Chapter 2

Empirical monetary economics

2.1 Motivation

In the previous lecture we examined the relationship between money and output using simple bivariate measures. While these are easy to understand, they allow for only a limited view of the way in which variables may interact. In the next two lectures we turn our attention to more sophisticated techniques which can easily be extended to multivariate analysis. We also introduce more structure to our empirical analysis so later we can more clearly see the links between empirical and theoretical monetary economics.

2.2 Key readings

Walsh (1999) *Monetary Theory and Policy*, MIT Press, Section 1.3

Balke and Emery (1994), "Understanding the Price Puzzle", Federal Reserve Bank of Dallas Economic Review, 4th Quarter, 15-26

Sims (1972) "Money, Income and Causality", *American Economic Review*, 62, no. 4, 540-542

Sims (1980), "Macroeconomics and Reality", *Econometrica*, 48, 1-48

2.3 Related reading

Bernanke and Blinder (1992) "The Federal Funds Rate and the Channels of Monetary Transmission", *American Economic Review*, 82, 901-21

Blanchard and Quah (1989) "The Dynamic Effects of Aggregate Supply and Demand Disturbances", *American Economic Review*, 79, 4, 655-673

Canova and De Nicolo' (1999) "Monetary Disturbances Matter for Business Cycle Fluctuations in the G-7", Federal Reserve Board, International Finance Division working paper 660

Canova and Pina (1998) "Monetary Policy Misspecification in VAR Models", *CEPR Discussion Paper*

Ehrmann and Ellison (2001), "The changing nature of the response of US industry to monetary policy", *mimeo*, European Central Bank and University of Warwick. Unpublished.

Friedman (1961) "The Lag in the Effect of Monetary Policy", *Journal of Political Economy*, 69, 447-466.

Garratt and Scott (1998) "Money and Output: Post hoc, propter hoc or ad hoc?", *mimeo*, University of Cambridge. Unpublished

Huh (1993) "Causality and correlations of output and nominal variables in a real business cycle model", *Journal of Monetary Economics*, 32, 147-168

Sims (1992) "Interpreting the macroeconomic time series facts: The effects of monetary policy", *European Economic Review*, 36, 976-1011.

Sims (1996) "Macroeconomics and Methodology", *Journal of Economic Perspectives*, Vol. 10, No. 1, 105-20

Strongin (1995) "The Identification of Monetary Policy Disturbances: Explaining the Liquidity Puzzle", *Journal of Monetary Economics*, 35, 463-497

Uhlig (1999) What are the effects of monetary policy on output? : results from an agnostic identification procedure", CentER for Economic Research Discussion Papers No.28

2.4 Vector autoregressions (VAR)

Vector autoregression models have rapidly established themselves as the dominant research methodology in empirical monetary economics. The flexibility of the autoregressive formulation not only allows a statistical description of a wide range of real data sets but also provides a unifying framework in which to analyse alternative theories and hypotheses. Such models do not represent the truth in economics but are a useful tool for gaining insight into the interactions between different variables. In practice, the models can often provide a quite adequate description of the data.

The basic form of a p-th order VAR in money m_t and output y_t is shown in Equation (2.1). The order of the VAR refers to the number of lags in each equation. e_{1t} and e_{2t} are Gaussian residuals which may well be correlated. Equation (2.1) can be estimated using standard OLS regression techniques.

$$\begin{aligned} y_t &= y_0 + a_{11}m_{t-1} + \cdots + a_{p1}m_{t-p} + b_{11}y_{t-1} + \cdots + b_{p1}y_{t-p} + e_{1t} \\ m_t &= m_0 + a_{12}m_{t-1} + \cdots + a_{p2}m_{t-p} + b_{12}y_{t-1} + \cdots + b_{p2}y_{t-p} + e_{2t} \end{aligned} \tag{2.1}$$

In estimating a VAR we are faced with two difficulties. Firstly, we have to decide which variables should be included. Economic theory can often guide us to make sensible choices but as we will see the results are often sensitive to exactly which variables we choose. The second difficulty relates to deciding on the order of the VAR. If too few lags are included then we have an omitted variables problem: too many lags and estimates will be imprecise. The standard solution to this problem is to rely on information criteria. The Akaike Information Criterion (AIC) and Schwarz-Bayesian (BIC) are amongst the most-widely used. However, they should be treated carefully and often give conflicting advice. As a rule of thumb, it is important that the order of the VAR is at least sufficient to eliminate serial correlation in the residuals.

