Monetary Shock Measurement and Stock Markets

by

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Abstract:

The narrative approach based measurement of monetary shocks suggests infrequent shocks are crucial for understanding the impact of monetary policy shocks on the economy. However, the narrative approach is dependent on costly data collection process, researcher judgment, and is prone to delays due to official document release. We present a stock market based regime switching unobserved components model to estimate the monetary shocks while preserving the key feature of infrequent shocks. Our estimated shocks are large and comparable to Romer and Romer (2004) shocks. The impulse responses in response to our estimated monetary policy shocks suggest that a one percent contractionary shock leads to two percent long term decline in industrial production with a peak effect of 3.5 percent decline and more than one percent long term decline in CPI.


Keywords: Monetary policy; Monetary Shocks; Stock market.

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1. Introduction

Estimation of monetary policy shocks is a crucial issue in understanding the effects of monetary policy on the economy. For our purposes we take the “gold standard” to be the narrative based approach to measuring monetary policy shocks, starting with Romer and Romer (1989) and further developed by Romer and Romer (2004), which relies on Federal Reserve economic forecasts based on official documents. While we regard this work as the gold standard, using narratives relies on expert judgement; thus it may be difficult to implement. Data collection often comes with substantial lags due to timing of release of official documents. In the case of countries with less clear historical evidence, the narrative approach may be infeasible.

The primary contribution of our paper is to offer an econometric method to estimate shocks that matches well with the findings from the narrative approach in Romer and Romer (2004). Central to matching well is the idea that monetary shocks are relatively infrequent. Our econometric model uses a two-step approach. In the first step, we estimate the reduced form residuals from a standard VAR based on stock market data, federal funds rate data and other standard indicators of economy. Novelty lies in our second step, in which we develop a Markov-switching, state-space model that explicitly allows for a “no shock” regime. This allows for monetary shocks to be infrequent, without forcing the “infrequent” property on the data. This second step is similar to the heteroskedasticity based identification proposed by Rigobon (2003) although we estimate the no-shock regimes instead of pre-identifying them. We use a simple bivariate model in the second step although the model can be easily generalized further to use more information.

Our estimated infrequent monetary shocks are large in size and similar to Romer and Romer (2004). The estimates are robust to the use of different VAR lags, shadow federal funds rate in the zero lower bound period, and the possibility of stock market feedback effects to the federal funds rate. The estimated regime probabilities show a long period of no large monetary shocks during the 1990s and early 2000s, supporting the evidence on increasing transparency and information disclosure efforts by the Federal Reserve. The dynamic responses of output to the shocks show large and persistent effects similar in size to the Romer and Romer (2004) study. The price effects show a similarly declining pattern but are smaller in size. The standard VAR based approach to estimating monetary shocks using regularly spaced time series,
as followed by Leeper, Sims and Zha (1996), Bernanke, Gertler and Watson (1997), Bernanke and Mihov (1998), Bernanke, Boivin and Eliasz (2005), finds small effects of monetary policy shocks on output\(^1\). The advantage of this approach is easy availability of the data used, both domestic and international, making it simpler to compare across countries and the ease with which one can integrate additional channels of transmission and modeling features in the analysis.\(^2\) The shocks themselves are estimated to be moderately sized. As a practical matter, the VAR approach estimates shocks from a continuous distribution occurring at whatever frequency is used in the VAR.

Measurement of infrequent monetary shocks has taken two approaches. The first is the Romer and Romer methodology. (See also Monnet (2014) for an interesting example of this approach using historical data from France.) The crucial outcome of this approach is large output effects. Monetary shocks of early 1980s play a major role in this approach. The second approach to measure infrequent monetary shocks is to use the daily or high-frequency federal funds futures data pioneered by Kuttner (2001). A primary appeal of Kuttner’s approach is the use of precisely measured (in real time) financial data that can help in measuring the current monetary shocks. The shocks are estimated to be moderately sized in this approach. However, a limitation of this approach is the availability of futures data that dates back to only late 1980s. This issue makes it impossible to analyze the events of early 1980s using this method.

A brief reminder of the Romer and Romer (2004) procedure may be helpful. The authors employed a two-step procedure. In the first step they identified monetary policy shocks to the federal funds rate as the change in the expected funds rate before and after FOMC meetings by reading the Fed’s Record of Policy Actions of the Federal Open Market Committee, Minutes of the FOMC, and Transcripts of the FOMC. The authors then applied expert judgment to make adjustments to the initial data, in particular in regard to situations where the FOMC signaled a future change without making a current change. After reading the narrative record and applying

\(^1\) The above referenced studies are selective examples chosen to highlight the issue. For a complete reference of other important studies using this approach and the related issues, please refer to Ramey (2016) and Stock and Watson (2016).

\(^2\) Jarocinski (2010) is an example of international comparison of effects of monetary shocks between EU New Member States and other EU members using standard time series data and integrating a hierarchical linear model in a structural VAR.
their best judgement, in their second step Romer and Romer ran their series against Greenbook forecasts to purge the measured shocks of endogeneity with regard to forecast future economic developments. The correlation of Romer and Romer shocks with shocks using Kuttner’s approach with daily data is 0.67 in the limited sample of approximately three years of overlapping data. The correlation of the Romer and Romer shocks with a structural VAR based federal funds shock (our estimation) is 0.39.

