THE TIME-VARYING EFFECT OF MONETARY POLICY ON ASSET PRICES

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Abstract—This paper studies how monetary policy jointly affects asset prices and the real economy in the United States. I develop an estimator that uses high-frequency surprises as a proxy for the structural monetary policy shocks. This is achieved by integrating the surprises into a vector autoregressive model as an exogenous variable. I use current short-term rate surprises because these are least affected by an information effect. When allowing for time-varying model parameters, I find that compared to the response of output, the reaction of stock and house prices to monetary policy shocks was particularly low before the 2007–2009 financial crisis.

I. Introduction

The goal of monetary policy is to stabilize fluctuations in output and inflation and keep these variables close to their desired targets. However, particularly during financial crises, output and inflation typically fall sharply and end up well below their targets for several years. To prevent such events, it may therefore be optimal to use monetary policy preemptively by leaning against developments that generally result in financial crises. Recent research finds that rapid increases in equity and house prices raise the likelihood and the severity of financial crises (Jordà, Schularick, & Taylor, 2015; Kiley, 2018; Paul, 2018). If central banks observe asset price booms, they could react to them by raising interest rates. But even if monetary policy is conducted in this way, it is unclear whether asset prices actually respond in times of frenzy. When there is momentum in the market and people are optimistic, do prices respond in the same way as they do in normal times? Do they respond more or less? And how does the reaction of asset prices compare and trade off against the impact of monetary policy on output and inflation?

Up to this point, the literature has not provided the necessary tools to study these questions. Within vector autoregressive models (VAR) that capture the interdependence between asset prices and the real economy, accessible methods have identified monetary policy shocks based on, for example, timing or sign restrictions (Christiano, Eichenbaum, & Evans, 1999; Uhlig, 2005). These identification approaches have been extended to time-varying settings (Primiceri, 2005). However, when the interest lies in the response of asset prices to changes in monetary policy, such methods cannot address some key identification issues. First, since asset prices incorporate news about monetary policy quickly, their response is particularly sensitive to obtaining shocks that come as surprises to the economy. Second, more specific to an identification based on imposing timing restrictions, it is generally assumed that a monetary authority can either react contemporaneously to a financial variable or a financial variable can respond to a change in monetary policy within the same period—but not both. However, for stock and house prices, both directions are possible.

In this paper, I develop a new methodology to address these identification problems, which allows studying the joint and time-varying effects of monetary policy on asset prices and the real economy. I follow Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005), among others, and obtain a series of monetary policy surprises. These are given by high-frequency price changes in federal funds futures around announcements of the Federal Open Market Committee (FOMC) and capture the unanticipated part within such announcements.

However, monetary policy surprises should not be taken as direct observations of monetary policy shocks. One concern is that the surprises may be confounded by a release of a central bank’s private information (Romer & Romer, 2000; Melosi, 2017). For example, Nakamura and Steinsson (2018) show that private forecasters increase their expectations of output growth to unexpected increases in interest rates—the opposite of what standard models predict. I show empirically that these results do not hold for surprises with respect to current short-term rates as opposed to future short-term rates (forward guidance). I provide additional evidence to interpret these findings. Relative to private forecasts, the Federal Reserve possesses additional information in predicting macroeconomic developments further out into the future. Surprises with respect to future short-term rates release such information and are therefore contaminated by this “information effect.” Hence, identified impulse responses based on such surprises would be biased since they would partly represent a response to the new information. I therefore use surprises with respect to current short-term rates in the empirical analysis instead.1

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1For the same reason, I focus on regular FOMC meetings and do not include unscheduled FOMC meetings. Nevertheless, even with these
However, even with this restriction, monetary policy surprises and shocks are at best imperfectly correlated. First, although price changes are measured in a small window around announcements, they may still reflect trading noise and news other than monetary policy that is revealed at the same time. Hence, they likely contain measurement error. Second, the monthly series of surprises contains random zero observations, since there are calendar months during which an FOMC meeting does not take place. Third, within a month, a range of other monetary policy news is released that is not taken into account, for example, through speeches of FOMC members.

I therefore use the monetary policy surprises as a proxy for the structural monetary policy shocks. That is achieved by integrating the surprises directly into a vector autoregressive model as an exogenous variable (VARX).\(^2\) I show analytically that this approach consistently identifies the true relative impulse responses—even when the surprises contain measurement error that is orthogonal to all other variables.\(^3\) Further, I show that one can extend a constant parameter VARX to allow for time-varying parameters in a simple way and use standard methods to estimate the model (as they are applied in Cogley & Sargent, 2001, for example).

Based on the time-varying parameter VARX, I obtain empirical evidence on the response of output, inflation, and stock and house prices to monetary policy shocks in the United States since the late 1980s. First, I find that stock and house prices always decrease following a monetary tightening. This result is in contrast to Gali and Gambetti (2015). They also study how monetary policy affects stock prices within a time-varying parameter VAR, but shocks are identified using timing restrictions. They find that stock prices increase after a monetary tightening during stock market booms and interpret these findings as evidence of the presence of rational bubbles. My results show that their findings are driven by the Cholesky identification of shocks that is subject to the mentioned concerns.

Second, I find that stock and house prices show substantial time variation to unanticipated changes in monetary policy. While the response of stock prices does not show a systematic pattern, the response of house prices strongly comoves with the level of house prices over most of the sample. They are less responsive when house prices are high and more responsive when prices are low. Third, I find that compared to output, the response of stock and house prices was particularly low before the Great Recession. Hence, attempts by the Federal Reserve to lean against the house price boom before the crisis may have been less effective.

