Monetary Policy and Asset Prices: An Empirical Investigation

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Abstract

This paper employs a structural vector autoregression to study the dynamic interactions among monetary policy, asset prices, and the aggregate economy. We find that monetary policy has more interaction with house price than with stock price. The importance of house price in accounting for variations in stock price is greater than the magnitude in the reverse direction. In addition, price level shocks are important for variations in both house and stock prices. We also find that adopting a passive monetary policy and not reacting to the state of the economy, contrary to what the Fed did historically, would not change the variability of asset prices much.

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1 Introduction

Asset prices, such as house price and stock price, has been widely regarded as being erratic and attract a great deal of attention from academic economists, policy makes, industry practitioners, and the common mass. Among the interesting questions surrounding them are how important are monetary policy in explaining the variability of asset prices, as well as aggregate economic fluctuations, and how changes in the aggregate economy and asset prices affect the actions taken by the monetary policy maker. Questions of this sort motivate the study in this paper, where we employ a structural vector autoregression ($SVAR$) to study the dynamic interactions among monetary policy, asset prices, and the aggregate economy under the standard recursiveness assumption. Monetary policy action is modeled as the systematic reaction to the state of the economy, plus a random shock. We undertake our analysis by investigating the impulse responses and variance decompositions implied by the estimated $SVAR$.

Our major findings are as follows. Both real house price and real stock price declines in response to a contractionary monetary policy shock, and that monetary policy is tightened in reaction to positive shocks to asset prices. Monetary policy appears to have more interaction with house price than with stock price. It also occurs that the importance of house price in accounting for variations in stock price is greater than the magnitude in the reverse direction. In addition, price level shocks are important for variations in both house and stock prices. Finally, using a counterfactual experiment, we find that adopting a passive monetary policy and not reacting to the state of the economy, contrary to what the Fed did historically, would not change the variability of asset prices much.

There has been recently a fast growing interest in studying the dynamic interaction of the housing market and the aggregate economy. Of particularly relevance to our study are papers that involve both monetary policy and house price within VAR frameworks. For example, Del Negro and Otrok (2007) use a VAR to investigate the extent to which expansionary monetary policy is responsible for the increase in house prices in the U.S. for the period 2001–2005. They find that the impact of policy shocks on house prices to be small in comparison with the magnitude of the change in house prices in that period. Iacoviello and Minetti (2003) use vector autoregressions to study the role of monetary policy shocks in house price fluctuations in Finland, Sweden, and U.K.. They find that the response of house prices to interest rate surprises is bigger and more persistent in periods characterized by more liberalized financial markets. These papers, however, do not involve stock price and is therefore silent on the interaction between stock price and house price.

There is also a large literature that studies the behavior of stock prices using VARs. However, to the best of our knowledge, this literature ignores the possible interaction between house price and stock price. We believe that there are good reasons to treat house price and stock price as dynamically related as they are both major forms of household wealth. Decisions by optimizing investors on accumulation of house asset are unavoidably interrelated with their decisions on purchases and sales of stocks. It also appears to us that the kind of counterfactual experiment concerning the effect of the systematic component of monetary policy on asset prices, as is done in this paper, has been absent in the literature.

The rest of the paper is organized as follows. Section 2 provides a brief overview of using $SVAR$s to study the effects of monetary policy, which can be skipped by readers familiar with the subject. Section 3 introduces asset prices into an otherwise standard $SVAR$ and presents the impulse responses and variance decompositions. This is followed by a counterfactual experiment in Section 4. The last section discusses future research.

2 Structural Vector Autoregressions and the Effects of Monetary Policy: A Brief Overview

The framework of structural vector autoregressions ($SVAR$s) have become the workhorse for empirical macroeconomics, especially the strand involving the investigation of the effects of monetary policy. This framework is relatively simple to describe. Let y_t denote an $n \times 1$ vector containing the values that n variables assume at date t. The reduced-form dynamics of y_t are presumed to be governed by the pth-order Gaussian vector autoregression (VAR):

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + ... + \Phi_p y_{t-p} + \varepsilon_t, \tag{1}$$

with $\varepsilon_t \sim i.i.d.\ N(0, \Omega)$. For a variety of purposes including the computation of the impulse response functions and variance decomposition we derive a vector moving average (VMA) representation of (1):

$$y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + ..., \tag{2}$$

where

$$\left(I - \Phi_1 L - \Phi_2 L^2 - ... - \Phi_p L^p\right)^{-1} \equiv I + \Psi_1 L + \Psi_2 L^2 + ...,$$

and

$$\mu \equiv (I - \Phi_1 - \Phi_2 - ... - \Phi_p)^{-1} c.$$

The matrix Ψ_s, $s = 1, 2, ...$ contain the dynamic multipliers of the system.

A structural vector autoregression ($SVAR$) of order p takes the form

$$B_0 y_t = k + B_1 y_{t-1} + B_2 y_{t-2} + ... + B_p y_{t-p} + u_t. \tag{3}$$

Allowing B_0 in (3) to be different from the identity matrix captures the simultaneity among elements in y_t. It is commonly assumed in the $SVAR$ literature the structural disturbances u_t, a vector white noise, has a diagonal variance-covariance matrix D, while the variance-covariance matrix of VAR disturbances ε_t, denoted by Ω, is not necessarily diagonal. It is easily seen that the parameters and disturbances of the $SVAR$ and the corresponding reduced-form VAR satisfy the following relationships: $c = B_0^{-1}k$, $\Phi_s = B_0^{-1}B_s$ for $s = 1, 2, ..., p$, and $\varepsilon_t = B_0^{-1}u_t$, implying

$$B_0^{-1} D B_0^{-1\prime} = \Omega. \tag{4}$$

The orthogonalized impulse responses, i.e., the responses of y to the structural disturbances u_t, are contained in the matrices $\Psi_s A \equiv \partial y_{t+s}/\partial u_t'$, $s = 1, 2, ..., p$, where $A \equiv B_0^{-1}$.

