprisingly, he found that none of the popular candidates could account for the bulk of economic fluctuations. He proffered the rather pessimistic possibility that “we will forever remain ignorant of the fundamental causes of economic fluctuations.” (Cochrane (1994), abstract)

Are we destined to remain forever ignorant of the fundamental causes of economic fluctuations? Are Slutsky’s “random causes” unknowable? In this chapter, I will summarize the new methodological innovations and what their application has revealed about the propagation of the leading candidates for macroeconomic shocks and their importance in explaining economic fluctuations since Cochrane’s speculation.
2. Methods for Identifying Shocks and Estimating Impulse Responses

2.1. Overview

Before discussing details of methodology, it is useful to consider more carefully what exactly a “shock” is and why macroeconomists focus on them. Perhaps the best way to answer this question is to compare how many microeconomists approach empirical research to how macroeconomists approach empirical research. One rarely hears an applied microeconomist, particularly the majority who estimate reduced forms, talk about shocks. For example, Angrist and Pischke’s (2010) article “The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics” only mentions the word “shocks” when describing a few papers in macro that use narrative methods. They only talk about these papers as being examples of “some rays of sunlight pok(ing) through the grey clouds of dynamic stochastic general equilibrium.” (p. 18). Alas, Angrist and Pischke seemed to miss the distinction between the empirical investigations of many applied microeconomist and those of macroeconomists. Many investigations in applied microeconomics focus on measuring a causal, though rarely structural, effect of variable $X$ on variable $Y$ in a static setting, ignoring general equilibrium, and rarely incorporating expectations. Often, these investigations apply insights from standard theories and do not attempt to estimate deep structural parameters of preferences or technology that might be used to test the theories.

In stark contrast, macroeconomists ask questions for which dynamics are all-important, general equilibrium effects are crucial, and expectations have powerful effects. Moreover, in contrast to microeconomics, the two-way flow between theory and empirics in macroeconomics is very active. Prescott (1986) argued that business cycle theory in the mid-1980s was “ahead of business cycle measurement” and that theory should be used to obtain better measures of key
economic series. Prescott did not use “ahead” to mean “superior,” but rather meant that theory had made more progress on these questions as of that time. Because of this constant interplay between theory and empirics in macroeconomics, most top macroeconomists have pushed both the theoretical and empirical frontiers in macroeconomics. Most empirical macroeconomists are closely guided by theory, either directly or indirectly, and most theoretical macroeconomists are disciplined by the empirical estimates.

Thus, what are the shocks that we seek to estimate empirically? They are the exact empirical counterpart to the shocks we discuss in our theories: shocks to technology, monetary policy, fiscal policy, etc. The empirical counterpart of the shocks in our theories must satisfy three conditions in order for us to be able to make proper inference about their effects: (1) They must be exogenous with respect to the other current and lagged endogenous variables in the model; (2) They must be uncorrelated with other exogenous shocks; otherwise, we cannot identify the unique causal effects of one exogenous shock relative to another; and (3) They must be unanticipated.

2.2. Illustrative Framework

To illustrate the relationship between some of the methods, it is useful to consider a simple trivariate model with three endogenous variables, \( X_1, X_2, \) and \( X_P \) and suppose that we are trying to identify the shocks to \( X_P \). In the monetary context, the first two variables could be industrial production and a price index, and \( X_P \) could be the federal funds rate; in the fiscal context, the first two could be real GDP and government purchases and \( X_P \) could be tax revenue; in the technology shock context, the first two variables could be output and consumption and \( X_P \) could be labor productivity. I will call \( X_P \) the “policy variable” for short, but it should be understood
that it can represent any variable from which we want to extract a shock component. Let \( X_t = [X_{1t}, X_{2t}, X_{Pt}] \) be the vector of endogenous variables. Following the standard procedure, let us model the dynamics with a structural VAR,

\[
A(L)X_t = \varepsilon_t
\]