Our two-step statistical model recreates the essence of Romer and Romer’s two steps. Romer and Romer first pulled changes in the expected funds rate out of the written record. This gives a series in which monetary shocks are infrequent, since the expected funds rate frequently didn’t change. In our first step we initially identify shocks as the errors in a standard VAR, which gives “shocks” that come from a continuous distribution. Romer and Romer’s second stage filters out the information in Greenbook forecasts. Such a filter can turn first-step zeros into small, continuously distributed final shock estimates. In our second stage, we use an unobserved-components state-space model to filter out endogeneity using the assumption that information about the future is incorporated in stock prices. The state-space model incorporates a discrete, Markov-switching model which allows shocks to be infrequent since the continuous part of the shock estimate is multiplied by a state that takes on the values 0 or 1. Because states are estimated rather than observed, our final shock estimates—like Romer and Romer’s—also have introduced small, continuous values. The question then is whether our approach comes close to identifying the shocks reported by Romer and Romer. The answer is that it does rather well, and particularly does an excellent job of identifying the small number of really large shocks, which are presumably those of particular interest. The remainder of the paper is arranged in the following order: In section 2 we lay out our basic empirical model, data sources and features, and estimation details. In section 3, we discuss the estimated monetary shocks, the shock probabilities, and the cumulative impulse responses of output and price to the estimated monetary shocks. We present multiple model and lag structure sensitivity analyses along with a special restricted model in section 4. We conclude in section 5.

2. The Monetary Shock Estimation Process and the Data

2a. The Monetary Shock Estimation Process
We use a two-step process for estimation of monetary shocks. In the first step, we use a reduced form VAR to extract the estimated residuals. In the next step, we use the reduced form VAR residuals from the stock returns and federal funds rate equations to estimate a regime switching model such that monetary shocks are specified to be occurring infrequently. Let $y_t$ denote our set of variables in the following reduced form VAR:

$$y_t = c + \sum_{i=1}^{k} A_i y_{t-i} + e_t$$  \hspace{1cm} (1)$$

We use a five variable VAR with S&P 500 returns, federal funds rate, industrial production growth, Consumer Price Index inflation rate and the unemployment rate. Beyond the stock market variable, the selection of the other variables follows Coibion (2012) that builds on previous studies such as Leeper, Sims and Zha (1996). Let $e_1$ and $e_2$ denote the estimated reduced form residuals from the S&P 500 (used in the next step to filter for endogeneity) and federal funds rate (the shock of interest) equations respectively.

Extracting the reduced form residuals from the first step, we then specify the following bivariate measurement equation with a regime-switching unobserved components model to estimate the unobserved monetary shocks:

$$e_{1,t} = u_{1,t} + a_{13} * S_t * u_{3,t}$$
$$e_{2,t} = u_{2,t} + S_t * u_{3,t}$$  \hspace{1cm} (2)$$

In the above model the $u$’s are unobserved state variables: $u_1$ is a S&P 500 specific shock, $u_2$ is a federal funds rate specific shock, and $u_3$ is the monetary shock estimated in terms of the federal funds rate and allowed to affect S&P 500 returns. The variables $u_1$, $u_2$, and $u_3$ are assumed to be Gaussian and mutually and serially uncorrelated. The implicit unit coefficient in federal funds shock equation identifies $u_3$ as the monetary shock and $a_{13}$ serves as a scaling factor. The variable $S_t$ is the unobserved, discrete, state variable following the regime switching process specified below:

$$S_t = 0, 1$$
$$P(S_t = 0|S_{t-1} = 0) = p$$
$$P(S_t = 1|S_{t-1} = 1) = q$$  \hspace{1cm} (3)$$

where the transition probability parameters $p$ and $q$ allow for persistent regimes and are estimated in our models.
While we estimate $u_3$ as a shock in each period, all that really matters is $S_t \ast u_{3,t}$. So if $S_t = 1$ is a low probability event, then effectively monetary shocks are relatively infrequent.

The measurement equations (2) can also be written in the compact form:

$$
\begin{bmatrix}
e_{1,t} \\
e_{2,t}
\end{bmatrix} = H S_t \ast u_{3,t} + \begin{bmatrix}
u_{1,t} \\
u_{2,t}
\end{bmatrix}
$$

(4)

The matrix $H$ in equation (4) is specified as

$H_0 = \begin{bmatrix}0 & 0 \\ 0 & 0\end{bmatrix}$ if $S_t = 0$ and $H_1 = \begin{bmatrix}a_{13} & 1 \\ 0 & 1\end{bmatrix}$ if $S_t = 1$. This implies when $S_t = 0$, the unobserved monetary shock common to both stock market residuals and Federal Funds rate residuals is not present, thereby making it the no monetary shock regime.

2b. Data Description and Estimation Details

Monthly data on seasonally adjusted industrial productions, seasonally adjusted consumer price index, seasonally adjusted civilian unemployment rate and effective federal funds rate were obtained from the Federal Reserve Bank of St. Louis’ Fred database. We computed the monthly (annualized) growth rate of real industrial production and the monthly (annualized) inflation rate. Daily S&P 500 data was obtained from Yahoo Finance web site and monthly returns were computed using monthly close prices. To address the issue of zero lower bound of Federal Funds rate from December, 2008, we use the Wu-Xia shadow federal funds rate made available by the authors. Wu and Xia (2016) use a non-linear term structure model to estimate a shadow federal funds rate during the zero lower bound regime. They keep the shadow rate equal to the effective federal funds rate outside the zero lower bound period of January, 2009 to November, 2015. Descriptive statistics of the variables used are reported in Table 1.