Identifying the structural parameters B_0 and D from the reduced-form VAR variance-covariance matrix Ω requires that B_0 and D have no more unknown parameters than Ω. Given that Ω is symmetric and that D is diagonal, B_0 can have no more than $n\,(n-1)\,/2$ free parameters. A standard identification assumption in the $SVAR$ literature is the (short-run) recursiveness assumption, according to which B_0 is lower triangular with unit coefficients along the principal diagonal. This restriction, together with the requirement that D is diagonal, allows the structural model to be just identified via triangular factorization or Cholesky decomposition of the matrix Ω: $\Omega = QQ'$, where $Q \equiv AD^{1/2}$.

Recent literature has demonstrated considerable interest in identifying the effects of monetary policy on the behavior of various sorts of variables. A common approach adopted in the literature is to postulate a monetary policy feedback rule, or reaction function, that represents the central bank's systematic policy responses to variations in the state of the economy. As a practical matter, it is recognized that not all variations in central bank policy can be accounted for as such reactions. The unaccounted variation is then formalized with the notion of a monetary policy shock. In particular, monetary policy setting is represented by an equation of the form

$$S_t = f\left(\Sigma_t\right) + u_t^s. \tag{5}$$

Here S_t is the instrument of the monetary authority, say the federal funds rate in the U.S. context or some monetary aggregate, and f—the feedback rule—is a function that relates S_t to the monetary authority's information set Σ_t. The random variable, u_t^s, is a monetary policy shock, which is i.i.d. with standard deviation σ^s. Integrating the monetary policy equation (5) into an $SVAR$ system for a set of macroeconomic variables, one obtains a dynamic system that can be used to study the interaction of monetary policy and the aggregate economy.

As Christiano, Eichenbaum, and Evans (1999, CEE henceforth) point out, it is unnecessary to assume that the matrix $A \equiv B_0^{-1}$ in (3) is strictly lower triangular to identify the effects of a monetary policy shock on the economy. Rather, only a block recursiveness assumption is needed, according to which monetary policy shocks are orthogonal to the information set of the monetary authority. In particular, partition y_t into three blocks: the k_1 variables, X_{1t}, whose contemporaneous values as well as lagged values appear in Σ_t, the k_2 variables, X_{2t}, which only appear with lags in Σ_t, and finally, S_t itself, with $k_1 + k_2 + 1 = n$, where n is dimension of y_t. That is,

$$y_t = \begin{bmatrix} X_{1t} \\ S_t \\ X_{2t} \end{bmatrix}. \tag{6}$$

The block recursiveness assumption places zero restrictions on Q, the Cholesky decomposition of Ω:

$$Q = \begin{bmatrix} \underset{(k_1 \times k_1)}{a_{11}} & \underset{(k_1 \times 1)}{0} & \underset{(k_1 \times k_2)}{0} \\ \underset{(1 \times k_1)}{a_{21}} & \underset{(1 \times 1)}{a_{22}} & \underset{(1 \times k_2)}{0} \\ \underset{(k_2 \times k_1)}{a_{31}} & \underset{(k_2 \times 1)}{a_{32}} & \underset{(k_2 \times k_2)}{a_{33}} \end{bmatrix}. \tag{7}$$

The zeros in the middle row of this matrix reflect the assumption that the policy maker does not see X_{2t} when S_t is set. The two zero blocks in the first row of Q reflect the assumption that the monetary policy shock is orthogonal to the elements in X_{1t} as the shock is assumed to have no contemporaneous effect on each element in X_{1t}. These blocks correspond to the two distinct channels by which a monetary policy shock could in principle affect the variables in X_{1t}. The first of these blocks corresponds to the direct effect of S_t on X_{1t}, which under the recursiveness assumption is zero. The second block corresponds to the indirect effect that operates via the impact of a monetary policy shock on the variables in X_{2t}, which under the recursiveness assumption is also zero.

This block recursiveness assumption is not sufficient to identify all the elements of Q.

However, it is sufficient to identify the dynamic response of y_t to a monetary policy shock. Specifically, one can establish that each member of the family of Q that satisfies $QQ' = \Omega$ generates precisely the same dynamic responses of the elements of y_t to a monetary policy shock. Furthermore, if we adopt the normalization of always selecting the lower triangular Q matrix from this family, then the impulse responses of the variables in y_t are invariant to the ordering of variables in X_{1t} and X_{2t}.

In this paper, we builds on CEE and introduces asset prices to an $SVAR$ system to study the interaction between monetary policy, asset prices, and the aggregate economy. We adopt CEE's identification strategy in order to just identify the parameters of our $SVAR$. An immediate question is that the ordering of the variables X_{1t} and X_{2t} matter for the estimated pattern of how non-monetary-policy shocks affect asset prices, and vice versa. Our strategy to deal with this concern is to experiment with different orderings of the variables within X_{1t} and X_{2t} and to see whether robust patterns might emerge from these experiments.

3 Asset Prices, Monetary Policy, and the Aggregate Economy: Dynamic Interactions

3.1 The Benchmark Specification

Our benchmark specification extends CEE's benchmark where the federal funds rate is regarded as the monetary policy instrument. Let Y_t, P_t, $PCOM_t$, FF_t, NBR_t,TR_t, and M_t denote the time t values of the log of real GDP, the log of the implicit GDP deflator, the log of the index of commodity prices, the federal funds rate, the log of nonborrowed reserves plus extended credit, the log of total reserves, and the log of either M_1 or M_2, respectively. The CEE specification of Σ_t includes current and four lagged values of Y_t, P_t, $PCOM_t$, as well as four lagged values of FF_t, NBR_t, TR_t, and M_t. Using the notations in (6), we have $X_{1t} = [Y_t, P_t, PCOM_t]'$, $S_t = FF_t$, and $X_{2t} = [TR_t, NBR_t, M_t]'$. The variable $PCOM$ is included in order to resolve the so-called "price puzzle." Without this variable the general price level would rise, rather than fall, persistently after a monetary contraction, contradicting the common sense. Adding this variable allows the monetary authority to react quickly to changes in this leading indicator of the business cycle and helps avoid producing the counterintuitive responses of the price level.

