IDENTIFYING THE EFFECTS OF MONETARY POLICY SHOCKS ON EXCHANGE RATES USING FED FUNDS FUTURES DATA

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1. Introduction

The role of monetary policy in explaining the dynamics and volatility of exchange rates is a central theme in empirical international finance. The current predominant approach to identifying structural monetary policy shocks, in both closed- and open-economy settings, involves working within the framework of a vector autoregression (VAR). This approach relies on making identifying assumptions relating structural shocks to the reduced form errors of the VAR. While many identification approaches have been proposed for identifying VARs, most often short-run restrictions are used. These specify that some structural shock has no contemporaneous effect on one or more variables. In an open-economy setting, such identifying assumptions are used by Eichenbaum and Evans (1995), Kim and Roubini (2000), and Kim (2001).

Identification of structural monetary policy shocks in VARs is contentious because, as the authors generally acknowledge, there are few highly credible identifying assumptions. Open economy VAR applications raise particularly thorny simultaneity issues. For example, most closed economy applications involve a single financial market variable, a short-term interest rate; long-term rates are generally excluded due to the identification problems that arise when they are included.[1] To be minimally credible, the open economy analogs simply must include 3 financial market variables: a short-rate in each country and the exchange

[1]See Leeper, Sims, and Zha (1996) for a thorough description of this issue and examples of VARs with long and short rates.

rate. Satisfactory identifying restrictions for sorting out the contemporaneous movements of these variables simply have not been found. For example, some papers assume that U.S. monetary policy shocks have no effect on foreign interest rates until a month after the policy move (Eichenbaum and Evans (1995), Kim and Roubini (2000)). This is at odds with the fact that foreign central banks regularly change policy in the wake of Federal Reserve policy decisions. Other authors assume that the Fed ignores any surprise movements in exchange rates and/or short-term interest rates that have occurred during the month in which decisions on the policy variable are made (Eichenbaum and Evans (1995) and Kim and Roubini (2000)). If true, these assumptions would call into question why the Federal Reserve Board staff invest tremendous effort in providing the Board with minute-by-minute information about surprising movements in financial markets.

Aware that the assumptions are not entirely credible, authors typically present results from a few alternative identifications or allude to results indicating that the published results hold up to alternatives. Such robustness checks are of course indispensable. Nonetheless, in cases where the alternative identifications are recursive, a sense of dissatisfaction lingers since we would expect simultaneity among variables, especially asset market variables.

Motivated by these considerations, Faust and Rogers (2002) apply an approach to identification, originally developed by Faust (1998). This is an approach that allows one to do inference in partially identified models. Using such methods, one can test whether the answers to key questions are robust to dropping implausible identifying assumptions. Using a standard open-economy VAR, Faust and Rogers find that some key results are highly sensitive to the assumed recursive structure of money market variables, while other results are robust. For example, the "delayed overshooting" response of the nominal exchange rate commonly found under the assumption that foreign interest rates do not respond contemporaneously to U.S. monetary policy shocks vanishes when even a slight response of foreign rates is allowed. On the other hand, the assumption that monetary policy shocks generate large deviations from uncovered interest rate parity is not sensitive to loosening the recursive structure.

The approach of Faust and Rogers can show which answers are sensitive to allowing simultaneity among financial market variables. When sensitivity is found, additional identifying information is needed to sharpen our inferences.

In this paper, we bring high frequency financial market data to bear in identifying the monetary policy shock following the approach of Faust, Swanson, and Wright (2002). The approach begins with calculating the change in the exchange rates, interest rates, and interest rate futures in a narrow window around announced Federal Open Market Committee (FOMC) policy moves. We assume that these high-frequency changes are driven by the unexpected component of the FOMC decision and give a measure of the impulse response of these variables to the policy shock. We then impose that the impulse responses of the exchange rate and U.S. and foreign short-term interest rates in a standard open-economy VAR match the responses we have estimated from the high frequency financial market data.

Our key results are these:

1. Most of the impulse responses of the system to U.S. policy shocks under the new identification are consistent with those from the recursive identification. However, the effect of the U.S. policy shock on foreign output and interest rates lasts longer than with the recursive identification. There is a price puzzle in the recursive identification, is avoided with the new identification. For Germany, we formally reject the recursive identification, but not for the UK.

2. The peak timing of the exchange rate response is imprecisely estimated as in Faust and Rogers (2002). Whereas the recursive identification suggests strong evidence of delayed overshooting, the confidence interval for the peak timing in the new identification includes immediate peaks and delay of several years.

3. All the approaches agree that monetary policy shocks generate large UIP deviations. The movements of the exchange rate following U.S. policy shocks do not seem to be driven by UIP.

4. The confidence interval for the variance share of the exchange rate due to the policy shock in the new identification is somewhat larger than in the recursive identification, but is bounded by about 1/3. This is somewhat tighter than the estimates of Faust and Rogers, reflecting the fact that additional information has been brought to bear.

Section 2 discusses the approach to identification. Section 3 presents our approach and results from the high frequency data exercise.. Section 4 contains the VAR results. Section 5 contains some tests of our identifying assumptions, and Section 6 concludes.

2. Identification

2.1 *The simplest case*

Consider the reduced form VAR,

$$A(L)Y_t = u_t \tag{1}$$

where Y_t is $G \times 1$, $A(L) = \Sigma_{j=0}^{\infty} A_j L^j$ and $A_0 = I$. Following the literature we assume that $A(L)$ is invertible so that the system can be written as,

$$Y_t = B(L)u_t \tag{2}$$

where $B(L) = A(L)^{-1}$.

The identified VAR literature makes the assumption that the G reduced form errors u_t are related to structural errors by the relation: $u_t = S\varepsilon_t$, where S is full rank. One of the structural shocks is assumed to be the monetary policy shock of interest. We can order things such that this is the first structural shock. The VAR can be written in terms of the structural shocks as,

$$Y_t = B(L)S\varepsilon_t \tag{3}$$

Call the first column of S, α; this is the column corresponding to the policy shock.

The impulse response of all variables in the VAR to the policy shock is,

$$B(L)\alpha = \sum_{j=0}^{\infty} B_j \alpha L^j$$

This is a $G \times 1$ vector of lag polynomials and the coefficients of the g^{th} element trace out the response of the g^{th} variable to the policy shock.

The Bs are given by the reduced form estimates and so identifying the impulse response requires picking the G elements of α. One restriction is a normalization, choosing the sign and units of the policy shock. In most work, one normalizes the standard deviation of the shock to be 1. In our work, the VAR includes the 3-month eurodollar interest rate and we normalize the shock to have a contemporaneous -25 basis point effect on this interest rate.

We complete the identification by requiring that certain impulse responses match values given from the high frequency data. For this section, simply take it as given that we have some restrictions saying that the impulse response of the j^{th} variable to the policy shock at lag h is r_{jh}. This restriction can be written,

$$B_{h:j}\alpha = r_{jh} \tag{4}$$

where $B_{h:j}$ is the j^{th} row of B_h. If we have G such restrictions, we can stack them to form

$$R\alpha = r$$

Clearly, if R and r are taken as known and R is full rank, α is uniquely identified as $R^{-1}r$.