Our estimation full sample is from July, 1955 to December, 2016. The starting date is chosen to allow for all estimated models to have the same starting point. The number of lags used in the VAR is five, as selected by AIC. All other information criterion chose shorter lags. We use two ending points as our samples for comparison: one ending in December, 2008 and the other ending in December, 2016. The samples using December, 2016 as the ending date use Wu-Xia shadow rate for the zero lower bound period. The maximum likelihood estimation of the
regime switching models based on equations (2) and (3) were done using the approximate maximum likelihood methods outlined in Kim and Nelson (1999).

3. The Estimation Results and Dynamic Effects on Output and Price

3a. The Estimation Results from the Regime Switching Models

In this section we present two sets of estimation results of monetary shocks. The benchmark model uses a five lag VAR residuals for the sample ending in December 2008. Our second set of results differs from the benchmark model only in that we use the Wu-Xia shadow rates to expand our sample till December, 2016. The estimated parameters from the benchmark model with the Federal Funds rate and the Wu-Xia Funds rate are reported in Table 2. The first column reports the parameter estimates of the benchmark model with the Federal Funds rate. All the parameters are fairly precisely estimated. As expected, the stock market shocks are most volatile. The no shock regime is highly persistent. Interestingly, the stock market reaction to a contractionary monetary shock is estimated to be around negative 1.0 percent; a correct sign but a lower number than the Bernanke and Kuttner (2005) estimates of around five percent.

Figures 1-3 present various estimates of the probability weighted monetary shocks, \( \Pr(S_t = 1) \times u_{3,t} \) as well as the filtered probability that \( u_{3,t} \) affected the market\(^3\). The estimated monetary shocks illustrated in the top panel of Figure 1 use filtered probabilities along with Romer and Romer (2004) monetary shocks for comparison. The estimated monetary shocks illustrated in the bottom panel of Figure 1 use smoothed probabilities. In the common sample, the big events match quite well with Romer and Romer (2004). The difference in the estimates of monetary shocks due to using either filtered or smoothed probabilities is extremely small. We will use only filtered probability based analysis from here onwards. The major contractionary shocks of early 1980s show similar signs. We estimate a 2.6 percent shock in March, 1980 whereas Romer and Romer (2004) report 1.4 percent. In May, 1981 we estimate a shock magnitude of 2.1 percent compared to the Romer and Romer (2005) estimates of 1.5 percent. In

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\(^3\) The alternative to using the filtered estimates of the shocks is to use the smoothed estimates of the shocks. We illustrate our results in the appendix with smoothed shocks. The results are similar. The estimated \( u_{3} \) shocks are also serially uncorrelated as specified in the model.
a very interesting case, we estimate the May, 1980 shock to be negative and large 5.4 percent but Romer and Romer (2004) report it to be only negative 0.78. However, they report the April, 1980 shock to be negative 3.2 percent whereas we do not estimate that as a shock month. In most cases the two shocks are similar with a positive correlation of 0.4 in the Romer and Romer (2004) sample period.

The estimated filtered probabilities of the monetary shock states in the benchmark model are reported in Figure 2. The model picks up the late 1950s shocks discussed in Bordo and Haubrich (2010); a big advantage of our approach is that it enables us to go beyond the sample period covered by Romer and Romer (2004). The big jumps are in early-1960s, mid-1970s, early-1980s. This is followed by a December, 1984 jump that is estimated to be an expansionary 1 percent shock. Romer and Romer (2004) estimate the November, 1984 shock to be expansionary 55 basis points followed by another 14 basis points in December 1984. This is related to the fall in the effective federal funds rate from 9.43 percent in November to 8.38 percent in December. We have no further shock state probabilities that exceed fifty percent in the 1990s and early 2000s.

The parameter estimates from the full sample Wu-Xia Funds rate are in the second column of Table 2. The estimated monetary shocks and the filtered shock probabilities are illustrated in Figure 3. The pattern of the parameter estimates are similar in magnitude to the previous estimates. The no-shock regimes are persistent and the stock market shock is much more volatile than the other shocks. The filtered probabilities are also similar in the pre-2009 sample. There is also a long stretch of no shocks from late 1980s consistent with the ‘great moderation’ phase of the US economy as analyzed by Kim and Nelson (1999), McConnell and Perez-Quiros (2000), and Stock and Watson (2002). Additionally, we offer estimated monetary shocks in the post-2008 period. In January, 2009 the filtered probability of a monetary shock is about 99 percent. Interestingly, it is estimated to be a contractionary shock of one percent, which is consistent with the Wu and Xia (2016) shadow rate estimates. This is right after the beginning of the zero lower bound period but before the quantitative easing events. Wu and Xia (2016) estimate a rise in the shadow federal funds rate in that month to 0.61 percent continuing to February to a peak of 0.87 percent.
Romer and Romer’s estimates of monetary shocks suggest a large number of small shocks and a small number of large shocks. Half the estimated shocks are under 10 basis points (in absolute value). Seven percent of shocks are 50 basis points or more and one-and-a-half percent of shocks are more than 100 basis points. For many purposes, identifying large shocks is of particular interest. The discrete state-switching model we present does an excellent job of identifying large shocks, albeit at the cost of doing little to identify small shocks. For the shocks greater than 100 basis points, the correlation between our estimates and the Romer and Romer estimates is 0.90. For shocks between 50 and 100 basis points, the correlation is 0.24. For shocks between 10 and 50 basis points the correlation is 0.29 and for shocks below 10 basis points the series are essentially uncorrelated, with a correlation of only -0.04.