Apart from the application in this paper, the exogenous variable approach can generally be applied when a proxy for the structural shock of interest is available. In this regard, the method is an alternative implementation of the external instrument or proxy SVAR approach, introduced by Stock and Watson (2012) and Mertens and Ravn (2013).\(^4\) Gertler and Karadi (2015) and Caldara and Herbst (2016) apply this method in the context of monetary policy identification. Both approaches consistently estimate the true relative impulse responses, and I provide analytical derivations with respect to their equivalence. However, they use the proxy differently—once as an exogenous variable and the other time as an external instrument. In a comparison of these two methods, the exogenous variable approach allows for the simple extension with time-varying parameters since the VAR is estimated in a single step. In addition, I compare the exogenous variable approach with the local projection instrumental variable approach (LP-IV), as proposed by Stock and Watson (2018) among others.\(^5\)

The response of stock prices to monetary policy news (Bernanke & Kuttner, 2005; Rigobon & Sack, 2004) or macroeconomic news more generally (Law, Song, & Yaron, 2017) is well explored in the literature. However, the relation is typically analyzed by the immediate response within a narrow window around news releases.\(^6\) In contrast, this paper identifies the dynamic response of stock prices to monetary policy shocks. The reaction of house prices to monetary policy shocks is less explored, but interest in this question increased after the 2007–2009 financial crisis. Kuttner (2013) provides an overview of the empirical findings.

Finally, I focus on the response of asset prices to monetary policy shocks, that is, to unanticipated deviations from a perceived monetary policy reaction function. Aastveit, Furlanetto, and Loria (2017) consider the other side of the coin: whether US monetary policy has historically reacted to asset prices and how this reaction has changed over time. However, both my paper and Aastveit et al. (2017) cannot speak to the question of whether monetary policy should incorporate asset prices into its reaction function and how agents would...

\(^1\)I have developed these results independently. Since then, I have been made aware that a similar derivation can be found in the unpublished notes by Montiel-Olea, Stock, and Watson (2012) that did not appear in their subsequent working paper (Montiel-Olea, Stock, and Watson, 2015). The derivation in this paper is more detailed and allows for additional insights that are discussed in section IID. Kilian and Luetkepohl (2017) also debate the connection between the different approaches, but do not prove their equivalence. Caldara and Herbst (2016) and Drautzburg (2017) develop Bayesian versions of the proxy SVAR approach.

\(^2\)See, for example, Swanson (2017), Lakdawala and Schaffer (2018), Lemmens et al. (2017), Brooks, Katz, and Lustig (2019), and Lumsford (2018) for recent applications on the effects of monetary policy on financial markets.
change their decisions because of that. Finding answers to these important questions is left to future research.

This paper is organized as follows. The next section outlines the model that describes the data generating process and introduces the concept of relative impulse responses. The section proceeds to show that the exogenous variable approach consistently estimates the true relative impulse responses. Motivated by the findings, section III extends the constant parameter VARX to allow for time-varying coefficients. Section IV uses the model and obtains evidence on the time-varying impact of monetary policy on stock and housing markets. Section V concludes.

II. General Methodology

Let \( y_t \) be an \( n \times 1 \) vector of observables, \( H \) and \( C_m \forall m \geq 0 \) conformable coefficient matrices, and \( \epsilon_t \) an \( n \times 1 \) vector of structural shocks. Assume that \( y_t \) evolves according to a system of linear simultaneous equations, written in its general structural form,

\[
H y_t = C_0 + C_1 y_{t-1} + \ldots + C_k y_{t-k} + \epsilon_t,
\]

(1)

with \( \mathbb{E} [\epsilon_t] = 0 \) and the normalization \( \mathbb{E} [\epsilon_t \epsilon_t'] = I_n \) where \( I_n \) is the identity matrix. Multiplying each side of the equation by \( H^{-1} \) yields the reduced-form representation

\[
y_t = B_0 + B_1 y_{t-1} + \ldots + B_k y_{t-k} + u_t,
\]

(2)

where \( B_m = H^{-1} C_m \forall m \geq 0 \). The reduced-form innovations \( u_t \) are given by

\[
u_t = S \epsilon_t,
\]

(3)

where the \( n \times n \) matrix \( S = H^{-1} \) collects the impulse vectors of the shocks. These capture the contemporaneous effect of the primitive shocks on the dependent variables. Assume that the interest lies in the identification of impulse responses to one of the structural shocks, denoted by \( \epsilon_{1,t} \). Accordingly, equation (3) can be rewritten as

\[
u_t = s \epsilon_{1,t} + S \epsilon_{2,t},
\]

(4)

where \( s \) is the impulse vector associated with \( \epsilon_{1,t} \) and the \((n-1) \times 1 \) vector \( \epsilon_{2,t} \) collects all other structural shocks. I distinguish between two types of impulse responses: absolute and relative impulse responses. Absolute impulse responses describe the change in \( y_t \) to units of standard deviation of \( \epsilon_{1,t} \). The response on impact to a 1 SD shock is given by \( s \), while subsequent responses are obtained by tracing the shock recursively through model (2).

Instead, relative impulse responses normalize the contemporaneous response of one of the endogenous variables. For example, one may consider a monetary policy shock that generates an initial fall in output of, say, 1%. However, the contemporaneous response of the other variables are left unrestricted, and subsequent responses are again obtained by tracing the shock through system (2). In contrast to absolute impulse responses, relative ones do not require identification of the entire impulse vector \( s \), only of ratios of elements in \( s \). To see why, consider a structural shock \( \epsilon_{1,t} \) that leads to a 1 unit increase of some variable \( j \) in \( y_t \). The contemporaneous relative impulse response of some other variable \( i \) in \( y_t \) with \( i \neq j \) is then given by

\[
r_{ij} = \frac{s_i}{s_j},
\]

(5)

where \( s_i \) and \( s_j \) are the elements in \( s \) related to variables \( i \) and \( j \).