2.2 *Factors complicating inference*

In the above discussion, we treated R and r as known. In practice R will be implied by the reduced form estimates of the VAR and r will be estimated from the futures market data. We must take account of uncertainty in each when doing our inference. More problematically, the identification rests on the rank condition that the rank of R is G. When we test the rank of our estimated Rs below, we cannot reject rank deficiency. Thus our restrictions $R\alpha = r$ leave the system only partially identified, and we must use methods appropriate for partially identified systems.

We take a classical approach to inference in partially identified systems in contrast to the Bayesian approach in Faust (1998) and Faust and Rogers (2002). One might suppose that failure of the rank condition dooms classical inference. When identifying the slope parameters of simultaneous equations models using linear restrictions, individual parameters are either fully identified or valid confidence intervals for them are unbounded. In the nonlinear case (relevant to objects such as variance shares), a valid confidence interval for a parameter may be bounded even if it is not fully identified.

While failure of the rank condition does not doom inference, we must take proper account of the partial identification. The most striking implication of partial identification is that we must give up on point estimation and only consider confidence intervals. Moreover, the confidence intervals must be constructed in a way that is robust to the failure of the rank condition.

2.3 *Confidence intervals under partial identification*

Suppose we want to learn about some scalar parameter f. This could be the share of the forecast error variance of output at horizon 48 due to the policy shock or the impulse response of prices to the policy shock at some horizon. Calling all the reduced form parameters of the VAR θ, f is a function of θ and α: $f(\theta, \alpha)$.

First, we form a $v_1\%$ confidence set for α by a method that takes account of uncertainty in R and r, and that does not rely on assumptions about the rank of R. The construction of this confidence set follows the work of Stock and Wright (2000) and is discussed in detail in Appendix A1. Call this confidence set A.

First fix θ at the reduced form point estimate $\hat{\theta}$. Under full identification, this would be associated with a unique estimate of f. In the current case, we can find the range of $f(\hat{\theta}, \alpha)$ consistent with α in our confidence set A:

$$[\inf_{\alpha \varepsilon A} f(\hat{\theta}, \alpha), \sup_{\alpha \varepsilon A} f(\hat{\theta}, \alpha)]$$

For any fixed α, the model is just identified, and so we can use a conventional bootstrap to construct a $v_2\%$ confidence interval for $f(\theta, \alpha)$.[2] Let this confidence interval be

[2] Each bootstrap replication holds α fixed but calculates a new θ from the bootstrap sample. The confidence interval then consists of the $\frac{100-v_2}{2}$ and $\frac{100+v_2}{2}$ percentiles of $f(\alpha, \theta)$ over these bootstrap replications. We did 500 replications in each application of the bootstrap.

$[\underline{c}(\alpha), \bar{c}(\alpha)]$. Next form the outer envelope of all of these intervals across all αs in A, as $[\inf_{\alpha \varepsilon A} \underline{c}(\alpha), \sup_{\alpha \varepsilon A} \bar{c}(\alpha)]$. This confidence interval has asymptotic coverage of at least $v_1 + v_2 - 100\%$, from the Bonferroni inequality, because asymptotically (i) the true α is included in A with probability $v_1\%$, and (ii) the bootstrap confidence interval has $v_2\%$ coverage for any fixed α. The technique is conservative in that coverage may asymptotically be higher than $v_1 + v_2 - 100\%$.[3] The resulting confidence interval may be wide, reflecting in part its construction as a conservative confidence interval using the Bonferroni inequality. Henceforth in this paper, we set $v_1 = 95$ and $v_2 = 73$ ensuring that the asymptotic coverage is at least 68%.

In this method it is straightforward to place bounds on the values of impulse responses in order to sharpen the identification. The typical identification imposes that there is a zero contemporaneous effect of the policy shock on prices. Since the price measure typically includes various auction market prices, this restriction is presumably not strictly correct. It is highly plausible, however, that the contemporaneous effect is small. Technically, we can impose that any impulse response fall in a certain region simply by limiting our set A of acceptable αs to those consistent with the restriction. Having done so, the rest of the inference procedure is unaltered.

3. High Frequency Asset Price Data and the impulse response to policy shocks

[3] For example, even when the true α is not in A, the confidence interval may contain the true f.

This section develops the claim, taken as given in the last section, that some impulse responses to a monetary policy shock can be measured from high frequency data on interest rates, interest rate futures and exchange rates.

3.1 *The principle assumptions*

Since February 1994, the FOMC has made a public announcement about its target for the Federal Funds rate, and about the broader stance of United States monetary policy at 2:15pm Eastern time on each of its eight regularly scheduled meeting dates every year. We assume that movements in asset prices from immediately before this announcement to immediately after it represent the effect of the unexpected component of the Fed's decision so that these movements can be attributed to a monetary policy shock. This assumption allows that the monetary policy shock in the monthly VAR will involve information about policy arriving at other times, but we assume that the surprise component of the FOMC-day announcement is part of the shock. That the surprise on FOMC days is part of the shock should be uncontroversial; that asset price movements in a brief window around the announcement are purely due to a policy shock is much more contentious. There are two principle ways this assumption would fail. First, other information could hit the market at the same time. Second, the Fed's announcement could itself contain information about the state of the economy unknown to the public. We present some tests of our assumption in section 5.

Based on this assumption we use data on U.S. and foreign interest rates, interest rate futures at horizons 3 and 6 months, and the exchange rate to estimate 6 impulse response coefficients—that is to estimate 6 r_{jh}s in (4). Remember that we normalize the size of the policy shock to have a -25 basis point effect in the U.S. short-term interest rate. We estimate the *relative* contemporaneous effects of policy shocks on the foreign short rate by regressing the change in the foreign rate at the time of the announcement on the change in the U.S. rate. The slope coefficient times -25 basis points then gives the contemporaneous response of the foreign rate—the $r_{0.}$ for the foreign rate. We estimate the contemporaneous effect on the exchange rate in an analogous manner.

Next we estimate the relative impulse response of interest rates at 3 and 6 month horizons using futures market data. Familiar reasoning states that the futures rate is the expected future spot rate plus a risk premium. We assume that the risk premium does not change in a narrow window around the time of the FOMC announcement so that the change in the futures interest rate can be attributed entirely to a change in the expected future spot rate. Under the assumption above, this change can in turn be attributed to the effects of the policy shock. Obviously, the assumption of constant risk premia at the time of policy shocks is a strong one. We test this assumption in section 5. Under this assumption, we can estimate the impulse response to the policy shock of the home and foreign interest rate at 3 and 6 lags using the change in the relevant futures rate in regressions analogous to those above. We now provide some details on this procedure and results.

3.2 *Asset price data*

Conceptually, we would like to have data on all of the asset prices in a very small window around the time of the FOMC announcement. We have observations at 5 minute intervals for the for sterling and the mark/euro exchange rates obtained from Olsen Associates. We measure the change around the FOMC announcement from 2:00pm and 2:30pm. The data on spot and future interest rates are observed at the daily frequency, so we are forced to use the change in daily quotes. Since these quotes are taken at different times for different assets, the main issue is whether we want the close from the day before to the day of the announcement or the change from the day of to the day after. We measure U.S., U.K and German interest rates using the spot 3-month eurodollar, spot 3-month sterling Libor and spot 3-month Fibor/Euribor deposit rates respectively (mark and euro rates are spliced). These rates are directly comparable to each other, the associated assets are very actively traded by international market participants, and there are very well developed futures markets corresponding to each. We measure expected future interest rates 3-months ahead and 6-months ahead using these eurodollar, Libor and Fibor/Euribor futures contracts that trade in Chicago, London and Frankfurt, respectively[4].