3b. The Dynamic Effects of Monetary Shocks on Output and Price

We estimate the dynamic response of output and price to the estimated monetary shocks using the same autoregressive distributed lag empirical framework as used by Romer and Romer (2004). Specifically, we use the following model, where $\Omega_t$ indicates the information set available through date $t$:

$$y_{it} = \alpha_i + \sum_{j=1}^{m} \beta_{i,j} y_{i,t-j} + \sum_{k=1}^{n} \theta_{i,k} \hat{u}_{3,t-k} + \varepsilon_{i,t}$$  \hspace{1cm} (5)

where

$$\hat{u}_{3,t} = P(S_t = 1|\Omega_t) * u_{3,t|\Omega_t} + P(S_t = 0|\Omega_t) * 0$$  \hspace{1cm} (6)

We use seasonally adjusted industrial production as our measure of output and seasonally adjusted consumer price index as our measure of price. Beyond the 24 autoregressive lags for both output growth and inflation, we use 36 lags of monetary shocks for the industrial production and 48 lags of monetary shocks for CPI as in Romer and Romer (2004). We do not include seasonal dummies in the estimating equations as our data is already seasonally adjusted. The contemporaneous effects are assumed to be zero in the two equations. The accumulated impulse responses using the two sets of estimated monetary shocks are illustrated in Figures 4 and 5. In the top panel of each graph, we show the response of industrial production and in the bottom panel we show the accumulated impulse response of CPI to one percent shock in federal funds rate.

Note that the estimated responses have the generated regressor issue, as outlined in Pagan (1984), since our monetary shocks are estimated. We use a Monte Carlo based approach to
account for that issue in constructing the confidence intervals. We first draw from a multivariate normal distribution of estimated parameters of the reduced form VAR with their variance covariance matrix. For each draw, we estimate the reduced form shocks, use them in our regime switching procedure to re-estimate a new set of monetary shocks. Additionally, we draw a shock from a zero mean normal distribution with the standard error of the estimated autoregressive distributed lag regression as the standard deviation. We reconstruct the endogenous variable of the autoregressive distributed lag with these two draws together and the estimated parameters with original data. We then re-estimate the autoregressive distributed lag model and construct the impulse responses. We do 1000 replications of this process. The 90 percent confidence intervals of the impulse responses are shown in the two figures as dotted lines.

In Figure 4, we show the responses using the benchmark model monetary shocks. The responses of the industrial production show a slow decline to a peak effect of -3.7 percent after 25 months and then gradually recovering to about -2.0 to -2.3 percent after five years. These numbers are very similar to the Romer and Romer (2004) estimates of -4.3 percent peak effect and -1.7 percent effect after four years. The CPI response show a similar dynamic pattern as Romer and Romer (2004) but the long-term effect is a smaller decline of about 1.8 percent. The results from the full sample Wu-Xia Funds rate monetary shocks are shown in Figure 5. The peak effect is a little lower at -3.4 percent and the five year effect is around -2.2 percent. The long term price responses are around -1.1 percent. The confidence intervals for the output responses are wide but still show mostly negative response, even in the long run. The confidence intervals for the price responses are also wide but mostly includes zeros in the long term response. Overall, we find a similar set of cumulative impulse responses of output and price to our estimated monetary shocks for both samples. The responses are comparable to Romer and Romer (2004) magnitudes and dynamics, especially for output.

4. Model Sensitivity Analyses

In this section, we perform four sets of model sensitivity analyses of our primary results. All of the analyses are chosen to highlight how our model assumptions affect the estimation of

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4 In this study, we use the five year accumulated response as the ‘long-term’ or ‘long-run’ effect.
monetary shocks and its dynamic effects on industrial production and CPI. The first set allows for further generalization of our benchmark model in section 2 to examine potentially restrictive misspecification on estimation of monetary shocks. In the first set we allow for a stock market feedback effect. We also allow for longer VAR lags in this set. In the second set, we restrict the lag structures of the autoregressive distributed lag models. This is to examine the issue of long lag structure in the ARDL equation, as highlighted by Coibion (2012), on the dynamic effects of the shocks. In the third set, we allow for the three additional reduced form shocks as controls in the regime switching estimation step. This is a robustness check for omitted variables. In the fourth set, we restrict the monetary shock state transition probability to zero thereby not allowing it to be persistent. This set highlights a further restriction one can put in on our benchmark model without seriously affecting the outcomes. Overall, the analyses help us to understand how different features of our benchmark model shaped the primary results.