We add two variables—real house price and real stock price in the U.S., denoted by PH_t and PS_t, respectively—into the system described above. In our benchmark specification, we use the Dow Jones Industrial Average index as our measure of stock price. Since we are interested in the behavior of real stock price, we deflate the nominal stock price index by the GDP deflator. As for house price, we use the Office of Federal Housing Enterprise Oversight (OFHEO) house price index, again deflated by the GDP deflator. The OFHEO index is a constant-quality house price index.

We append $[PH_t, PS_t]'$ to the end of the vector X_{2t}. Assigning asset prices to the bottom of the list of variables y_t in our system reflects the notion that asset prices should be allowed to react contemporaneously to a monetary policy shock. Asset prices, especially stock price, are widely regarded as being flexible rather than sluggish. In fact, locating asset prices this way in our system also allows them to react contemporaneously to all shocks in the system, including non-asset-price shocks. Furthermore, placing PH_t before

PS_t makes explicit the assumption that stock price reacts contemporaneously to all sorts of shocks to the economy, while house price reacts contemporaneously to all shocks except the shock to stock price, implying that stock price adjusts faster than house price. In effect, stock price is treated as the most responsive variable in our system, while real GDP and the general price level are treated as the most sluggish. Treating real GDP and the price level as sluggish captures the idea that changing the quantities and prices of most goods and services is subject to various sorts of adjustment costs, as Sims and Zha (2006) emphasize.

Our interpretation of the nature of the shocks in the $SVAR$ system is as follows. The disturbance in an equation represents the change in the variable corresponding to that equation which can not be explained by (reactions to) innovations to all other variables. Adopting this interpretation for the monetary policy equation, one would interpret the monetary policy shock as the variation in the monetary policy instrument that can not be explained by its reaction to shocks to all other variables in the system. Similarly, applying this interpretation to the stock price equation, one would interpret the house (stock) price shock as the variation in house (stock) price that is not explained by its reaction to shocks to all other variables in the system. Similarly, the real GDP shock could be interpreted as the variation in real GDP that is not explained by its reaction to other shocks. This interpretation, however, is silent on whether the real GDP shock originates from the demand side or the supply side.

In our benchmark specification we use $M2$ for the variable M_t. The data are of quarterly frequency, with the sample period being 1975Q1–2007Q4.

3.2 Results

Figure 1 shows the impulse responses generated by our benchmark $SVAR$ system. The variable name on the top of each column indicates the structural disturbance the responses to which we want to consider. The variable name to the left of each row indicates the variable whose responses are plotted, along with the 70% confidence bands.[1] (This is the level of confidence used by Sims and Zha (2006) in reporting their results. Given that there are so many parameters to estimate in the VAR system, the confidence bands at the conventional 90% level would be so wide that many impulse responses appear to be statistically insignificant.) Therefore the "FF" column describes the dynamic responses of all the variables in the system to a positive 75-basis-point shock to the federal funds rate. Real GDP exhibits a hump-shaped contractionary response to the funds rate innovation. The peak effect (about 0.33% decline in output) is reached at about 8 quarters after the shock to monetary policy. The price level increases slightly during the first year after the shock and then declines. The deflationary effect of the monetary policy shock becomes significant only after the fourteenth post-shock quarter. Both the hump-shaped response of output and the apparent "stickiness" of the price level are well known from the VAR literature. Meanwhile, the index of commodity prices shows a consistently declining pattern. Monetary aggregates, such as nonborrowed reserve and M2, contract after the shock, though we are less certain about the response of total reserve. Most interestingly, real house price declines with a hump-shaped pattern. The peak effect—a 0.67% drop—is reached 11 quarters after the shock. The fall in real stock price is larger, the peak effect

[1]The confidence bands are computed by the Monte Carlo method.

being -1.40%. But the noise concerning the estimated responses of stock price is large.

In addition to its negative response to a contractionary shock to monetary policy, real house price responds positively to innovations to real GDP and M2 and responds negatively to innovations to the GDP deflator, the index of commodity prices, nonborrowed reserve, total reserve, and real stock price. Similarly, real stock price responds positively to innovations to real GDP and negatively to innovations to the GDP deflator and the index of commodity prices. Its responses to innovations of monetary aggregates are, however, not as certain. These results suggest that unexpected rises in aggregate economic activities tend to be associated with increases in asset prices, while inflationary shocks tend to depress asset prices, as do contractionary monetary policy shocks. Of particular interest is the cross responses of asset prices. Real house price responds negatively to an innovation to real stock price, and vice versa. This suggests that house and stock are likely to be substitutes in investors' portfolio.

The fourth row of Figure 1 depicts the responses of the federal funds rate to the shocks in the system. It is evident that the federal funds rate increases in response to positive innovations to real GDP, the GDP deflator, the index of commodity prices, M2, real house price, and real stock price, signifying that there is a monetary tightening when there is an output expansion, an inflationary shock, an expansion in money demand, and an increase in asset prices.