2.5 Granger causality tests

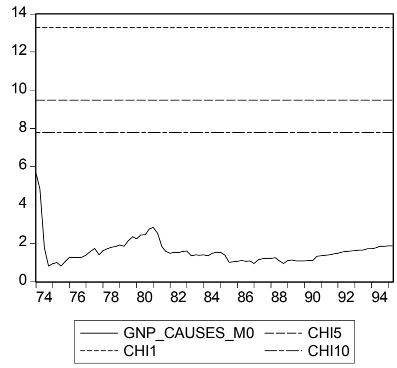
The VAR framework is also popular because of significant theoretical developments which enhance the basic model. The first of these is the Granger causality test introduced by Sims (1972). This enables us to say something about the causality links between two variables. It is always difficult to establish causality in econometrics so this is especially nowadays a fairly weak test. We say that money Granger-causes output if and only if lagged values of money have predictive power in forecasting output. In other words, if knowing past values of money enables us to predict output better then money Granger-causes output. In practice, a test of whether money Granger-causes output involves testing whether the coefficients on lagged money in the output equation in (2.1) are significant, i.e. we test

$$\text{equivalent} \begin{cases} H_0: \text{ Money does not Granger-cause output} \\ H_0: a_{11} = \cdots = a_{p1} = 0 \end{cases}$$

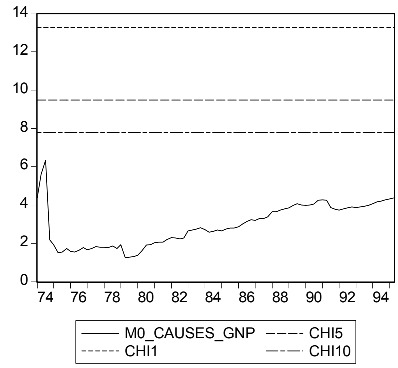
This can easily be tested with an F-test or a Wald test. Figure 2.1 shows recursive Granger-causality tests for the UK economy using the Ellison-Scott data. We use Δm_t and Δy_t and plot critical χ^2 values for the test at 1%, 5% and 10% levels respectively. The hypothesis is rejected if the test statistic exceeds the critical value. The results of this simple analysis do not suggest a great deal of Granger-causality between money and output. The only hypothesis that is rejected is for the non-causality of M4 by GNP in the early part of the sample. This is not surprising given that we saw M4 lagging GNP in the last lecture.

In a more robust analysis, Garratt and Scott (1998) perform Granger causality tests on a multivariate system of output, money, prices and short-term interest rates. They focus on three different sets of Granger causality tests: whether money predicts output, whether interest rates predict output and whether money and interest rates jointly predict output. The most striking result is the strong significance that M0 Granger-causes output, which we did not pick up in our simple bivariate analysis. By contrast, M4 only Granger-causes after 1994. For the US, the general result is that money does Granger-cause output, see Strongin (1995) and the references therein.

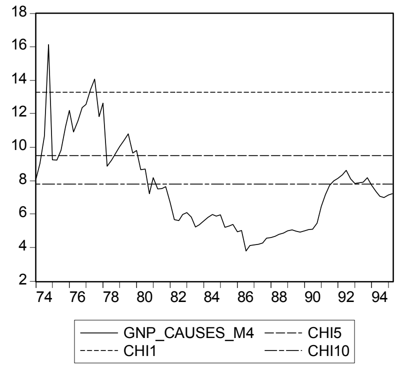
The usefulness of Granger causality tests has been questioned in an interesting paper by Huh (1993). He simulates a dynamic general equilibrium model in which output is exogenous with respect to money. Even in such a model with “reverse causation” from output to money, repeated applications of the Granger causality test to simulated data lead to the finding that money causes output more often than expected. This casts serious doubt on the validity of using Granger causality tests.



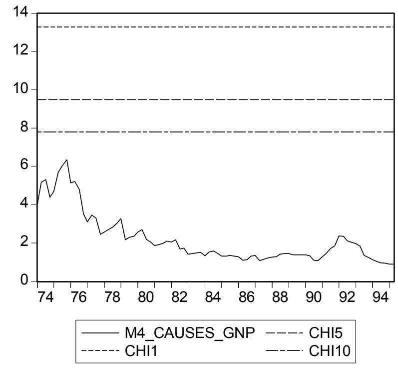
H_0 : GNP does not Granger-cause M0



H_0 : M0 does not Granger-cause GNP



H_0 : GNP does not Granger-cause M4



H_0 : M4 does not Granger-cause GNP

Figure 2.1: Granger causality tests for GNP and money in the UK economy

2.6 Structural VARs

To interpret the estimation results of an unrestricted VAR is still difficult. We are unable to say anything about how the economy reacts to different shocks. All we have are two Gaussian residuals which can be correlated. The general form of their variance-covariance matrix is given in (2.2).