(2.1)

where \( A(L) \) is a polynomial in the lag operator and \( A(L) = A_0 - \sum_{k=1}^{p} A_k L^k \). \( \varepsilon_t = [\varepsilon_1, \varepsilon_2, \varepsilon_P] \) is the vector of the normalized structural shocks. We assume that \( E[\varepsilon_t] = 0, E[\varepsilon_t \varepsilon_s'] = I \) and that \( E[\varepsilon_t \varepsilon_s] = 0 \) for \( s \neq t \). We can write the reduced form VAR as:

\[
X_t = \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + u_t
\]

(2.2)

where \( \phi_i = A_0^{-1} \phi_i \). \( u_t = [u_1^t, u_2^t, u_P^t] \) is the vector of reduced form residuals, which are related to the underlying structural shocks as follows:

\[
u_t = A_0^{-1} \varepsilon_t\]

Following the set-up of Mertens and Ravn (2013), we can express the reduced form errors as:

\[
u_1^t = \alpha_p \sigma_p \varepsilon_P + \alpha_2 u_1^t + \sigma_1 \varepsilon_1^t
\]

\[
u_2^t = \beta_p \sigma_p \varepsilon_P + \beta_1 u_1^t + \sigma_2 \varepsilon_2^t
\]

(2.3)

\[
u_P^t = \gamma_1 \sigma_1 \varepsilon_1^t + \gamma_2 u_1^t + \sigma_P \varepsilon_P^t
\]
The parameters $\gamma_1$ and $\gamma_2$ represent the endogenous response of the “policy” variable to $X_1$ and $X_2$. The $\alpha_p$ and $\beta_p$ parameterize the contemporaneous effect of the structural shocks to the two endogenous variables on the policy variable. The $\sigma$'s are the standard deviations of the (unnormalized) structural shocks.

### 2.3 Common Identification Methods

Let $n$ be the number of variables in the system, in this case three. The requirement that $E[u_t u_t'] = A_0^{-1} A_0^{-1'}$ provides $n(n+1)/2 = 6$ identifying restrictions for the equations in (2.3), but we require three more identifying restrictions to obtain all nine elements. We can now discuss various schemes for identifying the shock $\varepsilon_t^P$ in the context of this model, as well as several other schemes that go beyond this simple model.

#### 2.3.1 Cholesky Decompositions

The most commonly used identification method imposes alternative sets of recursive zero restrictions on the contemporaneous coefficients to identify the shock $\varepsilon_t^P$. The following are two widely-used alternatives.

A. The “policy” variable does not respond within the period to the other endogenous variables. This could be motivated by decision lags on the part of policymakers or other adjustment costs. This scheme involves constraining $\gamma_1 = \gamma_2 = 0$, which is equivalent to ordering the policy variable first in the Cholesky ordering. For example, Blanchard and Perotti (2002) impose this constraint to identify the shock to government spending; they
assume that government spending does not respond to the contemporaneous movements in output or taxes.

B. The other endogenous variables do not respond to the “policy” variable within the period. This could be motivated by sluggish responses of the other endogenous variables to shocks to the policy variable. This scheme involves constraining $\alpha_p = \beta_p = 0$, which is equivalent to ordering the policy variable last in the Cholesky ordering. For example, Bernanke and Blinder (1992) were the first to identify shocks to the federal funds rate as monetary policy shocks and used this type of identification. This is now the most standard way to identify monetary policy shocks.

2.3.2 Structural VARs

Another more general approach (that nests the Cholesky decomposition) is what is known as a Structural VAR, or SVAR, introduced by Blanchard and Watson (1986) and Bernanke (1986). This approach uses either economic theory or outside estimates to constrain parameters. For example, Blanchard and Perotti (2002) identify shocks to net taxes (the $X_p$ in the system above) by setting $\gamma_{2} = 2.08$, an outside estimate of the cyclical sensitivity of net taxes. As noted above, they used standard zero restrictions to identify the government spending shock $\varepsilon_{1}^{s}$. In conjunction with the assumed value of $\gamma_{2}$ they are able to identify the tax shock, $\varepsilon_{1}^{p}$.