Table 1 reports the variance decomposition of forecast errors. It is well known that the mean squared error (MSE) of the s-period-ahead forecast of the vector y can be written as the sum of n terms, one arising from each of the structural disturbances u_{jt}:

$$\begin{aligned} MSE\left(\widehat{y}_{t+s|t}\right) &= \Omega + \Psi_1 \Omega \Psi_1' + \Psi_2 \Omega \Psi_2' + ... + \Psi_{s-1} \Omega \Psi_{s-1}' \\ &= \sum_{j=1}^{n} \left\{ Var\left(u_{jt}\right) \left[a_j a_j' + \Psi_1 a_j a_j' \Psi_1' + \Psi_2 a_j a_j' \Psi_2' + ... + \Psi_{s-1} a_j a_j' \Psi_{s-1}' \right] \right\}, \end{aligned} \quad (8)$$

where a_j denotes the jth column of the matrix A and $Var\left(u_{jt}\right)$ is the row j, column j element of the matrix D. The term inside the braces on the right-hand side of (8) is the contribution of the jth structural disturbance to the MSE of the s-period-ahead forecast of y.

We are especially interested in the variance decomposition of the forecast errors associated with asset prices. We see from Table 1-4 that over short forecast-horizons (within a year), the MSE of the forecast errors for real house price is mainly attributable to the shock to house price itself, which contributes roughly 50% to the MSE. The monetary policy shock explains about 10%. The M2 shock, interpretable as the money demand shock given that the federal funds rate is specified as the monetary policy instrument, contributes about 15% to variations in the unforecastable component of real house price. The contribution of the price level shock has a comparable magnitude with that of the monetary policy shock. The contribution made by the real GDP shock is surprisingly small, comparable only to the contribution made by shocks to reserve aggregates. The contribution from the shock to stock price is even less, down to the point of being negligible. Since we interpret the shock to real house price as the variation that can not be explained by its reaction to changes in other variables in the system, we conclude that roughly 50% of the unforecastable real house price variations remain unexplained, aside from those explainable by changes in aggregate economic activities, the price levels, monetary policy settings, money demand, and stock market situations. Among the non-house-price shocks, the monetary policy shock assumes a weight of about 20% while the money demand shock assumes a weight of about 30%.

Over the medium forecast horizons (2–3 years), the importance of the house price shock declines gradually toward about 20% in accounting for the variations in real house price. The federal funds rate shock becomes the largest source of non-house-price shocks in explaining real house price variations. At the 3-year forecast horizon, the importance of this shock becomes almost the same as the house price shock. The monetary policy shock is followed in importance by price level shocks—shocks to the GDP deflator and the index of commodity prices. Shocks to reserve aggregates and M2 also assume a fair amount of importance in explaining the variations in real house price. The importance of the real GDP shock and the stock price shock are quite modest and remains so over longer forecast horizons. At forecast horizons above 3 years, shocks to the GDP deflator, the federal funds rate, and non-borrowed reserve become more important than the house price shock in accounting for the variations in real house price.

The limit of this variance decomposition, obtained by driving the forecast horizon to infinity, indicates that over the long-run, about 89% of the total variations in real house price is explained by non-house-price shocks, i.e., shocks to output, price level, the monetary policy instrument, monetary aggregates, and real stock price, the most important source being the price level shock. The monetary policy shock assumes an importance only second to that. Interestingly, real stock price shock is the least important in explaining the unconditional variations in real house price.

Like in the case of real house price, we see from Table 1-5 that over short forecast horizons, the MSE of the forecast errors for real stock price is mainly attributable to the shock to stock price itself, which contributes as high as about 80% to the MSE one quarter ahead and 56% four quarters ahead. The monetary policy shock explains about 5%. The shocks to M2 and real house price do not contribute much, either. The importance of real house price shock is also small, but visibly larger than the importance of real stock price shock in explaining the forecast error variance of real house price over comparable horizons. Price level shocks are important factors among the non-stock-price shocks. Over the medium forecast horizons, the importance of stock price shock declines from about a half to about a third in accounting for the variations in real stock price. Price level shocks remain the most important non-policy shocks that generate unforecastable variations in real stock price. The importance of real house price shock rises to over 8%, comparable to the importance of the real GDP shock. This pattern does not change much over longer forecast horizons.

Again, the limit of this variance decomposition that we can use to analyze the total unconditional variations in real stock price is obtained by letting the forecast horizon in Table 1.5 go to infinity. There is some interesting contrast of this limiting decomposition with the one we have done for real house price. First, a smaller percentage of total stock price variations (about 83%) is explainable by non-stock-price shocks. Although among them the most important is again the price level shock, it is followed in importance by real GDP shock, which in turn is followed by the real house price shock. Hence over the very long forecast horizons the real house price shock is more important in accounting for real stock price variations than the real stock price shock is in accounting for real house price variations. Furthermore, the monetary policy shock is among the least important in explaining the unconditional variations in real stock price.

To summarize, we find that the monetary policy shock is more important in accounting for the forecast error variance of real house price than in explaining the forecast error variance of real stock price. The importance of real house price in accounting for the forecast error variance of real stock price is greater than the magnitude in the reverse direction. In addition, price level shocks are important for variations in both house price and stock price.

We now turn to the variance decomposition for the forecast error of the monetary policy instrument. Over the short forecast horizons, monetary policy shock itself accounts for the greatest portion of the forecast error of the federal funds rate. Other than that, shocks to real GDP and the GDP deflator account for most of the rest of the variations in the federal funds rate. Asset price shocks are of very minor importance, albeit positive asset price innovations do lead to monetary tightening as we have seen in the description of the impulse responses. Over the medium forecast horizons, the importance of real GDP and the GDP deflator both decline, but not by much. The importance of the monetary policy shock is reduced by about a half. The importance of real house price shock increases to as high as 15% at 3-year horizon. The importance of real stock price shock, however, remains largely unchanged. over the long forecast horizons, shocks to real GDP and the GDP deflator remain the most important factors, with the shock to price level taking over the shock to output. Surprisingly, real house price shock explains more variations in the federal funds rate than monetary policy shock itself, though we are less confident in this result than in results pertaining to shorter forecast horizons. Along with our previous analysis of the contribution of the monetary policy shock in explaining variations in real house price, we are inclined to conclude that monetary policy has more interaction with house price than with stock price.