The econometric problem in identifying absolute and relative impulse responses is that the structural shocks \( \epsilon_t \) are not observed. In addition, the covariance matrix of the reduced-form innovations, \( \mathbb{E} [u_t u_t'] = SS' \), does not provide enough identifying restrictions to obtain at least one of the columns in \( s \) or ratios of elements within such a column. Until recently, the structural VAR literature has achieved identification from restrictions that are directly imposed on the system of simultaneous equations (2) (Christiano et al., 1999; Uhlig, 2005).

Here, I follow the approach of the external instrument literature. The idea of this identification approach is to bring in information from external sources to identify the effects of structural shocks. In particular, assume that a proxy \( z_t \) for the latent shock of interest \( \epsilon_{1,t} \) exists and that \( z_t \) satisfies the following conditions,

\[
\mathbb{E} [z_t \epsilon_{1,t}] = \phi,
\]

(6)

\[
\mathbb{E} [z_t \epsilon_{2,t}] = 0,
\]

(7)

with \( \phi \) unknown but different from 0 and \( z_t \) assumed to have a 0 mean for simplicity. \(^7\) Equation (6) implies that \( z_t \) is correlated with the primitive shock of interest, while equation (7) states that it is uncorrelated with the remaining structural shocks. The key difference between the external instrument approach and the one that I propose in this paper lies in how the proxy \( z_t \) is used. The external instrument approach proceeds in multiple steps. First, system (2) is estimated for a sample of observables. In a second step, the estimated reduced-form innovations \( \tilde{u}_t \) are regressed on \( z_t \). These steps give consistent estimates of the true relative impulse responses (see appendix A.1).

Instead of using the proxy in such external steps, I propose to integrate it directly into equation (2) as an exogenous variable, such that

\[
y_t = \tilde{B}_0 + \tilde{B}_1 y_{t-1} + \ldots + \tilde{B}_k y_{t-k} + \tilde{A} z_t + \tilde{u}_t,
\]

(8)

\(^7\)Throughout the description of the methodology, I assume that \( z_t \) is not serially correlated. If \( z_t \) is autocorrelated, then it should first be projected on its own lags and the error from this projection be used in lieu of \( z_t \). For the following application, I find that such a correction does not change the results.
where tildes are used to distinguish variables and coefficients from the notation thus far. The contemporaneous relative impulse response is now given by

$$\tilde{r}_{ij} = \frac{\tilde{A}_i}{A_j},$$

where $\tilde{A}_i$ and $\tilde{A}_j$ with $i \neq j$ are two elements in $\tilde{A}$. The subsequent impulse responses are again obtained by tracing an initial impulse through equation (8) via the lagged endogenous variables. Next, I show analytically that this approach also gives consistent estimates of the true relative impulse responses. In this regard, I distinguish between contemporaneous and subsequent impulse responses, since the necessary conditions to give consistent estimates for the two types of responses differ. The distinction is also useful for a comparison with the external instrument approach, as further discussed in section IID. Throughout, I consider only the case of a single instrument $z_t$ that is used to obtain impulse responses to a single structural shock of interest.\(^8\)

A. Contemporaneous Impulse Responses

**Proposition 1.** The exogenous variable approach gives consistent estimates of the true contemporaneous relative impulse responses.

**Proof.** See appendix A.3.1.

The intuition for this result is that any element $\tilde{A}_i$ in $\tilde{A}$ based on equation (8) converges to the product of a constant and the associated element $s_t$ in $s$. However, when taking ratios between any two elements $\tilde{A}_i$ and $\tilde{A}_j$ with $i \neq j$ in $\tilde{A}$, the constant cancels out, thereby giving a consistent estimate of the associated contemporaneous relative impulse response $r_{ij} = \frac{\tilde{A}_i}{\tilde{A}_j}$ as stated in equation (5). The proof to proposition 1 is left to appendix A.3.1.

B. Subsequent Impulse Responses

**Proposition 2.** If $z_t$ is uncorrelated with the remaining regressors in equation (8), then the exogenous variable approach gives consistent estimates of the true subsequent relative impulse responses.

**Proof.** See appendix A.3.2.

Intuitively, if $z_t$ is uncorrelated with the rest of the explanatory variables in equation (8), then the estimated coefficients on the remaining regressors are unchanged whether $z_t$ is included in the VAR as in equation (8) or left out. Since these coefficients are used to trace an initial impulse through the system via the lagged endogenous variables, any subsequent impulse response will be equivalent to the true response. Note that one can always achieve the condition for proposition 2 by projecting $z_t$ on all other regressors in equation (8) and using the error from this projection in lieu of $z_t$. The proof of proposition 2 is left to appendix A.3.2.\(^9\)

C. Robustness to Measurement Problems

Depending on a specific application, various types of measurement problems may exist that invalidate the use of $z_t$ as direct observations of the structural shock of interest $\epsilon_{t,1}$. For example, Mertens and Ravn (2013) argue that $z_t$ likely contains measurement error and has observations that are censored at 0 if it is derived from narrative sources for fiscal policy. Since the external instrument approach requires that $z_t$ is only imperfectly correlated with $\epsilon_{t,1}$, Mertens and Ravn (2013) show that this method is robust to various types of measurement problems. The following proposition and its proof illustrate that these results also hold for relative impulse responses derived with the exogenous variable approach.