2.3.3 Factor Augmented VARs

A perennial concern in identifying shocks is that the variables included in the VAR do not capture all of the relevant information. The comparison of price responses in monetary
VARs with and without commodity prices is one example of the difference a variable exclusion can make. To address this issue more broadly, Bernanke, Boivin, and Eliasz (2005) developed the Factor Augmented VARs (FAVARS) based on earlier dynamic factor models developed by Stock and Watson (2002) and others. The FAVAR, which typically contains over one hundred series, has the benefit that it is much more likely to condition on relevant information for identifying shocks. In most implementations, though, it still typically relies on a Cholesky decomposition.

2.3.4 Narrative Methods

Narrative methods involve constructing a series from historical documents to identify the reason and/or the quantities associated with a particular change in a variable. The first use of narrative methods for identification was Hamilton (1985) for oil shocks, which was further extended by Hoover and Perez (1994). These papers isolated political events that led to disruptions in world oil markets. Other examples of the use of narrative methods are Romer and Romer’s (1989, 2004) monetary shock series based on FOMC minutes, Ramey and Shapiro (1998) and Ramey’s (2011) series of expected changes in future government spending caused by military events gleaned from periodicals such as Business Week, and Romer and Romer’s (2010) narrative series of tax changes based on reading various legislative documents.

Until recently, these series were used either as exogenous shocks in sets of dynamic single equation regressions or ordered first in a Cholesky decomposition. For example, in the framework above, we would set $X_p$ to be the narrative series and we would constrain $\gamma_1 = \gamma_2 = 0$. As the next section details, recent innovations have led to an improved method for incorporating these series.
A cautionary note on the potential of narrative series to identify exogenous shocks is in order. Some of the follow-up research has operated on the principle that the narrative alone provides exogeneity. This is not true. Leeper (1997) made this point for monetary policy shocks. Another example is in the fiscal literature. A series on fiscal consolidations, quantified by narrative evidence on the expected size of these consolidations, is not necessarily exogenous. If the series includes fiscal consolidations adopted in response to bad news about the future growth of the economy, the series cannot be used to establish a causal effect of the fiscal consolidation on future output.

2.3.5 High Frequency Identification

Research by Bagliano and Favero (1999), Kuttner (2001), Cochrane and Piazzesi (2002), Faust, Swanson, and Wright (2004), Gürkaynak et al. (2005), Piazzesi and Swanson (2008), Gertler and Karadi (2015) and others has used high frequency data (such as news announcements around FOMC dates) and the movement of federal funds futures to identify unexpected Fed policy actions. This identification is also based in part on timing, but because the timing is so high frequency (daily or higher), the assumptions are more plausible than those employed at the monthly or quarterly frequency. As I will discuss in the foresight section below, the financial futures data is ideal for ensuring that a shock is unanticipated.

It should be noted, however, that without additional assumptions the unanticipated shock is not necessarily exogenous to the economy. For example, if the implementation does not adequately control for the Fed’s private information about the future state of the economy, which
might be driving its policy changes, these shocks cannot be used to estimate a causal effect of monetary policy on macroeconomic variables.

### 2.3.6 External Instruments/Proxy SVARs

The external instrument, or “proxy SVAR,” method is a promising new approach for incorporating external series for identification. Major elements of this idea appeared earlier in Hamilton (2003) and Evans and Marshall (2005, 2009), but the full application was developed independently by Stock and Watson (2012) and Mertens and Ravn (2013). This approach takes advantage of information developed from “outside” the VAR, such as series based on narrative evidence, shocks from estimated DSGE models, or high frequency information. The idea is that these external series are noisy measures of the true shock.