4 The Role of Systematic Monetary Policy

Our estimated model indicates that unpredictable shifts in monetary policy account for a relatively small proportion of variations in the value assumed by the monetary policy instrument, and that the bulk of monetary policy actions have historically been systematic reactions to the state of the economy, rather than unpredictable changes. Assessment of the overall effects of monetary policy, as opposed to merely the effects of unpredictable changes in policy, must therefore consider what would happen if the systematic component of monetary policy were different. This is done by analyzing the impulse responses for a system in which the model's estimated monetary policy reaction function is replaced by one in which the monetary policy instrument is completely unresponsive to other variables in the system, that is, the monetary authority holds the monetary policy instrument such as the federal funds rate fixed in face of nonpolicy disturbances.

The idea of the counterfactual experiment is that we take the estimated benchmark recursive $SVAR$ as the "true" model. That is, we take the estimated $B_0, B_1, ..., B_p$, and $D \equiv E(u_t u_t')$ as true parameters. We then perform a thought experiment on the true system, in the spirit of "*ceteris paribus*". In particular, we hold D and the non-monetary-policy rows of $B_0, B_1, ..., B_p$ fixed. We then change the monetary-policy rows of $B_0, B_1, ..., B_p$ by setting the coefficients on the current and lagged values of all variables other than the monetary policy instrument to be zero. In doing so we take the structure of the economy, which is represented by D and the non-monetary-policy rows of the B matrices, as given, but change the nature of the monetary policy. Similar counterfactual experiments have been performed by Bernanke *et al.* (1997), Carlstrom and Fuerst (2006), and Sims and Zha (2006), in contexts that do not involve asset prices.

Holding all equations of the system other than the monetary policy equation fixed means that we are ignoring changes in the dynamics of the private sector that would occur if private agents modified the way they forecast the economy under the new policy rule. That is, we are ignoring the Lucas critique. Sims and Zha (2006) argue that this is nonetheless an interesting exercise, for practical purposes even more interesting than an exercise that "takes account of" the Lucas critique via the unreasonable assumption that the policy change is immediately and fully understood and that the public believe that the change is permanent. Our counterfactual exercise therefore rests on the assumption that policy changes, but private agents are surprised by the change, even though it is in a systematic fashion.

Figure 2 display the (point estimates) of the impulse responses of the true $SVAR$ system (dark lines) as well as those of the counterfactual system (red lines). By design the federal funds rate only reacts to the monetary policy shock in the counterfactual system. Its responses to other shocks are represented by the zero lines. Our overall impression is that shutting off the reactions of monetary policy to non-policy shocks barely changes the impulse responses, especially at short and medium forecast horizons for which the impulse responses are estimated more precisely. Many of the impulse responses under the counterfactual system coincide with those under the true system. This lack of significant change also applies for the impulse responses of real stock and house prices to both policy and non-policy shocks, implying that adopting a passive monetary policy and not reacting to the state of the economy, contrary to what the Fed did historically, would not change the variability of asset prices much.

Still, there are some discernible differences between the performance of the two systems that merit discussion. We note that a positive shock to real GDP makes real GDP itself respond more persistently in the counterfactual system, though the impact effect is the same under the two systems. Meanwhile, the GDP deflator rises much more slowly in the counterfactual case. A year after the shock, real house price continues rising under the counterfactual, while it falls from its peak response under the true $SVAR$. The rise in real stock price is larger under the counterfactual two quarters after the shock. This suggests that passive monetary policy, by not raising the federal funds rate, enlarges asset price increases in response to a positive innovation to real GDP, thereby increases asset price variability. However, the responses of real house and stock prices to a positive shock to the GDP deflator indicate to the contrary that such monetary policy, again by not raising the federal funds rate, lowers asset price declines in response to an inflationary shock (this is especially true for real house price), thereby reduces asset price variability.

5 Future Research

This is a very preliminary version of the paper. In future research we plan to check the robustness of our results against different orderings of the variables within X_{1t} and X_{2t}, against using different stock price indices such as the S&P500 and NASDAQ, against using the price of residential structure instead of residential home, which can be thought of as a composite of structure and land, against using different price deflators for asset prices, and against using different identification assumptions such the long-run neutrality assumption as in Blanchard and Quah (1989). We also plan to look in depth at the interactions between monetary policy and asset prices during the first eight years of the twenty-first century, which are under heated debate. What we have investigated in the present version is the broad historical pattern.