$$\begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix} \sim \mathbf{N}\left[\mathbf{0}; \begin{pmatrix} \sigma_1 & \sigma_{1,2} \\ \sigma_{1,2} & \sigma_2 \end{pmatrix}\right] \tag{2.2}$$

Suppose that theory suggests that really there are two fundamental shocks u_{1t} and u_{2t} driving the system: output shocks and monetary policy shocks. These shocks are assumed to have unit variance and to be uncorrelated at all leads and lags. The problem is that both these shocks may affect both the variables. Output shocks could affect output and money, whereas money shocks could in turn affect both output and money. In other words, there is the identification problem shown in Figure 2.2.

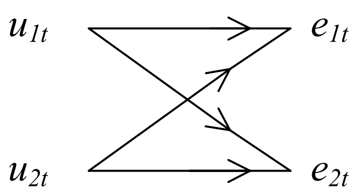


Figure 2.2: The identification problem

The idea of a structural VAR is to impose identifying restrictions on how the fundamental disturbances u_{1t} and u_{2t} affect the residuals e_{1t} and e_{2t}. The simplest idea and grandfather of all structural VAR models is by Sims (1980), with a nice application in Sims (1992). The idea is to order the disturbances in the model. In the bivariate system we would assume that output is causally prior to money. This means that output shocks have contemporaneous effects on both output and money but money only has contemporaneous effects on money itself. Sims justifies this by saying that monetary policy only affects output with a lag. Figure 2.3 shows the general idea. An identification scheme of this type is referred to as a recursive ordering or a Wold causal chain.

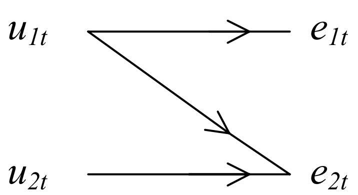


Figure 2.3: Bivariate identification by recursive ordering

Mathematically, the identification implies that there is a well-defined relationship between the fundamental disturbances and the residuals of the unrestricted VAR. Assuming linearity, equations (2.3) and (2.4) show that the residual in the output equation is only composed of output shocks but the residual in the money equation contains both output and monetary policy shocks.

$$e_{1t} = \theta_1 u_{1t} \tag{2.3}$$
$$e_{2t} = \theta_2 u_{1t} + \theta_3 u_{2t} \tag{2.4}$$

Since the fundamental disturbances have unit variance and are uncorrelated at all leads and lags the identity (2.5) must hold. This is obtained by looking at the variance-covariance of the residuals from the VAR.

$$
\begin{pmatrix} \sigma_1 & \sigma_{1,2} \\ \sigma_{1,2} & \sigma_2 \end{pmatrix} \equiv \begin{pmatrix} \theta_1^2 & \theta_1\theta_2 \\ \theta_1\theta_2 & \theta_2^2 + \theta_3^2 \end{pmatrix} \tag{2.5}
$$

This identity gives unique values for θ_1, θ_2 and θ_3 according to equations (2.6)-(2.8). It is then easy to recover the fundamental disturbances from the VAR residuals using equations (2.3) and (2.4).

$$
\theta_1 = \sqrt{\sigma_1} \tag{2.6}
$$

$$
\theta_2 = \frac{\sigma_{1,2}}{\sqrt{\sigma_1}} \tag{2.7}
$$

$$
\theta_3 = \sqrt{\sigma_2 - \frac{\sigma_{1,2}^2}{\sigma_1}} \tag{2.8}
$$

There is nothing unique about this causal ordering. Bernanke and Blinder (1992) take an opposite view and assume that the fundamental money shock affects both output and money whereas output shocks only affect output. The rational behind this is that the money supply is set by the central bank and output data is only available with a lag. Quite simply, money cannot react to output shocks because the information about output shocks is not available to the central bank. Not surprisingly, the results are somewhat sensitive to which ordering is used. Several other competing identification schemes exist, such as long-term restrictions (the recursive ordering essentially restricts the short-term behaviour of the economy) by Blanchard and Quah (1989) and sign restrictions by Uhlig (2000) and Canova and Nicolo' (2000). The recursive causal structure is the easiest to handle and can easily be extended to many dimensions. In the trivariate ordering in Figure 2.4 the first disturbance u_{1t} affects all three variables contemporaneously through e_{1t}, e_{2t} and e_{3t}. The second disturbance u_{2t} only affects contemporaneously the first two variables through e_{2t} and e_{3t}. The last disturbance u_{3t} only contemporaneously affects the last variable through e_{3t}. The multivariate system has a similar set of unique equations as the bivariate system (2.6)-(2.8). However, a neat mathematical trick involving a Choleski decomposition makes calculating the restrictions easier. For this reason, many papers talk about imposing structure through a Choleski decomposition. It is the same as imposing a Wold causal ordering.