We start out with relaxing the potentially restrictive zero stock market feedback assumption. We now allow for a potential stock market feedback to federal funds rate as stressed in Rigobon and Sack (2003) and Bjornland and Leitemo (2009). However, both studies found this feedback effect to be relatively small. Additionally, in an estimated Markov-switching DSGE model, Hur (2017) also found the feedback effect to be weak and driven by 1990s sample. In our benchmark model, we assume this feedback to be zero. Here we relax this assumption. We use the following bivariate measurement equation with a regime switching unobserved components model to estimate the unobserved monetary shocks:

\[
e_{1,t} = u_{1,t} + a_{13} * S_t * u_{3,t}
\]
\[
e_{2,t} = u_{2,t} + a_{21} * u_{1,t} + S_t * u_{3,t}
\]

The parameter estimates after allowing for stock market feedback effect using the full sample are in the first column of Table 3. We assume and impose a feedback effect of \(a_{21} = 0.01\) on the federal funds rate equation. The number 0.01 is lower than the Rigobon and Sack (2003) and the Bjornland and Leitemo (2009) estimates of 4-5 basis points in response to a one percent rise in stock prices. However, when we tried to estimate a non-negative feedback effect, the maximum likelihood estimate converged to zero; effectively the full sample benchmark model outcome is consistent with Crowder (2006) and Hur (2017) results. The log likelihood in the column reports a lower number than the Table 2 log likelihood for the full sample and can be
rejected at 1 percent level by the likelihood ratio test. The log likelihood substantially worsened when we tried imposing 2 basis points as the feedback effect on $a_{21}$. Most of the other parameter estimates are not sensitive to this issue. The estimated monetary shocks and the filtered shock probabilities are comparable to the full sample benchmark shocks and shock probabilities. In other words, the evidence is against a feedback effect, but the results are robust against an imposed moderately-sized feedback.

We proceed with our second sensitivity check using residuals from a longer lag length 12 lag VAR model using the full sample and the benchmark regime switching model. We denote this model as 12 lag VAR model using equations (2) – (4) for the regime switching framework. The parameter estimates from the 12 lag VAR model are in the last column of Table 3. The pattern of the parameter estimates are similar to the previous estimates although the point estimates of the standard deviation of the shocks are slightly smaller. The estimated monetary shocks and the filtered shock probabilities are extremely similar to the benchmark model.\textsuperscript{5} The impulse responses for both models using the autoregressive distributed lag model in equation (5) are illustrated in Figure 6. The solid lines show the impulse responses using the stock market feedback model and the dashed lines show the impulse responses using the 12 lag VAR model. The industrial productions responses are a little lower for the 12 lag VAR model although both models show the same pattern of responses. The long term price responses range from negative 1.5 to 1.9 percent.

Our next set of sensitivity analyses is driven by the issue of long lags in the autoregressive distributed lag model as highlighted by Coibion (2012) in table 2, panel A of that study. We first use 12 autoregressive lags for both industrial productions and consumer price index equations. We allow for 12 lags of estimated monetary shocks for the industrial productions equation and 39 lags of monetary shocks for the consumer price index equation as specified by Coibion (2012). Additionally, we also use six month shorter lags than our benchmark results in both autoregressive lags and distributed lags. This helps us to understand how the magnitudes and the shapes of the impulse responses change as we go from shorter to longer lags. We use Wu-Xia Funds rate shocks using the full sample. The impulse response

\textsuperscript{5} We report the estimated monetary shocks and the filtered shock probabilities from the stock market feedback model and the 12 lag VAR model in the appendix.
results are in Figure 6. Lines with solid dots show the responses from the shorter lags models and the lines with checks show the responses from the relatively longer lags models. As Coibion (2012) claims, the output effects are smaller for the shorter lags model. The long term output effects are still around -1.9 percent but there is not much difference between the peak effect and the long-term effect. More interestingly, in the longer lags model the peak effect is bigger, -3.7 percent, happens later around 2.5 years, but the response still flattens out after that. The differences in the magnitudes and the shape show how the middle lags (18 – 26) drive the magnitude differences and the late lags (30 – 36) drive the differences between the peak effect and the long term effect in the output responses. The long term price effects are zero to -1.2 percent but the dynamics is similar to our previous results. Overall, the differences in magnitude and shapes of the output effect show how long lag structures are critical for the Romer and Romer (2004) outcomes even in our much longer sample.

Our next two sets of sensitivity analyses examine expansion and restriction of our benchmark regime switching model in equation (2). We start out with the expanded model that allows for controlling the effects of the remaining three reduced form shocks while estimating the monetary shocks. This is effectively ordering the federal funds rate last in a recursively identified structural VAR model as the linear combination of the structural shocks will be represented by the reduced form shocks. Augmenting our regime-switching framework with the three shocks address the issue of potential bias due to omitted contemporaneous effects in estimating the monetary shocks. Additionally, we also allow the three shocks to influence S&P 500 residuals. (Note that data for output, prices and labor markets are released with a lag.) In the specification below $e_3$, $e_4$ and $e_5$ represent reduced form residuals from inflation, industrial production growth and unemployment equations respectively:

$$e_{1,t} = u_{1,t} + a_{13} \cdot S_t \cdot u_{3,t} + \sum_{j=3}^{5} \gamma_j e_{j,t}$$
$$e_{2,t} = u_{2,t} + S_t \cdot u_{3,t} + \sum_{k=3}^{5} \delta_k e_{k,t}$$

(8)

We estimate the extended model twice with our two samples and the parameter estimates are reported in the first and second columns of Table 4. The coefficients in stock market equation are statistically imprecise. While most other effects are small, the unemployment residual does show correct sign in the federal funds rate equation in both samples. In the top panel Figure 7 we show the estimated monetary shocks and the probabilities of the shocks states for the full
The results are similar to our benchmark results. The impulse responses (reported in the appendix), using the lag structure of our primary results in Section 3, show similar outcomes to those reported in Figures 4 and 5. Although this extended model is primarily a robustness analysis, the model and the outcomes highlight how one fit in a partially recursive structure in the model and isolate the potentially important additional information.