**Proposition 3.** The exogenous variable approach gives consistent estimates of the true contemporaneous relative impulse responses, even if $z_t$ contains random observations that are censored at 0 or an additive i.i.d. measurement error that is orthogonal to all other variables. If $z_t$ is additionally uncorrelated with the remaining regressors in equation (8), then the subsequent relative impulse responses are also consistently estimated.

**Proof.** See appendix A.3.3.

The proof of proposition 3 is left to appendix A.3.3. The presence of measurement error gives inconsistent least squares estimates of $\hat{A}$ in equation (8), such that $\hat{A}$ is biased toward 0. However, ratios of elements in $\hat{A}$ still give consistent estimates of the related true contemporaneous relative impulse responses. Moreover, random zero observations reduce the sample for $z_t$. But if the original sample is large enough, then estimated ratios of elements in $\hat{A}$ remain unchanged. If the measurement error in $z_t$ is also uncorrelated with the remaining regressors in equation (8), then the presence of $z_t$ again does not change the estimated coefficients on the remaining regressors.

D. Comparison with Alternative Identification Approaches

**External instrument approach.** Propositions 1 to 3 show that one can integrate the proxy $z_t$ directly into a VAR as an exogenous variable to identify the effects of structural shocks. In this regard, the exogenous variable approach is an alternative implementation of the external instrument approach;\(^*\)

\(^*\)Appendix A.6 illustrates the relation of proposition 2 with the Frisch-Waugh-Lovell theorem.
both consistently identify the true relative impulse responses. In fact, the *contemporaneous* relative impulse responses of the two approaches are *always the same*, even in small samples (see appendix A.4). Any differences in such responses can only be due to an incorrect rescaling and not, for example, measurement problems with respect to $z_t$.

However, relative impulse responses may differ subsequently. In large enough samples, such differences can *only* be due to the correlation of $z_t$ with the remaining regressors in a VAR—not because of other types of measurement problems of $z_t$ as considered in section IIC (see appendix A.4). A potential advantage of the external instrument approach is that it does not require that $z_t$ is available for the same sample as $y_t$, which may be beneficial if $z_t$ is available for a shorter sample than $y_t$ (as, for example, in Gertler & Karadi, 2015).

The key difference between the two approaches is that the VARX is estimated in a single step. This feature allows for a simple extension to time-varying parameters to identify the time-varying effects of structural shocks. In comparison with an external instrument approach, a time-varying parameter VARX largely simplifies the analysis, since it does not require any external steps that would have to account for a time-varying contemporaneous relation between $z_t$ and the reduced-form errors.\(^{10}\)

**Local projection instrumental variable approach.** Among others, Stock and Watson (2018) propose a so-called local projection instrumental variable approach (LP-IV) as an alternative to the external instrumental approach. In appendix A.5, I illustrate the equivalence between this approach and the VARX. To this end, I again differentiate between the contemporaneous impulse responses and any subsequent ones.

I show that the VARX and the LP-IV give the same contemporaneous relative impulse responses if they include the same controls. Moreover, if the VARX captures the dynamics of $y_t$ well through the variables included in $y_t$ and their lags, then any subsequent response will also be the same in large samples.\(^{11}\)

Moreover, as discussed in appendix A.5, one can also integrate the instrument directly into a local projection as opposed to using it in a separate instrumental variable step. If the impulse responses are scaled appropriately, then this approach again gives consistent relative impulse responses under slightly stronger conditions for the instrument.

\(^{10}\)De Wind (2014) considers the external instrument approach with respect to a time-varying parameter VAR. But his method does not allow for time-varying contemporaneous impulse responses, which is undesirable in a context where time-varying simultaneous relations are important, as in this paper.

\(^{11}\)See also Plagborg-Moeller and Wolf (2018) on the estimation of impulse responses with local projections and VARs. Regarding the use of external instruments, the proposed method by Plagborg-Moeller and Wolf (2018) to order an instrument first in a VAR and use a recursive identification coincides with the VARX in my paper if the instrument is uncorrelated with the controls in a VAR, including lags of the instrument itself (see also Noh, 2018).

III. The Time-Varying Parameter VARX

The time-varying parameter VAR follows Cogley and Sargent (2001), but also includes an exogenous variable. Let $y_t$ be an $n \times 1$ vector of endogenous variables that evolves according to

$$y_t = B_{0,t} + B_{1,t}y_{t-1} + \ldots + B_{k,t}y_{t-k} + A_t z_t + u_t$$

$$t = 1, \ldots, T,$$  \hspace{1cm} (9)

where $B_{0,t}$ is an $n \times 1$ vector of time-varying intercepts and $B_{j,t}$ for $j \in \{1, \ldots, k\}$ are $n \times n$ time-varying coefficient matrices with respect to the lagged endogenous variables. The innovations are given by the $n \times 1$ vector $u_t$. The model includes an exogenous variable $z_t$, with $n \times 1$ vector of time-varying coefficients $A_t$, which is again correlated with the structural shock of interest $\epsilon_{1,t}$ but not with any of the other structural shocks. An additional assumption compared with the constant parameter case is that $z_t$ is linked to the structural shock $\epsilon_{1,t}$ via

$$z_t = \phi \epsilon_{1,t} + \eta_t,$$  \hspace{1cm} (10)