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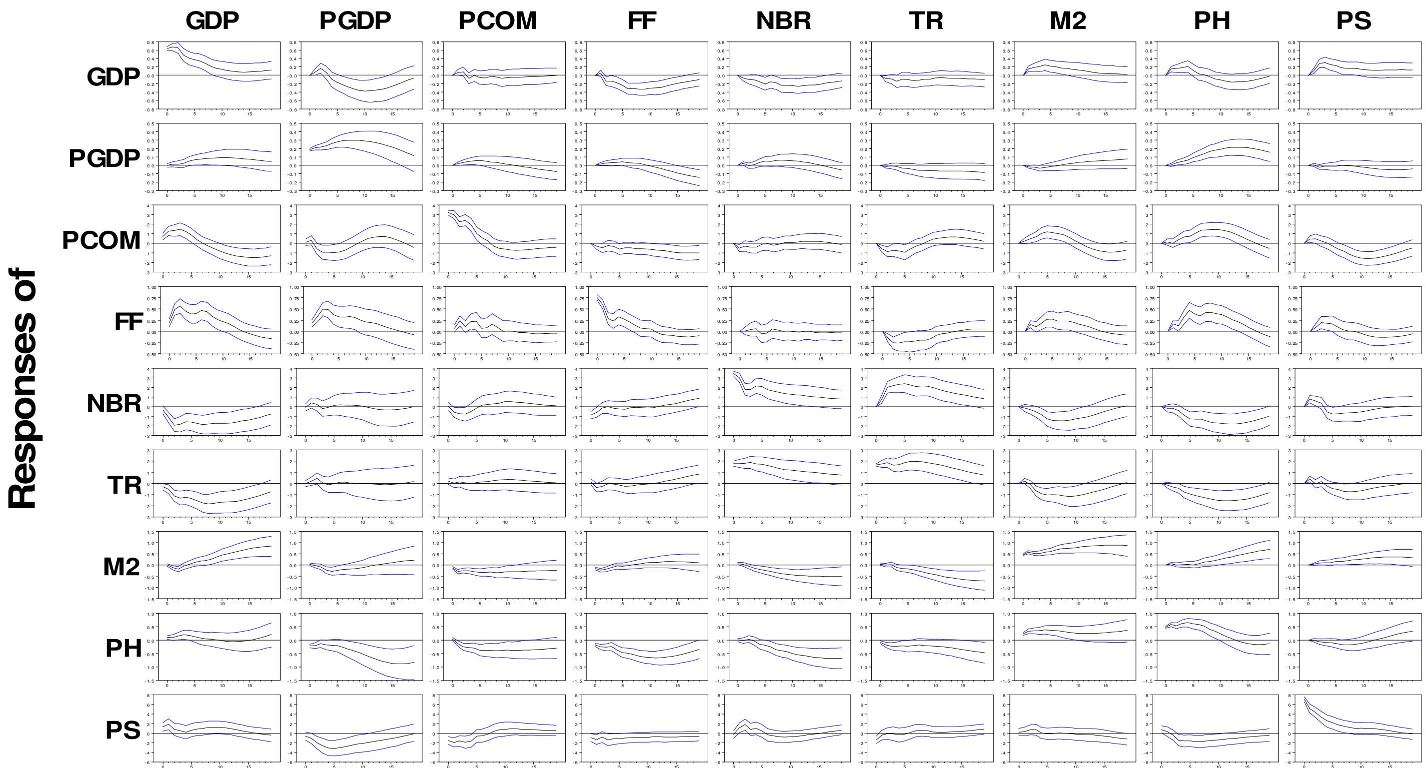

Figure 1. Impulse response of the benchmark system

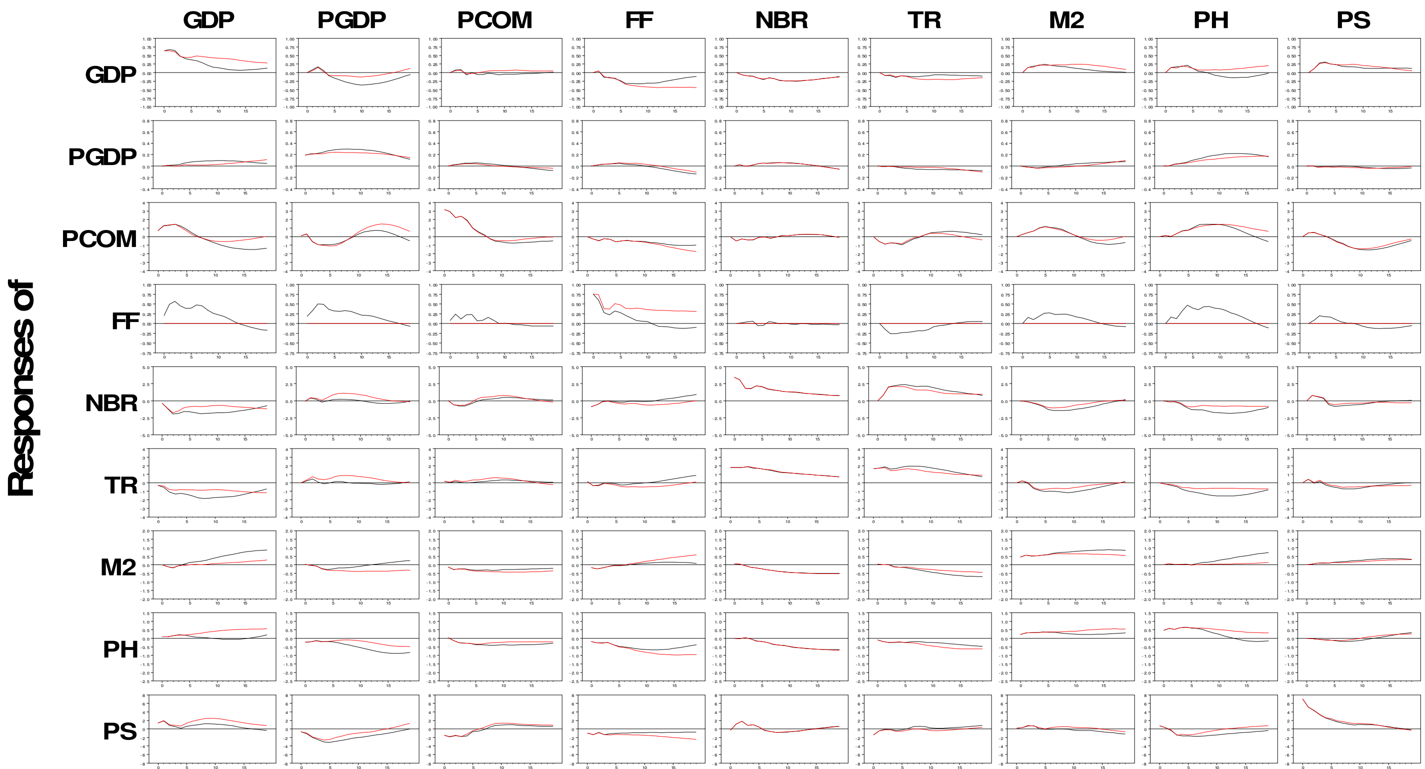

Figure 2. Impulse responses of the benchmark system (dark lines) versus the counterfactual system (red lines)