Suppose that $Z_t$ represents one of these external series. Then this series is a valid instrument for identifying the shock $\varepsilon_t^P$ if the following two conditions hold:

\begin{align}
(2.4a) \quad & E[Z_t \varepsilon_t^P] \neq 0, \\
(2.4b) \quad & E[Z_t \varepsilon_i^t] = 0 \quad i = 1, 2
\end{align}

Condition (2.4a) is the instrument \textit{relevance} condition: the external instrument must be contemporaneously correlated with the structural policy shock. Condition (2.4b) is the instrument \textit{exogeneity} condition: the external instrument must be contemporaneously uncorrelated with the other structural shocks. If the external instrument satisfies these two conditions, it can be used to identify the shock $\varepsilon_t^P$. 
The procedure is very straightforward and takes place with the following steps.\(^2\)

Step 1: Estimate the reduced form system to obtain estimates of the reduced form residuals, \(u_t\).

Step 2: Regress \(u^1_t\) and \(u^2_t\) on \(u^p_t\) using the external instrument \(Z_t\) as the instrument. These regressions yield unbiased estimates of \(\alpha_p \sigma_p\) and \(\beta_p \sigma_p\). Define the residuals of these regressions to be \(v^1_t\) and \(v^2_t\).

Step 3: Regress \(u^p_t\) on \(u^1_t\) and \(u^2_t\), using the \(v^1_t\) and \(v^2_t\) estimated in Step 2 as the instruments. This yields unbiased estimates of \(\gamma_1 \sigma_p\) and \(\gamma_2\). Define the residual of this regression to be \(v^p_t\).

Step 4: Estimate \(\sigma_p\) from the variance of \(v^p_t\).

As an example, Mertens and Ravn (2013a) reconcile Romer and Romer’s (2010) estimates of the effects of tax shocks with the Blanchard and Perotti (2002) estimates by using the Romer’s narrative tax shock series as an external instrument \(Z\) to identify the structural tax shock, \(\varepsilon^p_t\). Thus, they do not need to impose parameter restrictions, such as the cyclical elasticity of taxes to output. As I will discuss in section 2.3 below, Ramey and Zubairy (2014) extend this external instrument approach to estimating impulse responses by combining it with Jordà’s (2005) method.

\(^2\) This exposition follows Mertens and Ravn (2013a, online appendix). See Mertens and Ravn (2013a,b) and the associated online appendices for generalizations to additional external instruments and to larger systems.
2.3.7 Restrictions at Longer Horizons

Rather than constraining the contemporaneous responses, one can instead identify a shock by imposing long-run restrictions. The most common is an infinite horizon long-run restriction, first used by Shapiro and Watson (1988), Blanchard and Quah (1989), and King, Plosser, Stock and Watson (1991). To see how this identification works, rewrite the system above as:

(2.5) \[ X_t = C(L)\varepsilon_t \]

where \( C(L) = [A(L)]^{-1} \). Suppose we wanted to identify a technology shock as the only shock that affects labor productivity in the long-run. In this case, the “policy” variable would be the growth rate of labor productivity and the other variables would also be transformed to induce stationary (e.g. first-differenced). Letting \( C^{ij}(L) \) denote the \((i,j)\) element of the C matrix and \( C^p_1(1) \) denote the lag polynomial with \( L = 1 \), we impose the long-run restriction by setting \( C^p_1(1) = 0 \) and \( C^p_2(1) = 0 \). This restriction constrains the unit root in the policy variable (e.g. labor productivity) to emanate only from the shock that we are calling the technology shock. This is the identification used by Gali (1999).

An equivalent way of imposing this restriction is to use the estimation method suggested by Shapiro and Watson (1988). Let \( X_P \) denote the first-difference of the log of labor productivity and \( X_1 \) and \( X_2 \) be the stationary transformations of two other variables (such as hours). Then, imposing the long-run restriction is equivalent to identifying the error term in the following equation as the technology shock:
We have imposed the restriction by specifying that only the differences of the other stationary variables enter this equation. Because the current values of those differences might also be affected by the technology shock and therefore correlated with the error term, we use lags one through \( p \) of \( X_1 \) and \( X_2 \) as instruments for the terms involving the current and lagged values of those variables. The estimated residual is the identified technology shock. We can then identify the other shocks, if desired, by orthogonalizing the error terms with respect to the technology shock.