Our Eurodollar spot rate is the British Banker's Association trimmed mean of market quotes at 11am London time each day, well before the FOMC announcement. Libor and Fibor/Euribor interest rate futures prices are closing prices in London and Frankfurt, and

[4] These contracts all settle based on the spot eurodollar, Libor or Fibor/Euribor interest rate on the last day of the contract. Liquid contracts exist settling in March, June, September and December of each year. We use linear interpolation to compute the implied 3 and 6 month ahead forecast interest rates.

these markets close before the FOMC announcement. Thus, for all these series we take the change from the day of to the day after the announcement. The eurodollar futures prices are taken at the close of the Chicago Mercantile Exchange which is after the FOMC announcement. Thus, in this case, we use the change from the day before to the day of the announcement.

3.3 Estimating the structural impulse responses

We ran the regression of the change in the interest rates futures, the foreign spot interest rate and the exchange rate on the change in the U.S. spot interest rate for all of the 62 FOMC meetings from February 1994 to October 2001, inclusive. Before this period, the FOMC did not make a public announcement following each meeting. Clearly, for our analysis, it is essential that we know the exact time at which market participants became aware of the Fed's decision. We also exclude five intermeeting moves made by the FOMC over this period, as these intermeeting moves were made under unusual circumstances and may have reflected inside information.

The results of the regression, using the U.K. and Germany as the foreign countries are reported in Table 1. The coefficients on the 3-month and 6-month ahead U.S. interest rates are positive and highly significant. The coefficient on the foreign spot interest rate is positive and significant, in contradiction of the assumption in the recursive ordering that the U.S. monetary policy shock has no contemporaneous effect on foreign interest rates. The coefficients on 3-month and 6-month ahead interest rates are positive, and are significant for Germany but not the U.K.. The coefficient on the exchange rate is negative (a surprise loosening of monetary policy depreciates the dollar), and the coefficient is significant for the U.K. but not for Germany.

The magnitudes of the coefficients are, in our view, quite reasonable. Remember that the coefficient should be interpreted as the impulse response of the variable relative to the impulse response of the U.S. short-term interest rate. The effect on U.S. rates decays slightly over the 6 month horizon, but is nearly constant. The effect on the U.K. and German interest rates, begins at about 20 percent of the effect on the U.S. rate and grows slightly. The dollar exchange rate depreciates by about 20 basis points against the pound and the mark/euro in response to a 25 basis point loosening of U.S. policy.

The identification procedure takes these point estimates (scaled by -25 basis points) as the r_{jh}s in (4). We take account of uncertainty in these estimates using the conventional variance-covariance matrix of the estimates viewing the 6 regressions as a system.[5]

4. Results on the identified VAR

In this section we apply the methodology to a benchmark 7-variable VAR of Eichenbaum and Evans (1995). Our dataset consists of monthly observations from January 1974 through October 2001. The variables are domestic and foreign output (y and y^*) measured as industrial production, U.S. prices (p) measured as the CPI, the three-month U.S. and foreign

[5] We assume there is not covariance between these estimates and the estimated VAR coeficients discussed in the next section. This assumption strikes us as reasonable.

interest rates (i and i^*) described above, the ratio of nonborrowed reserves to total reserves in the U.S. ($nbrx$) and the exchange rate (s) measured as the dollar price of foreign currency. The two foreign countries are the United Kingdom and Germany. The details of the data sources are in the data appendix. All of the variables, except the i and i^* are in logs, and the VAR includes 6 lags and a constant.

Eichenbaum and Evans (EE) estimate a recursive VAR with the data ordered as y, p, y^*, i^*, $nbrx$, i, s, calling the shock in the NBRX equation the monetary policy shock. Figures 1 and 2 show the estimated impulse responses and 68% bootstrap confidence intervals for the recursive identification, for both countries. The results are generally reasonable by the standards of the literature and generally consistent with what EE find using slightly different data and a sample ending in May 1990. The surprise 25 basis point loosening of U.S. policy persists for about 6 months and then decays rapidly. The UK interest rate falls about half as much but is more persistent. Home output rises gradually to a peak effect of nearly a percentage point after two years and then decays. Foreign output follows a similar pattern, but at about half the magnitude. There is a "price puzzle" in that the home price level initially rises significantly following a monetary policy loosening. The exchange rate response is quite different from that in EE, however. It initially rises and then has a second mode at a horizon of about 3 years. The German results show roughly the same pattern.

We are particularly interested in three questions concerning the exchange rate response: i) What is the timing of the peak exchange rate effect? ii) What share of the variance of exchange rates is due to monetary policy shocks? (iii) Is the response to policy shocks consistent with uncovered interest rate parity (UIP)? These questions can all be motivated by Dornbusch's classic work on overshooting (1976). This model was designed to help explain the high volatility of exchange rates relative to macroeconomic fundamentals. In Dornbusch-style overshooting, the peak exchange rate effect should come contemporaneously with the shock, and the dynamics of the exchange rate are consistent with UIP.

With regard to the question of UIP, we know that UIP does not hold unconditionally in the data. The deviation from UIP is interpreted as a time varying risk premium and called the forward premium bias puzzle (see, e.g., Engel 1996). It remains conceptually possible, however, that UIP holds conditionally in response to money shocks. In this case, the monetary policy shock does not drive variance of the risk premium or equivalently, monetary policy shocks do not contribute to the forward premium bias. Most prior work finds that conditional UIP does not hold.[6]

To assess this issue we calculate the implied root mean square UIP deviation (UIPD) over 48 months following the money shock. The expected UIPD deviation at $t+h$ of a shock at t is given by,[7]

$$c(i,l) - c(i^*,l) - 400[c(s,l+3) - c(s,l)].$$

[6]Eichenbaum and Evans (1995), Cushman and Zha (1997) and Kim and Roubini (2000) report that policy shocks generate deviations from UIP that are several times larger than the generated interest rate differential. Cushman and Zha note that the pointwise coverage intervals on the the UIP deviations cover zero, but do not report a joint statistic on the statistical significance of the UIP deviations.

[7]This is annualized, presumes monthly data, and three-month interest rates in annual percentage rate units.

where $c(x, l)$ is the response of variable x at lag l to the policy shock. The RMSE of the UIPD comes from summing the squared deviations over the 48 month horizon, and taking the square root of this object.[8] A large RMSE UIPD implies either large absolute deviations or highly variable deviations, or both.

The top panel of Table 2 shows the estimates and 68% bootstrap confidence intervals for various parameters relevant to answering our 3 questions: (i) the fraction of the variance of exchange rates at horizons 12, 24, 36, 48 and 60 months that are due to the monetary policy shock, (ii) the time of the peak effect of the monetary policy shock on exchange rates and (iii) the RMSE UIPD.

The EE model draws mixed conclusions at best regarding Dornbusch overshooting as an explanation for exchange rate movements. For both countries and all horizons, the confidence interval for the variance share of the exchange rate accounted for by the policy shock is 11 percent or less. The UK shows the peak exchange rate effect occurring more than two years after the shock; the German peak is much earlier, but a second peak of similar magnitude occurs more than two years after the shock. Finally, for both countries the RMSE UIPD is quite large.