Table 1.1 Forecast Error Variance Decomposition

	GDP Forecast Error Variance Decomposition (Percentage)								
	GDPQ	PGDP	PCOM	FF	NBR	TR	M2	PH	PS
1	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	87.64	1.32	1.01	0.74	0.98	1.25	2.78	2.66	1.62
3	75.15	3.21	1.69	2.34	1.83	1.97	4.22	3.66	5.94
4	65.76	3.57	2.28	3.36	2.65	3.20	5.58	4.70	8.90
5	58.50	4.30	2.60	4.44	3.69	3.80	7.02	5.85	9.79
6	52.87	5.46	2.96	5.93	4.96	4.28	7.56	5.85	10.13
7	48.44	6.81	3.27	8.05	5.40	4.68	7.78	5.63	9.94
8	44.57	8.42	3.52	9.60	5.89	4.92	7.80	5.51	9.76
9	40.83	9.99	3.77	10.89	6.70	5.03	7.73	5.46	9.60
10	37.56	11.55	4.05	11.84	7.33	5.12	7.60	5.52	9.43
11	34.93	12.96	4.28	12.44	7.86	5.15	7.48	5.67	9.23
12	32.74	14.03	4.47	12.89	8.38	5.17	7.36	5.88	9.07
13	30.94	14.83	4.64	13.21	8.75	5.23	7.29	6.15	8.96
14	29.51	15.45	4.79	13.32	9.02	5.33	7.26	6.41	8.91
15	28.36	15.88	4.92	13.31	9.26	5.42	7.28	6.64	8.92
16	27.44	16.16	5.05	13.26	9.43	5.53	7.32	6.84	8.96
17	26.73	16.35	5.16	13.18	9.53	5.64	7.39	6.99	9.04
18	26.16	16.46	5.27	13.07	9.59	5.75	7.47	7.10	9.13
19	25.70	16.55	5.36	12.96	9.62	5.87	7.55	7.17	9.21
20	25.34	16.64	5.44	12.84	9.61	5.99	7.64	7.23	9.29
∞	16.88	18.23	6.60	16.01	9.41	7.17	8.10	9.73	7.88

Table 1.2 Forecast Error Variance Decomposition (continued)

	GDP deflator Forecast Error Variance Decomposition (Percentage)								
	GDPQ	PGDP	PCOM	FF	NBR	TR	M2	PH	PS
1	1.15	98.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.76	93.21	0.87	0.75	1.05	0.71	0.75	0.46	0.45
3	2.24	87.79	1.88	1.53	1.32	1.18	1.35	1.54	1.18
4	2.75	83.11	2.86	2.08	1.56	1.68	1.99	2.49	1.47
5	3.72	78.81	3.47	2.37	2.05	2.27	2.13	3.52	1.66
6	4.52	74.64	3.91	2.62	2.62	2.73	2.13	5.04	1.79
7	5.18	71.39	4.08	2.66	2.94	3.10	2.18	6.58	1.90
8	5.74	68.10	4.12	2.67	3.29	3.48	2.29	8.27	2.03
9	6.19	64.80	4.16	2.68	3.60	3.78	2.48	10.13	2.19
10	6.58	61.89	4.17	2.70	3.80	4.01	2.72	11.78	2.36
11	6.91	59.19	4.18	2.76	3.96	4.20	3.01	13.26	2.54
12	7.15	56.61	4.21	2.88	4.08	4.36	3.31	14.67	2.73
13	7.32	54.24	4.27	3.10	4.14	4.49	3.63	15.87	2.94
14	7.44	52.01	4.35	3.43	4.19	4.62	3.96	16.85	3.16
15	7.53	49.90	4.45	3.85	4.25	4.73	4.28	17.64	3.38
16	7.58	47.91	4.58	4.39	4.31	4.83	4.59	18.20	3.60
17	7.61	46.03	4.74	5.02	4.41	4.95	4.90	18.54	3.80
18	7.63	44.26	4.91	5.72	4.54	5.07	5.20	18.69	3.98
19	7.65	42.59	5.11	6.46	4.72	5.20	5.48	18.67	4.13
20	7.67	41.02	5.32	7.21	4.95	5.34	5.75	18.50	4.25
∞	12.98	19.27	6.53	9.82	11.41	11.74	9.41	12.96	5.89

Table 1.3 Forecast Error Variance Decomposition (continued)