This equivalent way of imposing long-run identification restrictions highlights some of the problems that can arise with this method. First, identification depends on the relevance of the instruments. Second, it requires additional identifying restrictions in the form of assumptions about unit roots. If, for example, hours have a unit root, then in order to identify the technology shock one would have to impose that only the second difference of hours entered in equation (2.6).\(^3\)

Another issue is the behavior of infinite horizon restrictions in small samples (e.g. Faust and Leeper (1997)). Recently, researchers have introduced new methods that overcome these problems. For example, Francis, Owyang, Roush, and DeCecio (2014) identify the technology shock as the shock that maximizes the forecast error variance share of labor productivity at some finite horizon \( h \). A variation by Barsky and Sims (2011) identifies the shock as the one that maximizes the sum of the forecast error variances up to some horizon \( h \). Both of these methods operate off of the moving average representation in equation (2.5).

\(^3\) To be clear, all of the \( X \) variables in equation (2.6) must be trend stationary. If hours have a unit root, then \( X_1 \) must take the form of \( \Delta \text{hours}_t \), so the constraint in (2.6) would take the form \( \Delta^2 \text{hours}_t \).
2.3.8 Sign Restrictions

A number of authors had noted the circularity in some of the reasoning analyzing VAR specifications in practice. In particular, whether a specification or identification method is deemed correct is often judged by whether the impulses they produce are “reasonable,” i.e. consistent with the researcher’s priors. Uhlig (2005) developed a new method to incorporate “reasonableness” without undercutting scientific inquiry by investigating the effects of a shock on variable Y, where the shock was identified by sign restrictions on the responses of other variables (excluding variable Y).

Uhlig’s sign restriction method has been used in many contexts, such as monetary policy, fiscal policy and technology shocks. Recently, however, two contributions by Arias, Rubio-Ramirez, and Waggoner (2013) and by Baumeister and Hamilton (2014) have highlighted some potential problems with sign restriction methods. The Arias et al paper demonstrates problems with particular implementations and offers new computational methods to overcome those problems. Baumeister and Hamilton develop Bayesian methods that highlight and link the relationship between the priors used for identification and the outcomes.

2.3.9 Estimated DSGE Models

An entirely different approach to identification is the estimated DSGE model, introduced by Smets and Wouters (2003, 2007). This method involves estimating a fully-specified model (a New Keynesian model with many frictions and rigidities in the case of Smets and Wouters) and extracting a full set of implied shocks from those estimates. In the case of Smets and Wouters, many shocks are estimated including technology shocks, monetary shocks, government spending
shocks, wage markup shocks, and risk premium shocks. One can then trace out the impulse responses to these shocks as well as to do innovation accounting. Other examples of this method include Justiano, Primiceri, Tambolotti (2010, 2011) and Schmitt-Grohe and Uribe (2012). Christiano, Eichenbaum and Evans (2005) took a different estimation approach by first estimating impulse responses to a monetary shock in a standard SVAR and then estimating the parameters of the DSGE model by matching the impulse responses from the model to those of the data.

These models achieve identification by imposing structure based on theory. It should be noted that identification is less straightforward in these types of models. Work by Canova and Sala (2009), Komunjer and Ng (2011), and others highlight some of the potential problems with identification in DSGE models.

2.4 Estimating Impulse Responses

Suppose that one has identified the economic shock through one of the methods discussed above. How do we measure the effects on the endogenous variables of interest? The most common way to estimate the impulse responses to a shock uses nonlinear (at horizons greater than one) functions of the estimated VAR parameters. In particular, estimation of the reduced form system and imposition of the necessary identification assumptions to identify \( A_0^{-1} \) provides the elements of the moving average representation matrix, \( C(L) \), in equation (2.5). Writing out \( C(L) = C_0 + C_1L + C_2L^2 + C_3L^3 + \ldots \), and denoting \( C_h = [c_{ijh}] \), we can express the impulse response of variable \( X_i \) at horizon \( t+h \) to a shock to \( \epsilon^p_t \) as:

\[ X_{i,t+h} = \sum_{k=0}^{\infty} C_k \epsilon^p_{t+k} \]
These $c_{ijk}$ parameters are nonlinear functions of the VAR parameters.