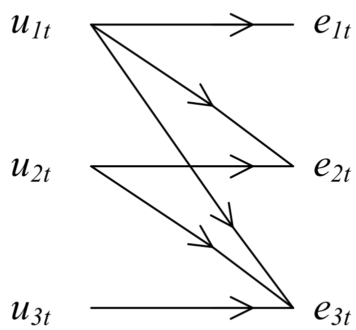


Figure 2.4: Trivariate identification by recursive ordering

Whilst traditionally Granger causality tests looked at the relationship between output and money, it has become increasingly common in structural VAR studies to use interest rates as the indicator of monetary policy. This partly reflects the stronger causal relationship between interest rates and the economy, but also a shift by central banks to using interest rates as the instrument of monetary policy. The rest of this section therefore studies systems in interest rates rather than money. As an example, we take monthly data from a study by Ellison and Ehrmann (2001), which looks at the relationship between capacity utilisation in US manufacturing and the federal funds rate - the key monetary policy interest rate in the US economy.[1] The causal ordering is such that interest rate shocks only have a delayed effect on capacity utilisation. Figure 2.5 shows the residuals of the unrestricted VAR and the shocks that are identified by the Wold causal ordering. In this simple bivariate model the residuals and shocks are somewhat similar, reflecting the low covariance between the two residuals. In models of higher dimension this may not be the case.

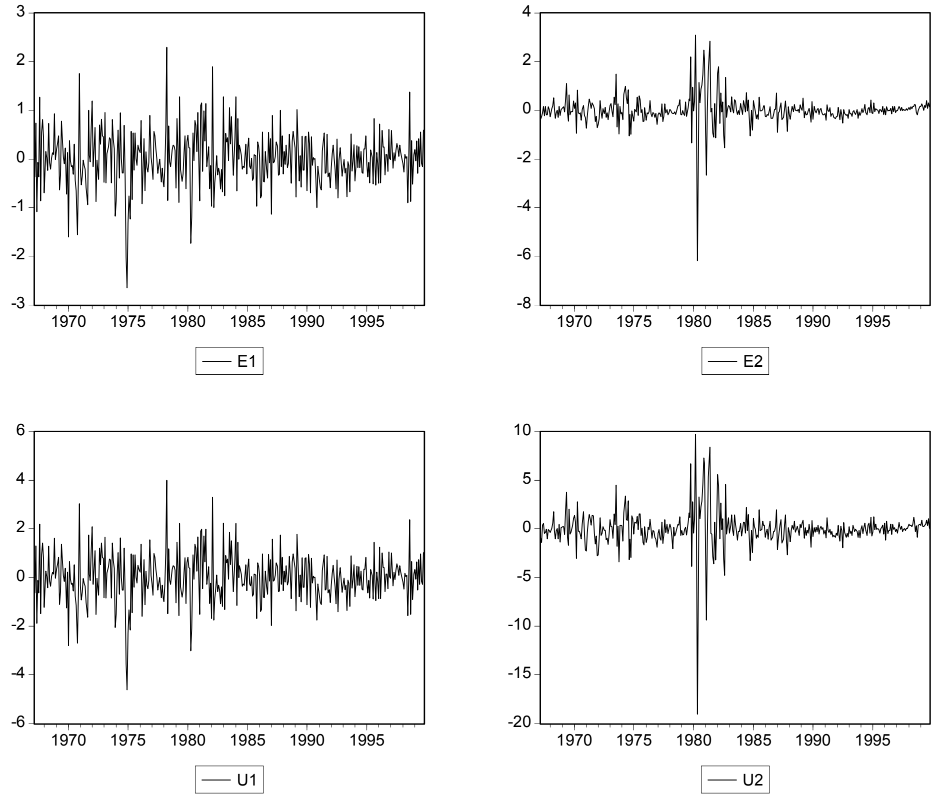


Figure 2.5: Residuals (e_{1t} and e_{2t}) and shocks (u_{1t} and u_{2t}) in the SVAR model

[1] The data is available for download on the course homepage.