Our last set of sensitivity analysis restricts the transition probability $q$ in equation (3) to zero. Setting $P(S_t|S_{t-1}) = 0$ may be thought of as a strong identification restriction of what it means to be a “shock” with an expected duration of one period. This is the model with least number of parameters. We then re-estimate the two step model with our two samples; one ending in December, 2008 with the regular Federal Funds rate and the other ending in 2016 with the Wu-Xia Funds rate. The estimated parameters are reported in the two columns of Table 5. Both columns show larger monetary shocks and higher response of the stock market than our benchmark results. The estimated shocks and the shock probabilities from the full sample are shown in the bottom panel of Figure 7. The shocks are also relatively less frequent when compared to our benchmark model estimates in Figure 3. We estimate the probability of a shock to be over 50 percent approximately 14 percent of the time in the benchmark model but only about 4 percent of the time in here. The impulse responses (reported in the appendix), using the lag structure of our primary results in Section 3, are quite similar in size and dynamics when compared to the comparable cases in Figures 4 and 5 with long term output effects around -2 percent. This restricted model helps us to understand the relatively important shocks driving our primary results.  

5. Conclusion

Narrative approach based measurement of monetary shocks suggests infrequent shocks are crucial for understanding the impact of monetary policy shocks on the economy. However, the

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6 To avoid unnecessary repetition, we do not show the 1955:7 to 2008:12 estimated monetary shocks and shock probabilities for these two sets of sensitivity analyses. The results are similar and available upon request.

7 We also experimented with estimating the impulse responses with randomly drawn false shocks. As expected, the outcomes are close to zero and do not show any pattern.
narrative approach is also dependent on a costly data collection process, researcher judgment and prone to delays due to official document release. In this study, we present a stock market based empirical model to estimate monetary shocks while preserving the key feature of infrequent shocks. We use easily available monthly time series data and a two-step estimation process to compute the shocks. Our estimated monetary shocks are large in size and are comparable to Romer and Romer (2004) shocks. The estimated cumulative impulse responses suggest that our estimated contractionary shocks lead to two percent long term decline in industrial production with a peak effect of more than three percent decline. We estimate a more than one percent long term decline in CPI.
References:


Table 1: Descriptive Statistics of Key Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P 500 Return</td>
<td>0.54</td>
<td>0.91</td>
<td>4.21</td>
</tr>
<tr>
<td>Federal Funds Rate</td>
<td>5.70</td>
<td>5.25</td>
<td>3.31</td>
</tr>
<tr>
<td>Wu-Xia Funds Rate</td>
<td>4.83</td>
<td>4.76</td>
<td>3.84</td>
</tr>
<tr>
<td>Industrial Production Growth</td>
<td>2.58</td>
<td>3.04</td>
<td>10.37</td>
</tr>
<tr>
<td>CPI Inflation</td>
<td>3.58</td>
<td>3.07</td>
<td>3.73</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>6.00</td>
<td>5.70</td>
<td>1.58</td>
</tr>
</tbody>
</table>

Source and Description

S&P 500                       | S&P 500, not seasonally adjusted, Yahoo Finance, ^GSPC. |
Federal Funds Rate            | Effective Federal Funds Rate, not seasonally adjusted, FRED database, FEDFUNDS. |
Wu-Xia Funds Rate             | Wu-Xia shadow rates, [https://sites.google.com/site/jingcynthiawu/home/wu-xia-shadow-rates](https://sites.google.com/site/jingcynthiawu/home/wu-xia-shadow-rates) |
Industrial Production Growth  | The Industrial Production Index, seasonally adjusted, FRED database, INDPRO. |
Consumer Price Index           | Consumer Price Index for All Urban Consumers: All Items, seasonally adjusted, FRED database, CPIAUCSL. |
Unemployment Rate             | Civilian unemployment rate, seasonally adjusted, FRED database, LNS14000000. |

Table 2: Parameter Estimates for the Benchmark Model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Federal Funds Rate</th>
<th>Wu-Xia Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev($u_1$)</td>
<td>4.091 (0.11)</td>
<td>4.084 (0.11)</td>
</tr>
<tr>
<td>Std. Dev($u_2$)</td>
<td>0.215 (0.01)</td>
<td>0.209 (0.01)</td>
</tr>
<tr>
<td>Std. Dev($u_3$)</td>
<td>1.003 (0.08)</td>
<td>1.001 (0.03)</td>
</tr>
<tr>
<td>$p$</td>
<td>0.978 (0.01)</td>
<td>0.979 (0.01)</td>
</tr>
<tr>
<td>$q$</td>
<td>0.890 (0.03)</td>
<td>0.881 (0.04)</td>
</tr>
<tr>
<td>$a_{13}$</td>
<td>-1.019 (0.41)</td>
<td>-1.028 (0.40)</td>
</tr>
<tr>
<td>Log L</td>
<td>-1963.875</td>
<td>-2218.346</td>
</tr>
<tr>
<td>N</td>
<td>642</td>
<td>738</td>
</tr>
</tbody>
</table>