4.1 *Identifying the VAR using the futures market information*

Remember that we can view the identification problem as choosing a vector α and that the 7

[8] Some tricky timing and definition questions arise. We use monthly average data for exchange rates and interest rates. If the identification is correct, then the calculated UIP deviations should be interpreted as the expected path of the monthly-average UIP deviation in response to a money shock.

elements of α give the impact effect of the policy shock on the 7 variables in the VAR. The element of α corresponding to the domestic interest rate is normalized to -0.25 (a surprise 25 basis point easing). We bound the parameter space for α such that (i) the elements corresponding to p, y and y^* are between 0 and 0.05, (ii) the element corresponding to i^* is between -0.25 and 0, (iii) the element corresponding to $nbrx$ is between 0 and 0.25 and (iv) the element corresponding to s is between 0 and 2.5. We therefore require that a surprise loosening of monetary policy cannot lower output (foreign or domestic), prices, or NBRX contemporaneously, that it cannot cause the dollar to appreciate contemporaneously and that it cannot cause foreign interest rates to rise, contemporaneously. Such assumptions are commonly applied either formally or informally in the literature (e.g., Faust (1998)). We also set fairly weak bounds on the magnitude of these contemporaneous effects. We think larger contemporaneous effects are implausible. Recursive identifications make the stronger restriction that there is no contemporaneous effect on variables such as output and prices that are higher in the ordering.

While we view these restrictions as quite reasonable, others may disagree. One of the nice features of this approach is that any restrictions that are viewed as implausible may be loosened as much as one like: the cost of removing restrictions is simply wider confidence intervals. We discuss some modifications of this variety below.

We use the results from Table 1 to obtain an estimate of r with an associated variance-covariance matrix. If the matrix R were of rank 7, then α would be just identified. We test hypotheses about the rank of the matrix R using the method described in Appendix A2. We know that the matrix R has rank of at least 3, since one restriction normalizes the monetary policy shock to lower interest rates by 25 basis points and the contemporaneous effect of the monetary policy shocks on exchange rates and foreign interest rates are also imposed. For both countries, the hypotheses that R has rank 3 or 4 are clearly rejected (Table 3). The hypotheses that it has rank 5 or 6 are not rejected. Thus α is not fully identified, and this partial identification means that we will not have any point estimates and must construct confidence intervals in a non-standard way, as described above and explained in detail in Appendix A1.

Figures 3 and 4 show pointwise confidence intervals on the impulse response of the variables in the system to the monetary policy shock taking simultaneous account of uncertainty in α and the reduced form parameters. These are conservative confidence sets with coverage of at least 68%, asymptotically. Since we effectively have only five identifying restrictions, one might suppose that our confidence intervals will be very wide—under weak identification there will always be certain parameters of the model that are very imprecisely estimated. In practice, our confidence intervals are quite similar (both in width and shape) to those found for the recursive identification.

We have substantially weakened all of the restrictions of the recursive identification, allowing simultaneity among all the variables. We have supplemented the identification with restrictions taken from the high frequency financial market data. While there has been some loss in precision as a result, the precision cost of giving up the recursivity assumption does not appear to be large in this case.

While the general character of the impulse response to the policy shock matches the recursive identification, there are some differences. For example, the effect on output is somewhat delayed and somewhat moderated relative to the recursive identification. The effect of the U.S. policy shock on foreign output and interest rates lasts longer than with the recursive identification. The confidence interval for prices is shifted up so that at no horizon is there a pointwise significant fall in prices following the policy loosening.

The confidence intervals for the variance share of the exchange rate due to the policy shock are considerably wider than those from the recursive identification, going from about 0 to 30 percent (Table 2, bottom panel). While these are wider than those for the recursive identification, they are considerably narrower than those reported by Faust and Rogers (2002) who drop the strict recursiveness assumption but do not use the financial market data. Thus, while there are other differences among the three approaches, it appears that the very small confidence intervals in the top panel of Table 2 rely on the strict recursiveness assumption. Dropping that as in Faust and Rogers leads to the possibility that policy shocks are the main source of exchange rate variation. Adding the restrictions implied by the financial market data, reduce the maximal share to under one-third.

Consistent with Faust and Rogers, we find that the peak timing is not tightly identified. Our confidence interval goes from an immediate peak to a peak at a horizon over 5 years.

Thus, the delayed overshooting found in EE seems to rely on the strict recursiveness. For those who find strict recursiveness implausible, further information will have to be brought to bear to further reduce our uncertainty on this point.

The recursive identification, Faust-Rogers approach and the new approach in this paper concur that UIP deviations following money shocks are quite large. The new identification actually narrows the confidence interval some relative to the recursive identification.

Recently, there has been some interest in the possibility that monetary policy loosenings represent cost-shocks that could boost aggregate supply and lower prices in the short-run (see, for example, Christiano and Eichenbaum (1992), Christiano, Eichenbaum and Evans (1997) and Barth and Ramey (2000)). In addition, it would be possible to argue that a monetary policy loosening could cause the dollar to appreciate. In order to allow for these possibilities we also considered relaxing these requirements to instead specify that the element of α corresponding to p is between -0.05 and 0.05 and the element corresponding to s is between -2.5 and 2.5. The results are very similar and our key conclusions emphasized above are not altered by this modification.[9]

4.2 *Testing the validity of the recursive identification*

Our method drops many strong restrictions implied by the recursive identification. The benefit is that we do not have to be concerned about robustness of our results to minor changes

[9] We have also re-run the original exercise but limiting the VAR estimation sample to begin in 1984:02. Once again the results are quite similar.

and plausible changes in assumptions such as allowing small simultaneous interactions where recursion imposes no response. The cost is that confidence intervals for some items are quite wide. Thus, it is worth checking whether the recursive identification can be maintained in the face of the information from financial markets.

The α implied by the Eichenbaum and Evans (1995) recursive identification is simply the fifth column of the Cholesky factor of the covariance matrix of the reduced form errors, using this ordering of the variables (in which $nbrx$ comes fifth). For the UK this choice of α is included in the confidence set A, but for Germany it is not. In other words, the recursive identification is rejected by our identification for Germany but not the UK (p-values 0.42 and 0.00 for the UK and Germany, respectively).[10] One factor contributing to this rejection is our finding that the foreign interest rate responds significantly to surprise FOMC moves within the month whereas the recursive identification implausibly restricts this effect to zero.

5. Support for the identifying assumptions

Our approach to identification relies on the following principle assumptions.

1. The futures market provides an efficient forecast of the change in the trajectory of the underlying interest rate, or at least risk premia in the futures market do not change on the day of our policy announcements.

[10] These are the p-values for the test of $R\alpha = r$ used in constructing our set A as described above. In this test, we are taking the α implied by the recursive identification as fixed.

2. Our changes in the exchange rate, interest rates and futures rates around the policy announcement are due to the policy shock we wish to analyze. No other news moves the market at these times and the policy announcement itself does not reveal information about other shocks.

We take up these assumptions in this section.

5.1 *Does Futures Market Provide Efficient Forecasts?*

Eurodollar, libor and euromark/euribor futures all settle in the middle of March, June, September and December. We assess the efficiency of the interest rate forecasts from each of these markets as predictors of the actual interest rate on the settlement day[11] 1 or 2 quarters later by the standard forecast rationality regression. Specifically, we regress the forecast error on a constant and the forecast interest rate If there is no time varying term premium, then the slope coefficient should not be significantly different from 0. The results are reported in Table 4. In all cases the hypothesis that the slope coefficient is 0 is not rejected, so that we can think of the term premia in interest rate futures as being time invariant.