where $\eta_t \sim N(0, \sigma^2_\eta)$ and $\eta_t$ is orthogonal to all other variables.\(^{12}\) This assumption implies that the identified time variation in $A_t$ is not due to time variation in the relation between $z_t$ and $\epsilon_{1,t}$, which is useful to compute impulse responses over time as discussed below and in section IVC. Next, I define $B_t$ to be a vector that stacks all coefficients on the right-hand side of equation (9)—coefficients to the constant terms, the lags of the endogenous variables, and the exogenous variable. $B_t$ is assumed to follow a driftless random walk:

$$B_t = B_{t-1} + \nu_t.$$  

The model’s innovations are assumed to be jointly normally distributed with mean 0 and the variance-covariance matrix to be block diagonal, which takes the form

$$V = \text{Var} \begin{bmatrix} u_t \\ v_t \end{bmatrix} = \begin{bmatrix} \Omega & 0 \\ 0 & Q \end{bmatrix},$$  \hspace{1cm} (11)

where $\Omega$ and $Q$ are positive definite matrices and termed hyperparameters. Denote by $B^T = [B'_1, \ldots, B'_T]$ the history of coefficients $B_t$. I use Bayesian methods and Gibbs sampling to evaluate the posterior distributions of $B^T$ and the hyperparameters $V$. The steps of the sampler are summarized in appendix A.9.

Given the estimated model and a structural shock $\epsilon_{1,t}$ that leads to a 1 unit increase in some variable $j$ in $y_t$ at time $t$, the contemporaneous relative impulse response of some other variable $i$ in $y_t$ at time $t$ is given by

\(^{12}\)The squared correlation between $z_t$ and $\epsilon_{1,t}$ is then given by $\frac{\sigma^2}{\sigma^2 + \sigma^2_\eta}$ which is directly related to the signal-to-noise ratio $\frac{\sigma^2}{\sigma^2_\eta}$ (see also Caldara & Herbst, 2016).
\[ r_{t,ij} = \frac{\bar{A}_{t,j}}{\bar{A}_{t,i}}, \]  

(12)

where \( \bar{A}_{t,j} \) and \( \bar{A}_{t,i} \) are the posterior means of the coefficients for variables \( i \) and \( j \), respectively, that are associated with \( z_t \) at time \( t \). The posterior means of the remaining coefficients in \( B_t \) are then used to derive any subsequent impulse responses. To obtain relative impulse responses over time, one has to normalize the initial response of one of the endogenous variables for a particular period. For example, one can consider a monetary policy shock that lowers output in period \( k \) by, let’s say, 1%. This shock implies a particular variation in \( z_t \) that can then be used to calculate the impulse responses for the remaining periods to ensure a consistent comparison over time.\(^\text{13} \) I discuss this normalization in more detail for the application in section IVC.

IV. Time-Varying Response of Stock and House Prices

I use the described framework to obtain evidence on the time-varying impulse responses of stock and house prices to monetary policy shocks. I estimate a monthly model for the US economy. Define the vector of endogenous variables to be

\[ y_t = [i_t, \Delta q_t, \Delta d_t, \Delta h p_t, \Delta p_t, \Delta \tilde{y}_t]' , \]

where \( i_t \) denotes the federal funds rate, \( q_t \) the (log) real stock price index (S&P 500), \( d_t \) the associated (log) real dividends, \( h p_t \) the (log) real S&P/Case-Shiller national home price index, \( p_t \) the (log) consumer price index (CPI), and \( \tilde{y}_t \) (log) real industrial production (IP). Hence, I have added all variables in first differences (of their log levels) apart from the federal funds rate.\(^\text{14} \)

A. Monetary Policy Surprises

To address the identification problems mentioned in section I, I use monetary policy surprises based on federal funds futures. For reasons explained shortly, I consider surprises extracted from thirty-day federal funds futures that are settled at the end of the month \( t \) during which a policy announcement is made (also denoted MP1 by Gürkaynak et al., 2005).\(^\text{15} \) These surprises therefore reflect unanticipated movements in current short-term interest rates. Let \( f^k_t \) be the settlement price for the current month’s federal funds futures following an FOMC meeting \( k \) that takes place in month \( t \). Denote by \( f^k_{t-1} \) the settlement price before the FOMC meeting \( k \) in month \( t \). Then a surprise \( S^k_t \) around FOMC meeting \( k \) is given by

\[ S^k_t = f^k_t - f^k_{t-1} , \]

which is measured in a 30-minute window around a policy announcement.\(^\text{16} \) This gives a sufficiently tight window to minimize any potential bias due to other information released around the policy announcement that might also trigger financial market or monetary authority reactions. The series of surprises \( S^k_t \) are on a meeting-by-meeting basis and are converted into a time series of surprises \( S_t \) with the same frequency as the variables that enter the VAR. If a meeting occurs in some period \( t \), the associated surprise is assigned to that period. If multiple FOMC meetings occur within a period \( t \), then the surprises with respect to these meetings are summed up (as in Romer & Romer, 2004).\(^\text{17} \) However, as explained in section I, the resulting series of surprises \( S_t \) should not be taken as direct observations of the primitive monetary policy shock, but the two are rather imperfectly correlated. \( S_t \) therefore enters the following models as an exogenous variable \( z_t \), as in equations (8) and (9).

The Federal Reserve’s private information. A potential concern regarding the series of monetary policy surprises is that the Federal Reserve (Fed) may have a different information set than the private sector does prior to FOMC meetings and releases its private information when changing interest rates. A positive monetary policy surprise may reflect the fact that the Fed’s forecasts about the behavior of the economy in the near future are more positive than the private sector’s forecasts. The monetary policy surprises could therefore be affected by this information release and could bias the impulse responses.