If the VAR adequately captures the data generating process, this method is optimal at all horizons. If the VAR is mispecified, however, then the specification errors will be compounded at each horizon. To address this problem, Jordà (2005) introduced a local projection method for estimating impulse responses. The comparison between his procedure and the standard procedure has an analogy with direct forecasting versus iterated forecasting (e.g. Marcellino, Stock, and Watson (2006)). In the forecasting context, one can forecast future values of a variable using either a horizon-specific regression (“direct” forecasting) or iterating on a one-period ahead estimated model (“iterated” forecasting). Jordà’s method is analogous to the direct forecasting whereas the standard VAR method is analogous to the iterated forecasting method.

To see how Jordà’s method works, suppose that $\varepsilon_t$ has been identified by one of the methods discussed in the previous section. Then, the impulse response of $X_i$ at horizon $h$ can be estimated from the following single regression:

\begin{equation}
X_{l,t+h} = \theta_{l,h} \cdot \varepsilon_{t}^P + \text{control variables} + \zeta_{t+h}
\end{equation}

$\theta_{l,h}$ is the estimate of the impulse response of $X_i$ at horizon $h$ to a shock to $\varepsilon_t^P$. The control variables do not have to include the other $X$’s as long as $\varepsilon_t^P$ is exogenous to those other $X$’s. Typically, the control variables include deterministic terms (constant, time trends), lags of the $X_i$, and lags of other variables that are necessary to “mop up;” the specification can be chosen using information criteria. One estimates a separate regression for each horizon and the control
variables do not necessarily need to be the same for each regression. Note that except for horizon \( h = 0 \), the error term \( \xi_{t+h} \) will be serially correlated because it will be a moving average of the forecast errors from \( t \) to \( t+h \). Thus, the standard errors need to incorporate corrections for serial correlation, such as a Newey-West (1987) correction.

Because the Jordà method for calculating impulse response functions imposes fewer restrictions, the estimates are often less precisely estimated and are sometimes erratic. Nevertheless, this procedure is more robust than standard methods, so it can be very useful as a heuristic check on the standard methods. Moreover, it is much easier to incorporate state-dependence (e.g. Auerbach and Gorodnichenko (2013)).

Ramey and Zubairy (2014) recently proposed a new use for the Jordà method that merges the insights from the external instrument/proxy SVAR literature. To see this, modify equation (2.8) as follows:

\[
X_{i,t+h} = \theta_{i,h} \cdot X_{p,t} + \text{control variables} + \zeta_{t+h}
\]

As discussed above, \( X_p \) is the policy variable, but may be partly endogenous so it will be correlated with \( \xi_{t+h} \). We can easily deal with this issue, however, by estimating this equation using the identified exogenous shock \( \varepsilon^P_t \) as an instrument for \( X_{p,t} \). For example, if \( X_i \) is real output and \( X_{p,t} \) is the federal funds rate, we can use Romer and Romer’s (2004) narrative-based monetary shock series as an instrument. As I will discuss below, in some cases there are multiple potential external instruments. We can easily incorporate these in this framework by using multiple instruments for \( \varepsilon^P_t \). In fact, these overidentifying restrictions can be used to test the restrictions of the model (using a Hansen’s J-statistic, for example).
2.5 The Problem of Foresight

A potential identification problem highlighted recently in multiple literatures is the issue of news or policy foresight.\(^4\) For example, Beaudry and Portier (2006) explicitly take into account that news about future technology may have effects today even though it does not show up in current productivity. Ramey (2011) argues that the results of Ramey and Shapiro (1998) and Blanchard and Perotti (2002) differ because most of the latter’s identified shocks to government spending are actually anticipated. Leeper, Walker, and Yang (2013) work out the econometrics of “fiscal foresight” for taxes, showing that foresight can lead to a non-fundamental moving average representation.