Note: The estimation samples are 1955:07 to 2008:12 and 1955:07 to 2016:12. The terms Std. Dev($u_i$) denote the standard deviations of the shock $u_i$ where $i = 1, 2, 3$, and estimated as parameters of the model. Standard errors are reported in the parentheses. The log likelihoods in the two columns are not comparable as they are defined over different dataset lengths for the estimation of the parameters.
Table 3: Further Parameter Estimates for Sensitivity Analysis

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Stock Market Feedback Model</th>
<th>12 lag VAR Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Std. Dev}(u_1)$</td>
<td>4.070 (0.11)</td>
<td>3.960 (0.10)</td>
</tr>
<tr>
<td>$\text{Std. Dev}(u_2)$</td>
<td>0.214 (0.01)</td>
<td>0.191 (0.01)</td>
</tr>
<tr>
<td>$\text{Std. Dev}(u_3)$</td>
<td>0.990 (0.05)</td>
<td>0.815 (0.07)</td>
</tr>
<tr>
<td>$p$</td>
<td>0.978 (0.01)</td>
<td>0.975 (0.01)</td>
</tr>
<tr>
<td>$q$</td>
<td>0.878 (0.04)</td>
<td>0.899 (0.03)</td>
</tr>
<tr>
<td>$a_{13}$</td>
<td>-1.353 (0.41)</td>
<td>-0.803 (0.42)</td>
</tr>
<tr>
<td>$a_{21}$</td>
<td>0.01*</td>
<td>-</td>
</tr>
<tr>
<td>Log L</td>
<td>-2234.888</td>
<td>-2173.517</td>
</tr>
<tr>
<td>N</td>
<td>738</td>
<td>738</td>
</tr>
</tbody>
</table>

Note: The estimation sample is 1955:07 to 2016:12. The terms $\text{Std. Dev}(u_i)$ denote the standard deviations of the shock $u_i$ where $i = 1, 2, 3$, and estimated as parameters of the model. Standard errors are reported in the parentheses. The log likelihoods in the two columns are not comparable as they are defined over different datasets for the estimation of the parameters. * indicates that the coefficient for $a_{21}$ in the Stock Market Feedback Model is imposed, not estimated.
Table 4: Parameter Estimates from the Expanded Model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Federal Funds Rate</th>
<th>Wu-Xia Funds Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Std. Dev}(u_1)$</td>
<td>4.083 (0.11)</td>
<td>4.079 (0.11)</td>
</tr>
<tr>
<td>$\text{Std. Dev}(u_2)$</td>
<td>0.207 (0.01)</td>
<td>0.202 (0.01)</td>
</tr>
<tr>
<td>$\text{Std. Dev}(u_3)$</td>
<td>0.975 (0.12)</td>
<td>0.974 (0.06)</td>
</tr>
<tr>
<td>$p$</td>
<td>0.975 (0.01)</td>
<td>0.976 (0.01)</td>
</tr>
<tr>
<td>$q$</td>
<td>0.882 (0.04)</td>
<td>0.873 (0.04)</td>
</tr>
<tr>
<td>$a_{13}$</td>
<td>-0.998 (0.42)</td>
<td>-1.002 (0.40)</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>-0.076 (0.06)</td>
<td>-0.065 (0.06)</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td>0.007 (0.02)</td>
<td>0.002 (0.02)</td>
</tr>
<tr>
<td>$\gamma_5$</td>
<td>1.108 (1.10)</td>
<td>0.660 (1.13)</td>
</tr>
<tr>
<td>$\delta_3$</td>
<td>0.010 (0.00)</td>
<td>0.010 (0.00)</td>
</tr>
<tr>
<td>$\delta_4$</td>
<td>0.001 (0.00)</td>
<td>0.002 (0.00)</td>
</tr>
<tr>
<td>$\delta_5$</td>
<td>-0.220 (0.06)</td>
<td>-0.150 (0.06)</td>
</tr>
<tr>
<td>Log L</td>
<td>-1950.560</td>
<td>-2206.601</td>
</tr>
<tr>
<td>N</td>
<td>642</td>
<td>738</td>
</tr>
</tbody>
</table>