	FF Forecast Error Variance Decomposition (Percentage)								
	GDPQ	PGDP	PCOM	FF	NBR	TR	M2	PH	PS
1	6.57	5.77	1.83	85.83	0.00	0.00	0.00	0.00	0.00
2	18.31	9.88	5.14	59.08	0.61	1.90	1.94	2.22	0.92
3	24.68	16.61	4.44	41.11	1.23	4.50	2.15	2.61	2.66
4	24.22	19.24	5.36	31.82	1.80	5.88	3.05	5.27	3.36
5	22.48	18.26	6.01	27.21	2.21	6.46	4.41	9.27	3.70
6	22.03	17.75	5.85	24.58	2.58	7.07	5.52	10.82	3.79
7	22.77	17.44	5.85	22.34	2.89	7.41	6.01	11.48	3.81
8	22.93	17.28	6.13	20.27	3.09	7.46	6.40	12.60	3.84
9	22.40	17.29	6.24	18.78	3.28	7.57	6.81	13.68	3.95
10	21.79	17.32	6.32	17.79	3.48	7.60	7.10	14.47	4.13
11	21.25	17.37	6.42	17.05	3.66	7.53	7.29	15.07	4.36
12	20.75	17.51	6.51	16.49	3.84	7.47	7.42	15.37	4.63
13	20.28	17.69	6.61	16.11	4.01	7.44	7.51	15.42	4.93
14	19.87	17.85	6.70	15.83	4.16	7.41	7.57	15.39	5.22
15	19.56	17.99	6.78	15.60	4.31	7.41	7.63	15.26	5.46
16	19.32	18.11	6.86	15.43	4.44	7.41	7.71	15.05	5.66
17	19.15	18.20	6.92	15.26	4.56	7.43	7.80	14.85	5.83
18	19.04	18.27	6.97	15.10	4.65	7.46	7.88	14.68	5.95
19	18.98	18.31	7.01	14.92	4.74	7.48	7.96	14.57	6.02
20	18.92	18.36	7.06	14.72	4.81	7.50	8.03	14.54	6.08
∞	16.88	19.40	7.32	12.32	6.52	7.63	8.84	13.88	7.21

Table 1.4 Forecast Error Variance Decomposition (continued)

	PH Forecast Error Variance Decomposition (Percentage)								
	GDPQ	PGDP	PCOM	FF	NBR	TR	M2	PH	PS
1	3.66	13.29	1.14	9.08	0.88	2.47	13.50	55.98	0.00
2	3.23	9.93	3.07	10.25	1.33	4.71	15.21	51.85	0.42
3	4.13	8.07	6.07	10.67	1.78	6.47	15.56	46.21	1.05
4	5.14	7.73	7.38	9.92	2.07	6.99	15.00	44.25	1.53
5	5.29	7.51	8.06	11.02	2.88	6.91	14.40	42.03	1.90
6	5.10	7.54	9.21	12.96	3.59	6.92	13.64	38.75	2.29
7	4.88	8.11	9.86	14.33	4.40	6.73	12.93	35.96	2.80
8	4.74	8.99	10.23	15.56	5.70	6.47	12.14	32.98	3.20
9	4.66	10.01	10.57	16.97	6.90	6.34	11.35	29.72	3.48
10	4.63	11.22	10.71	18.15	7.91	6.32	10.63	26.78	3.65
11	4.63	12.54	10.72	19.00	9.02	6.32	9.99	24.09	3.70
12	4.65	13.92	10.75	19.52	10.07	6.35	9.42	21.64	3.67
13	4.69	15.38	10.73	19.67	10.94	6.43	8.95	19.56	3.66
14	4.74	16.78	10.63	19.51	11.71	6.55	8.58	17.84	3.67
15	4.79	18.03	10.51	19.14	12.37	6.71	8.28	16.44	3.72
16	4.84	19.14	10.36	18.59	12.91	6.94	8.07	15.31	3.84
17	4.91	20.04	10.20	17.93	13.38	7.19	7.93	14.40	4.02
18	5.00	20.72	10.02	17.22	13.78	7.48	7.86	13.66	4.25
19	5.15	21.17	9.85	16.52	14.10	7.80	7.85	13.03	4.54
20	5.36	21.43	9.67	15.85	14.35	8.13	7.87	12.50	4.85
∞	11.45	18.89	7.48	14.10	11.35	9.25	9.82	10.88	6.77

Table 1.5 Forecast Error Variance Decomposition (continued)

	PS Forecast Error Variance Decomposition (Percentage)								
	GDPQ	PGDP	PCOM	FF	NBR	TR	M2	PH	PS
1	4.04	1.69	4.57	2.52	1.10	3.93	1.02	1.88	79.26
2	6.52	3.04	6.65	4.00	2.72	3.35	1.48	2.05	70.19
3	6.28	5.84	7.27	4.21	4.95	3.37	2.16	2.35	63.57
4	6.14	9.15	8.11	5.08	5.12	3.60	2.71	3.63	56.45
5	6.02	12.45	8.57	5.35	5.40	3.96	2.88	4.77	50.59
6	6.11	15.13	8.31	5.59	5.44	4.27	3.03	5.60	46.51
7	6.34	16.76	8.22	5.77	5.53	4.48	3.20	6.43	43.27
8	6.64	17.80	8.14	5.92	5.66	4.69	3.38	7.12	40.66
9	7.04	18.44	8.15	6.02	5.85	4.89	3.53	7.59	38.49
10	7.42	18.82	8.29	6.13	6.03	5.01	3.70	7.92	36.69
11	7.75	19.10	8.42	6.23	6.15	5.08	3.89	8.19	35.20
12	8.02	19.31	8.57	6.31	6.23	5.13	4.10	8.35	33.97
13	8.23	19.45	8.71	6.39	6.29	5.18	4.33	8.46	32.96
14	8.37	19.55	8.81	6.49	6.33	5.24	4.56	8.58	32.07
15	8.46	19.62	8.88	6.59	6.37	5.32	4.81	8.68	31.28
16	8.54	19.65	8.95	6.66	6.41	5.40	5.08	8.77	30.54
17	8.61	19.64	9.00	6.73	6.46	5.48	5.39	8.85	29.84
18	8.68	19.61	9.03	6.78	6.53	5.58	5.72	8.92	29.16
19	8.74	19.56	9.05	6.81	6.60	5.69	6.08	8.97	28.51
20	8.81	19.50	9.04	6.84	6.69	5.80	6.46	9.00	27.86
∞	11.67	18.91	7.99	8.43	8.39	8.03	10.21	9.34	17.03