2.7 Impulse response functions

The structural VAR is a powerful framework in which to see how the variables in the system interact. We can use the technique of impulse response functions to show how the fundamental shocks we have identified feed through into the economy. As an example, suppose we are interested in the effect of interest rate shocks and ask what would be the effect of an interest rate shock in the absence of a simultaneous output shock. To see this we can set $u_{1t} = 0$ and $u_{2t} = 1$ and suppose the economy is in steady-state at time $t - 1$, with $y_t = R_t = 0$. The size of the interest rate shock is normalised to one standard deviation to enable easy interpretation. The effects of this shock each period are given algebraically in Table 2.1. The first line shows the impact of the shock using the equations (2.3) and (2.4) - not surprisingly given our identification scheme the interest rate shock does not contemporaneously affect output. The remaining rows are obtained by feeding the impact effect through the autoregressive structure of the model.

$$
\begin{array}{ll}
t = 0 & \begin{array}{l} y_t = 0 \\ R_t = \theta_3 \end{array} \\
t = 1 & \begin{array}{l} y_t = a_{11}\theta_3 \\ R_t = a_{12}\theta_3 \end{array} \\
t = 2 & \begin{array}{l} y_t = a_{11}a_{12}\theta_3 + a_{21}\theta_3 + b_{11}a_{11}\theta_3 \\ R_t = a_{12}a_{12}\theta_3 + a_{22}\theta_3 + b_{12}a_{11}\theta_3 \end{array} \\
\vdots &
\end{array}
$$

Table 2.1: Response to an interest rate shock

Calculating impulse response functions numerically is much easier than analytically. Eviews and most other econometric packages have built-in routines to estimate and identify systems quickly. Impulse response functions estimated from the Ehrmann-Ellison (2001) data are shown in Figure 2.6. The dashed lines surrounding each impulse response are error bands, giving an idea of the significance of the response. They can be obtained either analytically or by standard bootstrapping techniques.

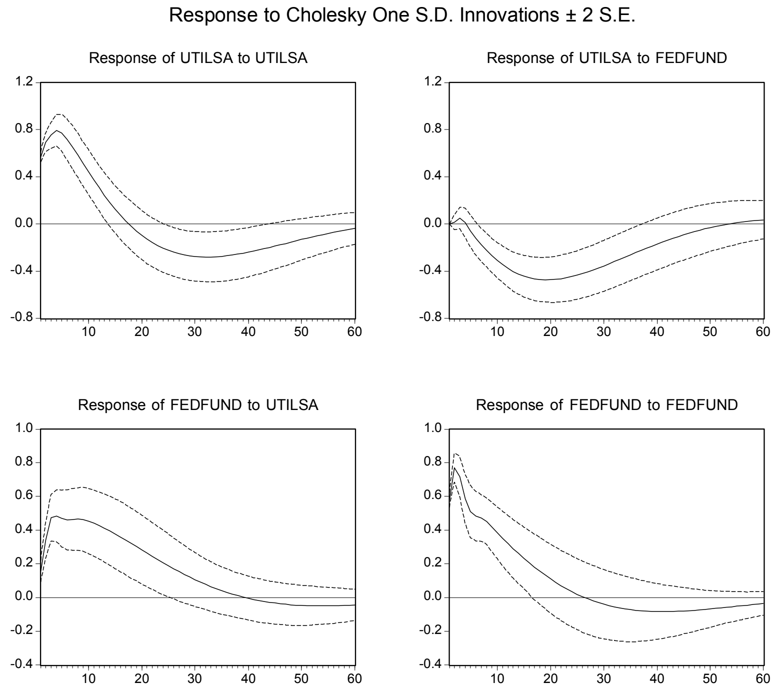


Figure 2.6: Impulse response functions with the Ehrmann-Ellison (2001) data

Now, at last, we can start to see some monetary economics. The right column in Figure 2.6 shows the response of the economy to an interest rate shock. In the lower right-hand panel, interest rates obviously rise but also stay above baseline for a long period, reflecting a high degree of persistence in interest rates. The upper right-hand panel shows how output (proxied by capacity utilisation) reacts. We see that a positive interest rate shock depresses output. However, the effect is not immediate and it takes about 2 years for the output effect to hit a maximum. This is a robust result across many countries and data sets. It was originally referred to by Friedman (1961) as due to the "long and variable" lags of monetary policy.