Interestingly, if we redo this exercise using the forecast of interest rates from the futures market 4 or 8 quarters ahead, then the slope coefficient is significantly below 0. This indicates that the term premia vary over time, and may therefore be affected by a monetary policy shock. This, combined with the lower liquidity on longer dated contracts, are the reasons why we do not use future interest rates more than 6 months ahead.

[11] This is implied by the settlement price of the contract.

5.2 *Is FOMC day surprise strictly due to a monetary policy shock?*

There are two ways that this assumption could fail. The simplest way is that other important information could hit the market on the day of announced target changes. Second, the Fed's decision on FOMC day could reveal private information of the Fed about the state of the economy.

We checked whether any of important pieces of macro data were announced on the day of FOMC meetings. We find that on the 62 FOMC days in our sample, durable goods and GDP were released once each, PPI was released twice, industrial production was released three times and CPI was released 5 times. There were no FOMC meeting days in our sample on which retail sales were released. The clear majority of FOMC days are not also days of important macroeconomic data releases.

Federal Reserve might, however, have an information advantage through earlier access to data (especially data that are produced by the Federal Reserve, such as industrial production) or through superior economic analysis provided by the Fed's staff economists. In short, the Fed announcement itself might effectively release macroeconomic data.

We conducted a test of this view, the intuition for which is as follows. We form a measure of the surprise component of macroeconomic data announcements based on survey measures of expectations. We collect those instances where the survey is taken just before an FOMC meeting and the data come out just afterward. If the interest rate surprise effectively *releases* macro data, then the interest rate surprise should be correlated with the macro announcement surprise. In this case, the interest rate surprise can be used by the market to update its expectation of the macro announcement.

The details of our test are as follows. For each FOMC meeting we regress the difference between the next monthly release of a macroeconomic indicator and its pre-FOMC forecast value on (i) a constant, (ii) the Eurodollar interest rate rate surprise on the day of the FOMC meeting and (iii) the pre-FOMC forecast for that macroeconomic release. The pre-FOMC forecasts for the macroeconomic releases refer to the forecasts made by Wrightson Associates on the Friday before the FOMC meeting. We test the hypothesis that the coefficient on the interest rate rate surprise is equal to zero. We consider the following macroeconomic indicators: nonfarm payrolls, CPI, industrial production, retail sales, real GDP and the GDP deflator.[12] In the regression corresponding to each macroeconomic indicator, we omit any FOMC meeting that occurs after the date of the release of that macroeconomic indicator for that month. Because each macroeconomic release refers to the previous month, the interest rate surprise can have predictive power for the macroeconomic release only through the Federal Reserve having an information advantage, and not through any contemporaneous effects of the interest rate rate surprise. Applying this test, we find that the estimated coefficient on the interest rate surprise is not significantly different from zero for any macroeconomic indicator (Table 5).[13]

[12] Note that there is a GDP release every month, although this data is quarterly. The first month of every quarter, there is the first release of GDP for the previous quarter while a revision, referring to this same quarter, is then released in each of the next two months.

[13] In a related paper, Faust, Swanson, and Wright (2002), do this same test on a slightly longer sample

6. Conclusions

Structural inference about the effects of monetary policy shocks on exchange rates suffers from the normal problems in identifying structural models and more. In the open economy context one must sort out the simultaneous interaction of at least 3 financial market variables: home and foreign interest rates and the exchange rate. No recursive relation among these variables is very plausible. Nonetheless, various recursive identifications have been proposed and generally plausible answers have emerged from this work.

In this paper, we bring high frequency financial market information to bear in identifying the reaction of financial market variables to a policy shock. Essentially, we require that the impulse response of the VAR match the high frequency response of financial market variables around the time of FOMC announcements. Using this new approach, we find support for the general characteristics of the impulse response of the system to policy shocks.

We find this quite reassuring. We drop all recursiveness assumptions and use instead very different restrictions coming from financial market data. The basic pattern of most of the responses is little changed in the face of large changes in the approach to identification. However, the effect of the U.S. policy shock on foreign output and interest rates lasts longer than with the recursive identification. There is a price puzzle in the recursive identification, is avoided with the new identification. With specific regard to the exchange rate response, our

using the interest rate surprise measured from the Federal Funds futures market. The results are very similar, except that the Fed annoucement is correlated with the surprise in the industrial production data announcement at the 5 percent level. This weak evidence interesting in part because the Fed produces these data and may be most likely to have special knowledge in this area.

results are between those of Eichenbaum and Evans (1995) and Faust and Rogers (2002). We find that the peak timing of the exchange rate effect is quite imprecisely estimated: it may come nearly immediately as in Dornbusch overshooting or come several years later. The estimated variance share of exchange rate movements due to the policy shock—bounded at about 1/3—is between the Eichenbaum-Evans and Faust-Rogers estimates. Like both previous studies, we find added support for the view that policy shocks generate large UIP deviations.

Appendix

A1 *Testing the rank of* R

We wish to test the hypothesis that $\rho(R) = L$ against the alternative that $\rho(R) > L$, where $\rho(.)$ denotes the rank of the argument. Assume that $T^{1/2}(\hat{\theta} - \theta) \rightarrow_d N(0, V_\theta)$. See Hamilton (1994) for primitive conditions for this convergence results and $\hat{V}_\theta$, a consistent estimator of V_θ. The matrix R is a nonlinear function of θ and can be estimated by $\hat{R}$, where this denotes this same nonlinear function of $\hat{\theta}$. By the delta method, $T^{1/2}(vec(\hat{R}) - vec(R)) \rightarrow_d N(0, V_R)$ where $V_R = \frac{dvec(R)'}{d\theta} V_\theta \frac{dvec(R)}{d\theta}$.

To test the hypothesis about that rank of R, we use the test statistic

$$T \min_{P \varepsilon \pi(L)} (vec(\hat{R}) - vec(P))' \hat{V}_R^{-1} (vec(\hat{R}) - vec(P))$$

where $\hat{V}_R$ is $\frac{dvec(\hat{R})'}{d\theta}\hat{V}_\theta\frac{dvec(\hat{R})}{d\theta}$ and $\pi(L)$ is the space of all conformable matrices of rank L. By Theorem 1 of Cragg and Donald (1997), under the null hypothesis, this test statistic has a χ^2 null limiting distribution.

A2 *Partial Identification*

Here we describe how to construct the confidence set A for the vector α when the restrictions $R\alpha = r$ must be satisfied, R is estimated by $\hat{R}$, r is estimated by $\hat{r}$, R may be rank deficient, $T^{1/2}(vec(\hat{R}) - vec(R)) \rightarrow_d N(0, V_R)$ and $T^{1/2}(\hat{r} - r) \rightarrow_d N(0, V_r)$. Consider the GMM objective function

$$S(\alpha) = T(\hat{R}\alpha - r)'[(\alpha \otimes I_K)\hat{V}_R(\alpha' \otimes I_K) + \hat{V}_r]^{-1}(\hat{R}\alpha - r).$$

In standard GMM terminology, this is the continuous updating GMM objective function. The estimator $\hat{\alpha}$ that minimizes this objective function is not consistent for the true α because of the rank deficiency of the matrix R. However $S(\alpha_0)$ has a χ^2 null distribution regardless of the rank of R where α_0 denotes the true value of the vector α. Accordingly, the confidence set

$$A = \{\alpha \varepsilon A^+ : S(\alpha) \leq F_{\chi^2}\}$$

is a confidence set for α with asymptotic coverage 95%, regardless of the rank of R, where F_{χ^2} denotes the 95th percentile of a χ^2 distribution (degrees of freedom equal to the number of elements in r). This confidence set is therefore immune to the rank deficiency of R.