The following set of regressions tests for this “information effect.” Similar to Campbell et al. (2012) and Nakamura and Steinsson (2018), I regress revisions of the private sector forecasts for real GDP growth on the series of surprises \( S^k_t \),

\[ \Delta \text{Forecast}_{t+1,t} = \alpha + \beta S^k_t + \xi_t, \]

(13)

where the dependent variable is given by changes in the Blue Chip Economic Indicators forecasts from month \( t \) to \( t + 1 \) and meeting \( k \) takes place between these two forecasts. Nakamura and Steinsson (2018) find that \( \beta \) is the “wrong” sign; it is positive and statistically significant, such

\(^\text{13} \)Note that by equation (10), the relation between \( z_t \) and \( \epsilon_{t,ij} \) is constant over time. By fixing the implied variation in \( z_t \), one therefore considers same-size \( \epsilon_{t,ij} \) shocks over time.

\(^\text{14} \)See appendix A.13 for the time series in log levels and in first differences. The time series of stock prices is the end of the month price of the S&P 500. The time series of the associated dividends is the one provided on Robert Shiller’s web page for monthly US data.

\(^\text{15} \)When considering federal funds futures with respect to the current month, one has to adjust the surprise series for the remaining days within a month, since thirty-day federal funds futures are bets on the average federal funds rate within a month. In this regard, the surprise series are adjusted as suggested by Kuttner (2001), multiplying \( S^k_t \) by \( \frac{T}{T-n} \), where \( T \) is the total number of days in month \( t \) and \( n \) the number of days that have elapsed until meeting \( k \).

\(^\text{16} \)The surprise series are based on calculations in Gürkaynak et al. (2005). I thank Peter Karadi, Mark Gertler, Eric Swanson, and Michiel de Pooter for sharing their data in this regard.

\(^\text{17} \)Such an aggregation is not needed for the series of surprises used for the main analysis in this paper. That is because this series excludes intermeeting surprises, and at most one scheduled FOMC meeting takes place per month.
that private forecasters increase their expectations of output growth in the near future after positive monetary policy surprises—evidence of the information effect. However, Nakamura and Steinsson (2018) consider a combination of monetary surprises with respect to current and future short-term rates. Instead, I restrict the series of surprises to the current month’s short-term rates only (MP1). Based on this series, table 1 shows the results for the change in forecast of average real GDP growth over the next year. I also differentiate by whether unscheduled FOMC meetings are taken into account. Such meetings typically occur in turbulent times and may be more prone to a release of a central bank’s private information.

The estimated $\hat{\beta}$ are statistically significant and of the wrong sign, when unscheduled meetings are included. In contrast, if surprises with respect to unscheduled meetings are excluded, then the coefficients are not statistically different from 0 and much smaller in magnitude. In tables 3 and 4 in appendix A.10, I also show the results for forecast revisions of inflation and unemployment and additionally differentiate by various forecast horizons. Again, when unscheduled meetings are included, the coefficients tend to be of the wrong sign and statistically significant. In contrast, for scheduled FOMC meetings only, the coefficients are mostly of the correct sign and largely statistically insignificant. Hence, including unscheduled meeting surprises leads to revisions in the private sector forecasts that strongly indicate a release of private information.

Next, I estimate regression (13) for series of monetary policy surprises with respect to short-term rates at various horizons. Table 2 shows the estimation results. The information effect becomes visible for future contracts that capture unanticipated changes in short-term interest rates several months after a scheduled policy meeting, from around five months onward after a meeting. Similar results can be obtained when separating movements in futures into target and path factors according to Gürkaynak et al. (2005). Applying their decomposition for scheduled FOMC meetings, it is the path factor that shows an information release. The results for the target factor are very close to the ones for MP1 series that I use. Since the target factor is orthogonal to any future policy change, the results cannot simply be explained by a change in the timing of policy.

The reason for these results may be that the Fed’s forecasts contain additional information relative to the private sector’s forecasts for macroeconomic developments further out in the future. Surprises with respect to short-term rates several months after a policy announcement reveal such information. In contrast, surprises with respect to short-term rates in the very near future are less contaminated in this way since there is potentially less disagreement about the current state of the economy.

In appendices A.11 and A.12, I provide evidence in favor of such an interpretation. Differences between the Fed’s and the private sector’s forecasts predict surprises farther out in the future (see tables 7, 8, and 9). In turn, surprises with respect to future short-term rates help to predict the Fed’s forecast, controlling for the private sector’s forecast (see tables 10 and 11). Finally, following the empirical strategy in Romer and Romer (2000), I show that one would attach a higher weight to the Fed’s forecasts compared to private forecasts, when both are available, with respect to future macroeconomic developments as opposed to more current ones (see tables 12, 14, and 13).

While an information effect cannot be entirely excluded for surprises with respect to current short-term rates around scheduled meetings, the results show that such surprises are
less likely to be biased in this way. I therefore use the MP1 series around scheduled meetings in the following analysis. The series is shown in figure 1. It is available from the start of the futures market in 1988 M11 until 2017 M9, restricting the estimation to this sample period.\footnote{From 1994 M1 onward, the Fed released a statement immediately after each meeting. Before 1994 M1, changes to the target rate had to be inferred by the size and type of open market operations. Hence, it might have taken market participants some time to absorb the relevant information and the thirty-minute window to extract the surprises might be too restrictive. The results in the next sections are robust to starting the sample in 1994 M1 or using daily surprises pre-1994 (as, e.g., Kuttner, 2001).}