The left-hand column in Figure 2.6 shows the effect of an output shock on the economy. In the upper left-hand panel the output shock has a persistent effect on output - probably the easiest way to think of this is as a demand shock. The lower left-hand panel shows that interest rates rise in response already at time $t = 0$. This is the response of the central bank: After a demand shock they increase interest rates to stabilise the economy. Again there is an effect on interest rates for a long period.

2.8 Problems with SVARs

Structural VARs are not without their problems and critics. In making the identifying assumptions, we are imposing *a priori* beliefs about how the economy behaves.[2] These cannot be tested - Granger causality

[2] A paper by Canova and Pina (1998) shows that stochastic dynamic general equilibrium models typically do not imply a recursive structure on the model. In these models, both interest rate and output shocks impinge upon both variables

tests do not help because they say nothing about contemporaneous causality - so many econometricians consider SVARs as more art than science. An insightful debate into this was published in a volume of the *Journal of Economic Perspectives* in 1996. Structural VARs do though form a useful baseline against which to assess the theoretical models in the next lectures.

One way to assess the robustness of the results is to see whether the impulse responses match our economic intuition. In the previous example, we found that a positive interest shock caused a contraction in output, which accords well with our expectations from economic theory. This is an example of an over-identifying assumption - we expect high interest rates to cause recessions - which can be tested to check our results. The bivariate case creates no problems but in higher order systems there are many more things that can go wrong. Consider a trivariate system in output, prices and the interest rate. Figure 2.7 concentrates on one of the estimated impulse responses: the response of prices to a monetary policy shock.

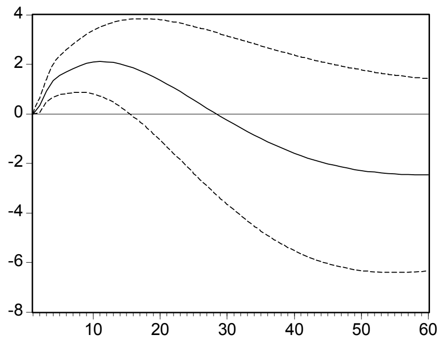


Figure 2.7: The estimated response of prices to an interest rate shock - the price puzzle

This picture is worrying. The interest rate shock actually leads to an increase in the price level for 2-3 years. This again is a very robust result across many countries and datasets and is referred to in the literature as the *price puzzle*. Whilst this is not impossible, it does not fit well with established wisdom concerning the deflationary effect of positive interest rate shocks. What is wrong then? One answer would be to conclude that our theory is wrong and set out to write a theory which predicts the sort of response we estimate. More likely though, there is something wrong in our econometric approach. The shock we have identified as an interest rate shock does not really look like an interest rate shock at all and this seems to be the heart of the problem.

One explanation of the price puzzle that has become standard in the literature is that the shock identified as an interest rate shock is actually a shock to inflation expectations. If people expect higher prices in the future then prices are already driven up today. Simultaneously, the central bank increases interest rates to control future price information. In other words, the expectations shock increases both prices and interest rates together. The solution to this is to control for the inflation shocks in the estimation. The standard way to do this is by including an index of world commodity prices as an exogenous variable in the model. This acts as a proxy for changes in expectations. Balke and Emery (1994) have a clear explanation of

simultaneously.

the price puzzle problem and how to solve it. Figure 2.8 shows the response of prices to an interest rate shock in the Ehrmann-Ellison (2001) data once world commodity prices have been included as a proxy for expectations shocks. Now the price puzzle is much briefer and less dramatic. Including commodity prices has not completely eradicated the price puzzle but has certainly reduced it significantly.

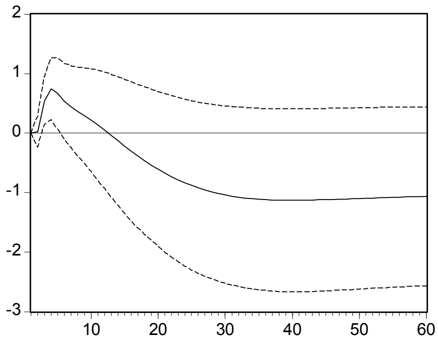


Figure 2.8: The estimated response of prices to an interest rate shock after controlling for commodity prices

This concludes our brief review of empirical monetary economics. We will return to these results in various parts of the remainder of the course to assess the validity of the theoretical models we develop. There are thousands of structural VAR studies already done but this is still very much an active area of research. Contributions are still very welcome.