The use of such confidence sets in models that are not fully identified was proposed by Stock and Wright (2000), where they are referred to as S-sets. If the matrix R is rank deficient, then there exists a subspace of vectors α that are observationally equivalent to α_0. Any vector in this subspace must be included in A with probability 95%, asymptotically. Any other vector α will be excluded from A with probability 1, asymptotically. This is a correct statement of what we do and do not know about α, when R is rank deficient. More formally, the confidence set A is unbounded with probability 0.95, asymptotically: this must be the case for any confidence set for an unidentified parameter if the confidence set is to have 95% asymptotic coverage uniformly in the parameter space (Dufour (1997)). Notwithstanding the fact that our confidence set for α is unbounded, the confidence interval for a nonlinear function of α and θ, such as a variance share, does not necessarily have to be unbounded.

A3 *Data*

High frequency data. The spot and futures interest rate data were acquired from Datastream and CBOT and consist of daily closing prices, as described in the text. The exchange rate data consist of 2pm and 2:30pm Eastern Time quotes (midpoint of bid and ask) obtained from Olsen and Associates.

VAR data. The data were acquired from the Federal Reserve Board's database. All series are expressed in natural logarithms except interest rates, which are expressed in percentage points. The series definitions and as follows:

y (y^*) = index of U.S. (foreign) industrial production - total, 1992 base;

p = U.S. CPI - all urban, all items;

nbr = non-borrowed reserves plus extended credit, seasonally adjusted, monthly average;

tr = total reserves, seasonally adjusted, monthly average;

$nbrx = nbr/tr$;

s = spot exchange rate; monthly average; US$/foreign currency;

i, i^*=monthly average 90 day interest rate.

References

Barth, M.J. and V.A. Ramey (2000): The Cost Channel of Monetary Transmission, working paper, UC San Diego.

Christiano, L.J, and M. Eichenbaum (1992): Liquidity Effects and the Monetary Transmission Mechanism, *American Economic Review*, 82, pp.346-353.

Chrisitano, L.J., M. Eichenbaum and C. Evans (1997): Sticky Price and Limited Participation Models of Money: A Comparison, *European Economic Review*, 41, pp.1201-1249.

Cragg, J.G. and S.G. Donald (1997): Inferring the Rank of a Matrix, *Journal of Econometrics*, 76, pp.223-250.

Cushman, D., and T. Zha (1997): "Identifying monetary policy in a small open economy under flexible exchange rates," *Journal of Monetary Economics*, 39, 433–448.

Dornbusch, R. (1976): "Expectations and Exchange Dynamics," *Journal of Political Economy* 84, 1161-1176.

Dufour, J.M. (1997): Some Impossibility Theorems in Econometrics with Applications to Structural and Dynamic Models, *Econometrica*, 65, pp.1365-1387.

Eichenbaum, M. and C.L. Evans (1995): Some Empirical Evidence on the Effects of Shocks to Monetary Policy on Exchange Rates, *Quarterly Journal of Economics*, 110, pp.975-1010.

Engel, C. (1996) "The Forward Discount Anomaly and the Risk Premium: A Survey of Recent Evidence," *Journal of Empirical Finance.*

Faust, J. (1998): The Robustness of Identified VAR Conclusions about Money, *Carnegie-Rochester Series on Public Policy*, 49, pp.207-244.

Faust, J. and J.H. Rogers (2002): Monetary Policy's Role in Exchange Rate Behavior, *Journal of Monetary Economics*, forthcoming.

Faust, J., E. Swanson and J.H. Wright (2002): Identifying VARs Based on High Frequency Futures Data, International Finance Discussion Paper 720, Federal Reserve Board of Governors, Washington.

Hamilton, J.D. (1994): Time Series Analysis, Princeton University Press, Princeton.

Kim, S. (2001): International transmission of U.S. monetary policy shocks: evidence from VARs, *Journal of Monetary Economics*, forthcoming.

Kim, S., and N. Roubini (2000): Exchange Rate Anomalies in the Industrial Countries: a Solution with a Structural VAR Approach, *Journal of Monetary Economics*, 45, 561–586.

Krueger, J.T. and K.N. Kuttner (1996): The Fed Funds Futures Rate as a Predictor of Federal Reserve Policy, *Journal of Futures Markets*, 16, pp.865-879.

Kuttner, K.N. (2001): Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market, *Journal of Monetary Economics*, 47, pp. 523-44.

Leeper, E.M., C.A. Sims and T. Zha (1996): What Does Monetary Policy Do?, *Brookings Papers on Economic Activity*, pp.1-63.

Sims, C.A. (1980): Macroeconomics and Reality, *Econometrica*, 48, pp.1-48.

Stock, J.H. and J.H. Wright (2000): GMM with Weak Identification, *Econometrica*, 68, pp.1055-1096.

Uhlig, H. (1997): What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure, Center for Economic Policy Research Discussion Paper, London.

Table 1: Measures of the impulse response to a policy shock

		UK VAR		*German VAR*	
variable	horizon	rel. response	Std. err.	rel. response	Std. err.
i	3	0.842	0.130	0.842	0.130
	6	0.940	0.143	0.940	0.143
i^*	0	0.137	0.091	0.271	0.093
	3	0.206	0.162	0.303	0.091
	6	0.246	0.179	0.421	0.101
s	0	-0.847	0.309	-0.784	0.401

Notes: The results are for a least squares regression of the change in the spot/future interest rate or exchange rate on the change in the spot eurodollar rate, with no intercept, around the FOMC meeting. There are 62 observations; the standard errors are conventional OLS standard errors.

Table 2: Summary of the response of the exchange rate to the monetary policy shock

	variance share at horizon													
	12		24		36		48		60		Peak time		UIPD	
	Recursive Identification													
UK pt. est.	0.01		0.01		0.01		0.02		0.02		1		0.45	
UK CI	0.01	0.05	0.01	0.06	0.02	0.09	0.02	0.11	0.02	0.11	30	34	0.47	0.98
Germany pt. est.	0.01		0.01		0.00		0.01		0.01		1		0.47	
Germany CI	0.01	0.05	0.01	0.06	0.01	0.07	0.01	0.08	0.01	0.09	1	1	0.47	1.05
	new identification													
UK CI	0.00	0.16	0.01	0.14	0.01	0.13	0.02	0.17	0.02	0.22	0	62	0.38	0.98
Germany CI	0.00	0.21	0.01	0.29	0.01	0.32	0.01	0.31	0.02	0.31	1	67	0.36	0.94

Notes: The confidence intervals are 68 conservative percent bootstrap intervals as discussed in the text. The peak time and variance share horizons are in months. UIPD is the root mean square UIP deviation at horizon 48.