B. Constant Parameter VAR

Next, I gather some intuition using a constant parameter VARX in equation 8. Figure 2 shows impulse responses to a contractionary monetary policy shock.\footnote{I choose a lag length of $k = 4$ based on Akaike’s IC. The responses for $k = 3$ (the lag length of the TVP-VAR) are much the same. In addition, I find that VARs with 12 lags—in both log levels and first differences of log levels—give very similar results.} The size of the shock is normalized to match the initial increase in the federal funds rate to a 1 SD monetary policy shock as obtained with the external instrument approach (shown below).\footnote{The series of surprises is projected on the lags of $y_t$, and the residual from this projection is used as the exogenous variable $z_t$, instead, which ensures that the condition in proposition 2 is satisfied. The orthogonalization is repeated for each bootstrap repetition after the distorted $y_t$ are obtained. I find that the impulse responses are nearly equivalent when using the original $z_t$ instead. For each bootstrap repetition, the size of the shock is renormalized in the same way. The proxy $z_t$ is corrected for autocorrelation as discussed in note 7. The same is the case for any of the following estimations. All results are nearly equivalent when using the uncorrected $z_t$ instead.} Based on the critique by Lunsford and Jentsch (2016), confidence bands are computed via a residual-based moving block bootstrap, resulting in relatively wide confidence intervals.\footnote{See also Montiel-Olea et al. (2015) and Mertens and Ravn (2018) in this regard.}

The federal funds rate and the real interest rate (indicated by the dashed line in the same plot in figure 2) both increase in the short run. The model shows standard responses of macroeconomic variables since IP and the CPI both decrease. However, the response of the CPI shows a price puzzle initially, and the 68% confidence interval includes the zero response. Stock prices, their associated dividends, and house prices all decrease persistently following a monetary tightening, and the zero responses lie outside the 1 SD confidence intervals for the first few months. The stock price response is also stronger than the implied fundamental price response based on discounted dividends and constant risk premiums, indicated by the dashed line in the same plot (see appendix A.8 for a derivation). The difference can be accounted for by an increase in risk premiums. The results are therefore in line with the findings in Bernanke and Kuttner (2005), who show that stock returns decrease after a monetary tightening, and risk premiums account for a substantial part of this response.

In comparison, figure 9 in appendix A.14 shows the impulse responses based on a Cholesky identification. The results are counterintuitive, since the CPI increases persistently to a monetary tightening, and IP and stock prices rise mildly after several periods. Clearly, a recursive identification is undesirable within the context of this paper.

I conduct several robustness checks. First, the previous sample includes the effective lower bound (ELB) episode from late 2008 to the end of 2015. Over this period, the surprises with respect to the current month’s federal funds rate are essentially zero (see figure 1). Hence, this episode provides little information for the estimation of the contemporaneous impulse responses. However, it is also not an obstacle for the estimation approach since the contemporaneous
Cumulative impulse responses to a contractionary monetary policy shock, normalized to give the same initial increase in the federal funds rate as obtained with external instrument approach to a 1 SD monetary policy shock, median response along with 68% and 95% confidence intervals. The dashed line in the plot of the federal funds rate shows the real interest rate. The dashed line in the plot of stock prices shows the fundamental price response (see appendix A.8 for the derivation). Residual-based moving block bootstrap as in Lunsford and Jentsch (2016) is used to obtain confidence bands (block size: 20). Sample: 1988 M11–2017 M9.

25 Leaving in the ELB episode has the advantage that the surprises after the ELB episode are taken into account. To check whether the results are sensitive to the inclusion of the ELB episode, I estimate the VAR for a sample that ends in 2007 M12. Figure 10 in appendix A.14 shows the impulse responses. Compared with figure 2, house prices respond more strongly and the zero response lies outside the 2 SD confidence intervals for several months after the shock. While the CPI still shows a price puzzle initially, in the long run it responds more negatively. The other impulse responses are much the same.

Second, Gertler and Karadi (2015) and Caldara and Herbst (2016) show that financial markets provide an important channel through which monetary policy works. Following these papers, I include the excess bond premium by Gilchrist and Zakrajsek (2012). The results are shown in figure 11 in appendix A.14. The excess bond premium rises to a monetary tightening, and the responses of the remaining variables are much the same compared with the ones in figure 2.

Third, I further check whether the price puzzle disappears if the monetary surprises are purged of the Federal Reserve’s expectations about the behavior of the economy in the near future. I project the surprises on the Greenbook forecasts and use the residual from this projection instead of the original $z_t$. However, even with this new series of surprises, I find that the price puzzle persists. The FOMC may therefore respond to more information than the Greenbook forecasts capture. Ramey (2016) obtains similar results. However, she finds that the price puzzle vanishes if a zero restriction on the contemporaneous response of slow-moving macroeconomic variables is imposed. I therefore assume that the CPI does not respond on impact. This additional constraint indeed resolves the price puzzle (see figure 12 in appendix A.14).

Next, I use the proxy $z_t$ as an external instrument (see appendix A.1 for a description). Figure 13 in appendix A.14 shows the impulse responses. As shown in appendixes A.1 and A.4, this identification approach also gives consistent relative impulse responses, and they coincide with the ones based on the VARX in large samples given propositions 1 to 3. The obtained impulse responses in figures 2 and 13 are therefore nearly equivalent—both contemporaneously as

27 The surprises are orthogonalized against the Greenbook forecasts for real GDP (current quarter, one quarter ahead, two quarters ahead), the GDP deflator (current quarter, one quarter ahead, two quarters ahead), and the unemployment rate (current quarter), resembling the information set used in Romer & Romer (2004). Given the availability of the Greenbook forecasts, the sample is restricted to end in 2013 M12.