The principal method for dealing with this problem is to try to measure the expectations with data or time series restrictions. For example, Beaudry and Portier (2006) extracted news about future technology from stock prices, Ramey (2011) created a series of news about future government spending by reading Business Week and other periodicals, Fisher and Peters (2010) created news about government spending by extracting information from stock returns of defense contractors, Leeper, Richter, Walker (2012) used information from the spread between federal and municipal bond yields for news about future tax changes, and Mertens and Ravn (2012) decomposed Romer and Romer’s (2010) narrative tax series into one series in which implementation was within the quarter (“unanticipated”) and another series in which implementation was delayed (“news”). In the monetary shock literature, many papers use financial futures prices to try to extract the anticipated versus unanticipated component of

\(^4\) The general problem was first recognized and discussed decades ago. For example, Sims (1980) states: “It is my view, however, that rational expectations is more deeply subversive of identification than has yet been recognized.”
interest rates changes (e.g. Rudebusch (1998), Bagliano and Favero (1999), Kuttner (2001), and Gertler and Karadi (2014)).

The typical way that news has been incorporated in VARs is by adding the news series to a standard VAR. Perotti (2011) has called these “EVARs” for “Expectational VARs.” Note that in general one cannot use news as an external instrument in Mertens and Ravn’s proxy SVAR framework. The presence of foresight invalidates the interpretation of the VAR reduced form residuals as prediction errors, since the conditioning variables may not span the information set of forward looking agents (Mertens and Ravn (2013, 2014)).

On the other hand, one can use a news series as an instrument in the Jordà framework in certain instances. Owyang, Ramey, and Subairy (2013) and Ramey and Zubairy (2014) estimate what is essentially an instrumental variables regression, but in two steps. In particular, they (i) regress the change in output from t-1 to t+h for various horizons h on current military news; (ii) regress the change in government spending from t-1 to t+h for various horizons h on current military news; and then (iii) estimate the government spending multiplier as the integral of the output responses up to some horizon H divided by the integral of the government spending responses up to some horizon H. They perform their estimation in two steps because of the complexities of the state dependent model they estimate. In a linear model, one can obtain identical results by estimating the model in one step. To do this, one must first transform the endogenous variables to be integrals of responses up to horizon H, i.e., the changes in output from t-1 to t+h summed from h = 0 to h = H and the similar transformation for government spending. Call each of these \( \sum_{h=0}^{H} X_{i,t+h} \). Then one estimates the following equation using news in period t as an instrument for \( \sum_{h=0}^{H} X_{p,t+h} \):
\[(2.9) \quad \sum_{h=0}^{H} X_{i,t+h} = \theta_{i,h} \cdot \sum_{h=0}^{H} X_{p,t+h} + \text{control variables} + \zeta_{t+h} \]

In the government spending example, $X_i$ is output, $X_p$ is government spending, and $Z$ is military news derived from narrative methods.

### 2.6 DSGE Monte Carlos

Much empirical macroeconomics is linked to testing theoretical models. A question that arises is whether shocks identified in SVARs, often with minimal theoretical restrictions, are capable of capturing the true shocks. This question has been asked most in the literature on the effects of technology shocks. Erceg, Guerrieri, and Gust (2005) were perhaps the first to subject an SVAR involving long-run restrictions to what I will term a “DSGE Monte Carlo.” In particular, they generated artificial data from a calibrated DSGE model and applied SVARS with long-restrictions to the data to see if the implied impulse responses matched those of the underlying model.

This method has now been used in several settings. Chari, Kehoe, and McGrattan (2008) used this method to argue against SVARs’ ability to test the RBC model, Ramey (2009) used it to show how standard SVARs could be affected by anticipated government spending changes, and Francis, Owyang, Roush, and DiCecco (2014) used this method to verify the applicability of their new finite horizon restrictions method. This method seems to be a very useful tool for judging the ability of SVARs to test DSGE models. Of course, like any Monte Carlo, the specification of the model generating the artificial data is all important.
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