Table 3: Test of the rank of R in $R\alpha = r$, test statistic and (p-value)

Null	UK	Germany
$\rho = 3$	226.62	244.86
	(0.00)	(0.00)
$\rho = 4$	98.45	108.54
	(0.00)	(0.00)
$\rho = 5$	11.48	8.54
	(0.32)	(0.58)
$\rho = 6$	1.40	1.19
	(0.84)	(0.88)

Notes: See Appendix A2 for details on this test.

Table 4: Forecast efficiency tests for interest rate futures

	$\hat{\alpha}$	$\hat{\beta}$
Eurodollar	-0.16	-0.01
1 quarter ahead	(0.52)	(0.90)
Eurodollar	0.00	-0.08
2 quarters ahead	(1.00)	(0.51)
Sterling LIBOR	-0.08	0.00
1 quarter ahead	(0.94)	(0.97)
Sterling LIBOR	-0.53	0.04
2 quarters ahead	(0.37)	(0.55)
Euribor	-0.12	0.02
1 quarter ahead	(0.32)	(0.37)
Euribor	-0.40	0.06
2 quarters ahead	(0.14)	(0.19)

Notes: These results refer to the standard efficiency test evaluating the forecast of 1 and 2 quarter ahead spot interest rates implicit in interest rate futures markets. The forecast error is regressed on a constant and the forecast. There are four observations per year, corresponding to the settlement days of the interest rate futures contracts. The p-values associated with coefficient estimates are shown in parentheses. For one-quarter ahead forecasts, conventional OLS standard errors are used. For two-quarter ahead forecasts, Hansen-Hodrick standard errors are used.

Table 5: Tests of the exogeneity of the monetary policy shocks

Macroeconomic Indicator	Intercept	Coefficient on Forecast	Coefficient on FOMC Surprise
Nonfarm Payrolls	-20.70	0.10	-45.68
(mom change, 000s)	(0.71)	(0.72)	(0.93)
CPI	0.039	-0.383	-0.444
(mom change, percent)	(0.55)	(0.09)	(0.43)
Industrial Production	0.0526	-0.075	1.116
(mom change, percent)	(0.54)	(0.80)	(0.42)
Retail Sales	-0.068	0.143	1.671
(mom change, percent)	(0.58)	(0.59)	(0.44)
Real GDP	-0.051	0.032	1.500
(qoq change, ann percent)	(0.75)	(0.42)	(0.61)
GDP Deflator	0.140	-0.090	0.050
(qoq change, ann percent)	(0.20)	(-0.09)	(0.95)

Notes: The test regresses the forecast error in survey forecasts of macroeconomic releases on a constant, the forecast value and the FOMC surprise that came between the construction of the forecast and the data release. The test is described more fully in the text. The sample period is from February 1994 to October 2001. The *p*-values associated with coefficient estimates, using conventional OLS standard errors, are shown in parentheses.

Fig. 1: Recursive Identification Impulse Responses for UK (with 68% bootstrap intervals)

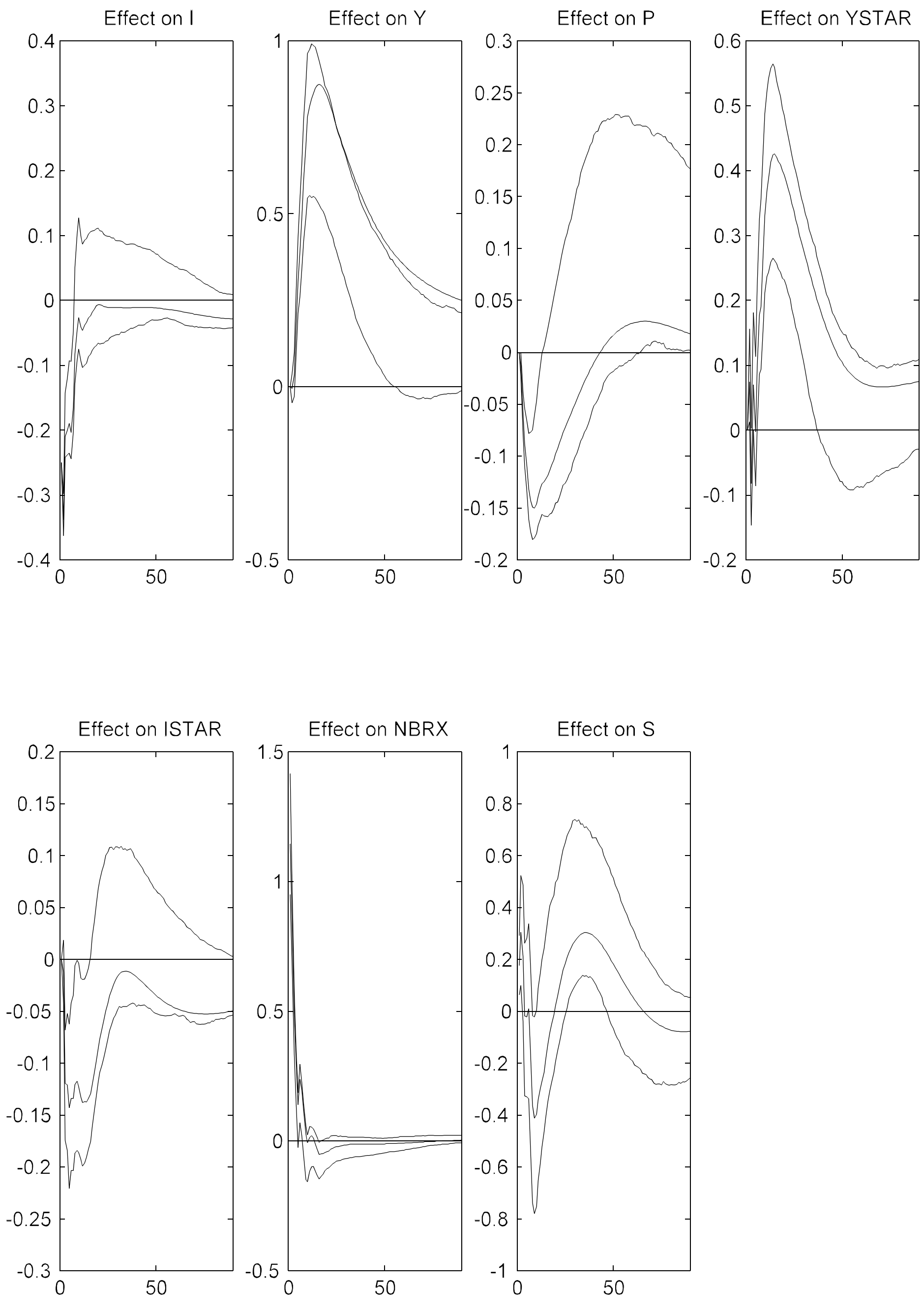

Fig. 2: Recursive Identification Impulse Responses for Germany (with 68% bootstrap intervals)