Note: The estimation sample is 1955:07 to 2008:12 for the second column and 1955:07 to 2016:12 for the last column. The terms $\text{Std. Dev}(u_i)$ denote the standard deviations of the shock $u_i$ where $i = 1, 2, 3$, and estimated as parameters of the model. Standard errors are reported in the parentheses. The log likelihoods in the two columns are not comparable as they are defined over different dataset horizons for the estimation of the parameters.
<table>
<thead>
<tr>
<th>Parameters</th>
<th>Federal Funds Rate</th>
<th>Wu-Xia Funds Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Std. Dev(u_1)$</td>
<td>4.086 (0.11)</td>
<td>4.076 (0.11)</td>
</tr>
<tr>
<td>$Std. Dev(u_2)$</td>
<td>0.312 (0.01)</td>
<td>0.296 (0.01)</td>
</tr>
<tr>
<td>$Std. Dev(u_3)$</td>
<td>1.656 (0.28)</td>
<td>1.583 (0.24)</td>
</tr>
<tr>
<td>$p$</td>
<td>0.955 (0.01)</td>
<td>0.955 (0.01)</td>
</tr>
<tr>
<td>$q$</td>
<td>0*</td>
<td>0*</td>
</tr>
<tr>
<td>$a_{13}$</td>
<td>-1.346 (0.50)</td>
<td>-1.436 (0.50)</td>
</tr>
<tr>
<td>Log L</td>
<td>-2085.487</td>
<td>-2360.1422</td>
</tr>
<tr>
<td>N</td>
<td>642</td>
<td>738</td>
</tr>
</tbody>
</table>

Note: The estimation sample is 1955:07 to 2008:12 for the second column and 1955:07 to 2016:12 for the last column. The terms $Std. Dev(u_i)$ denote the standard deviations of the shock $u_i$ where $i = 1, 2, 3$, and estimated as parameters of the model. Standard errors are reported in the parentheses. The log likelihoods in the two columns are not comparable as they are defined over different dataset horizons for the estimation of the parameters. * indicates that the coefficient for $q$ in the two restricted models is imposed, not estimated.
Figure 1: Estimated Monetary Shocks using the Federal Funds Rate

Figure 2: Estimated Shock Probabilities using the Federal Funds Rate

Note: The horizontal axis represents months from July, 1955 to December, 2008. The vertical axis represents probabilities.
Figure 3: Estimated Monetary Shocks and Probabilities using Wu-Xia Funds Rate

Note: The horizontal axis represents months from July, 1955 to December, 2016. The left vertical axis represents percentages. The right vertical axis represents probabilities.
Figure 4: Dynamic Effects of Monetary Shocks using the Federal Funds Rate

Note: The horizontal axes represents monthly time periods. The vertical axes represents percentages. The solid lines show cumulative responses in percentages. The dotted lines show 90 percent confidence interval using 1000 Monte Carlo repetitions after accounting for the generated regressor problem.
Figure 5: Dynamic Effects of Monetary Shocks using Wu-Xia Funds Rate

Note: The horizontal axes represents monthly time periods. The vertical axes represents percentages. The solid lines show cumulative responses in percentages. The dotted lines show 90 percent confidence interval using 1000 Monte Carlo repetitions after accounting for the generated regressor problem.
Figure 6: Model and Lag Sensitivity Analysis of Dynamic Effects using Monetary Shocks

Note: The horizontal axes represent monthly time periods. The vertical axes represent percentages. The graphs show cumulative responses in percentages. The top panel shows the effects on industrial production and the bottom panel shows the effects on Consumer Price Index.
Figure 7: Monetary Shocks and Probabilities from Expanded and Restricted Models

Note: The horizontal axis represents months from July, 1955 to December, 2016. The left vertical axes represent percentages. The right vertical axes represent probabilities. The top panel shows the estimates from the expanded model while the bottom panel shows the estimates from the restricted model.

Appendix:
Figure A1: Shock Probabilities and Effects of Shocks using the Federal Funds Rate

Explanation: The above three panels compare the outcomes between the filtered probabilities and the smoothed probabilities for the benchmark model using sample till 2008:12.

Figure A2: Shock Probabilities and Effects of Shocks using the Wu-Xia Funds Rate
Explanation: The above three panels compare the outcomes between the filtered probabilities and the smoothed probabilities for the full sample model using Wu-Xia Funds rate.

Figure A3: Estimated Monetary Shocks and Probabilities with Stock Market Feedback
Estimated Monetary Shocks
--- Estimated Probabilities of a Monetary Shock

Note: The horizontal axis represents months from July, 1955 to December, 2016. The left vertical axis represents percentages. The right vertical axis represents probabilities.

Explanation: The solid line shows the estimated monetary shocks and the dashed line shows the filtered probabilities of a monetary shock. Both are estimated from the stock market feedback model. The results are similar to those reported in Figure 3.

Figure A4: Estimated Monetary Shocks and Probabilities with 12 Lag VAR Model
Note: The horizontal axis represents months from July, 1955 to December, 2016. The left vertical axis represents percentages. The right vertical axis represents probabilities.

Explanation: The solid line shows the estimated monetary shocks and the dashed line shows the filtered probabilities of a monetary shock. Both are estimated from 12 lag VAR model. The results are similar to those reported in Figure 3.

Figure A5: Dynamic Effects from Expanded and Restricted Models
Note: The horizontal axes represent monthly time periods. The vertical axes represent percentages. The graphs show cumulative responses in percentages. The top panel shows the effects on industrial production and the bottom panel shows the effects on Consumer Price Index.
Explanation: The impulse responses reported in Figure A5 use the lag structure of our primary results in Section 3. The solid lines show the impulse responses from the expanded model using the sample till 2008. The dashed lines show the impulse responses from the expanded model using the full sample. The outcomes are similar to those reported in Figures 4 and 5. The solid dotted and dashed lines show the impulse responses from the restricted model using the sample till 2008 and the lines with checks show the impulse responses from the restricted model using the full sample.