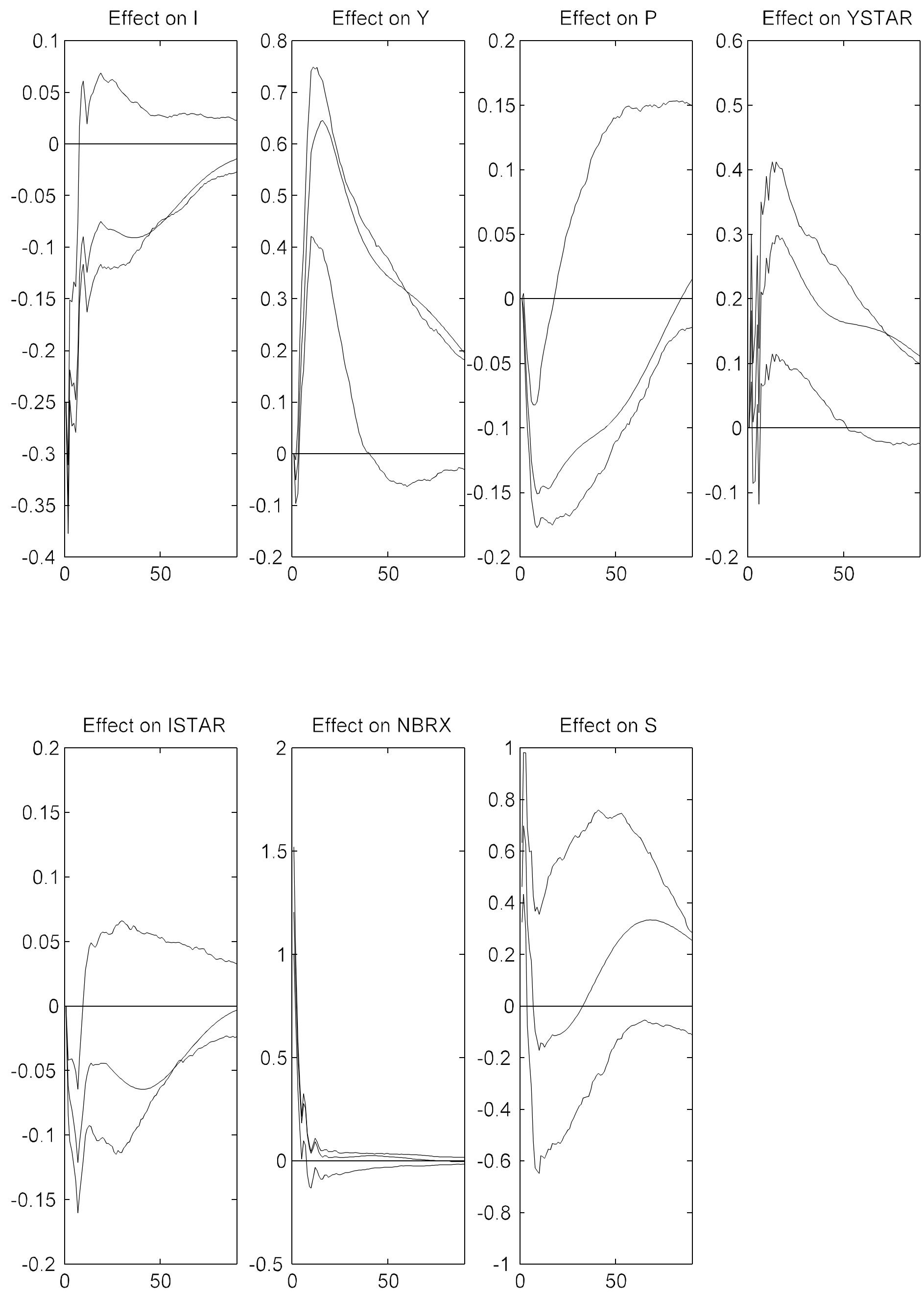

Figure 3: New Identification Confidence Intervals for UK

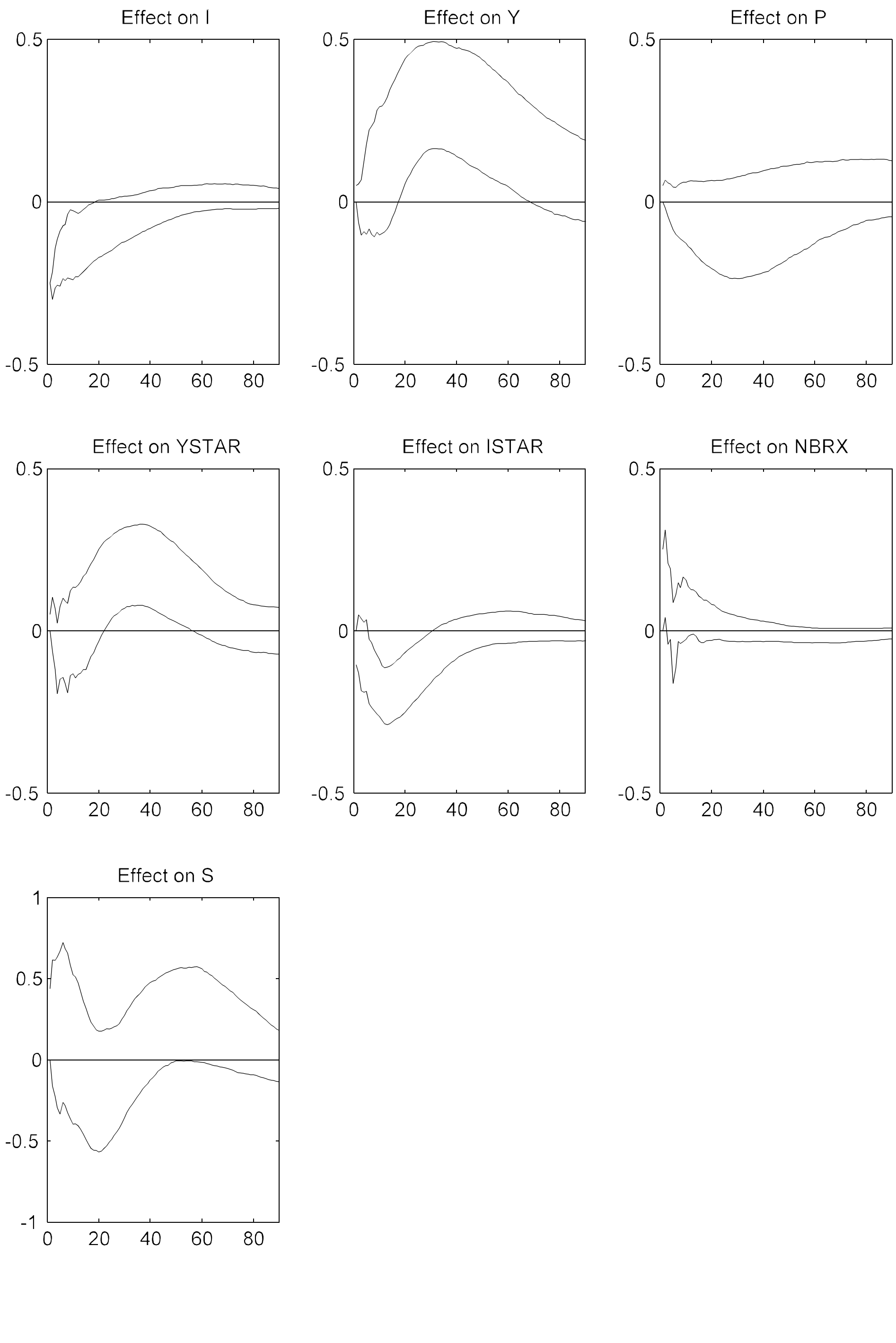

Figure 4: New Identification Confidence Intervals for Germany