28 The external steps of the external instrument approach can also be expressed as a 2SLS estimation (Gertler & Karadi, 2015). Given the application here, the $F$-statistic from the first-stage regression is 16.78, which should also be tested when applying the VARX framework.
C. Time-Varying Parameter VAR

Priors. Based on the description in section III, I consider a VAR with time-varying parameters collected in \( B \) and use Bayesian methods to evaluate the posterior distribution of \( B^T \) and the hyperparameters

\[
V = \text{Var} \left( \begin{bmatrix} u_t \\ v_t \end{bmatrix} \right) = \begin{bmatrix} \Omega & 0 \\ 0 & Q \end{bmatrix}.
\]

Following Primiceri (2005), the prior distributions are calibrated based on a training sample of around twelve years (1978 M11–1990 M12). Unfortunately, for a large part of the training sample, the series of monetary policy surprises is not available since the futures market started trading only in 1988 M11. I therefore set the surprises equal to 0 for periods with no available data. While this is certainly a limitation to calibrating the priors, the robustness checks in section IVD show that this constraint does not affect the findings of the paper. Based on the OLS estimates of a constant parameter VAR for the training sample, mean, and variance of \( B_0 \) and scale matrix and degrees of freedom for the inverse-Wishart prior of \( \Omega \) and \( Q \) are set to

\[
B_0 \sim N \left( \widehat{B}_{OLS}, 4 \times V(\widehat{B}_{OLS}) \right), \\
\Omega \sim IW \left( I_n, n + 1 \right), \\
Q \sim IW \left( k^2 Q \times \tau \times V(\widehat{B}_{OLS}), \tau \right).
\]

\( \widehat{B}_{OLS} \) collects the OLS point estimates for the training sample, \( V(\widehat{B}_{OLS}) \) their variance, and \( \tau = 143 \) is the size of the training sample. The parameter \( k Q \) pins down the prior belief about the amount of time variation in \( B_t \). For the main analysis, I set \( k Q = 0.015 \). The robustness checks in section IVD report the results for different values of \( k Q \). The simulation of the model is based on 5,000 iterations of the Gibbs sampler, and the first 2,000 are discarded for convergence. The lag length is reduced to \( k = 3 \) to lower the dimension of both \( B_t \) and \( Q \) to ensure convergence. I check parameter convergence via trace plots and autocorrelation functions of the draws. The results show that the estimation algorithm produces posterior draws efficiently.

Results. Figure 3 shows the time-varying impulse responses for the 1991 M1–2017 M9 sample. Before discussing the results, it is worth explaining in more detail how the impulse responses are calculated. I start by normalizing the response of the federal funds rate on impact to 20 basis points at the beginning of the sample (1991 M1), giving a particular value \( \zeta \) of the instrument to achieve this response.\(^{29}\) Then use the same variation \( \tilde{\zeta} \) to obtain contemporaneous impulse responses for any other variable in 1991 M1 or any subsequent period.\(^{30}\) This procedure ensures that one considers the reaction to the same-size shocks \( \epsilon_1 \) over time, since the relation between \( \epsilon_1 \) and \( \tilde{\zeta} \) is assumed to be constant (see equation [10]).

As an alternative, one could also normalize the impact response of the federal funds rate for each period. However, such a normalization would consider monetary policy shocks of different sizes for the following reason. Note that a contractionary monetary policy shock can occur without an increase of the federal funds rate (or even a decrease). For example, if the private sector expected the federal funds rate to drop by 50 basis points, but in fact it remains unchanged, then this is recorded as a positive surprise. The response of the federal funds rate to the same-size monetary policy shocks can then change over time, as shown in figure 3, since the private sector’s expectations about future movements in the federal funds rate fluctuate.

While the response of the federal funds rate fluctuates over time, it typically increases to a monetary tightening, as shown in figure 3. The recent ELB episode is reflected in the fact that the response has been close to 0 since late 2008. However, it is still possible to capture responses to hypothetical monetary policy shocks over this period. Nonetheless, due to the lack of substantial additional variation of the monetary policy surprises (see figure 1), the posterior distribution of the relevant parameters is not sharpened over this period.

Continuing with the responses in figure 3, IP always decreases to a monetary tightening, and the same is the case for the CPI over most of the sample. House and stock prices always fall, and their responses are significantly different from 0 at the 1 SD and 2 SD confidence intervals over the whole sample.\(^{31}\) The behavior of stock prices is in contrast to the findings in Galí and Gambetti (2015) that stock prices increase to a monetary tightening during stock market booms.

For a selected period, figure 16 in appendix A.15.1 shows the impulse responses with posterior credibility intervals. Based on a Cholesky identification as in their paper, figure 15 in appendix A.15 shows the time-varying impulse responses. Again, the results are counterintuitive, since IP, the CPI, and stock and house prices all increase after a monetary tightening.

Figure 4 illustrates the results in a different format, showing the response of stock and house prices after one and three years (left axis). Additionally, the stock market and the house price index are displayed in log levels (right axis).

\(^{29}\)The variation in \( \tilde{\zeta} \) is given by \( \tau = 2 / \tilde{x}_{1991 M1,1} \), where \( \tilde{x}_{1991 M1,1} \) is the estimated posterior mean for the federal funds rate at time 1991M1.

\(^{30}\)The contemporaneous impulse response of variable \( i \) at time \( t \) is therefore given by \( A_{i,j} \times \tilde{\zeta} \), where \( A_{i,j} \) is the estimated posterior mean for variable \( i \) at time \( t \). The contemporaneous relative impulse response of any two variables \( i \) and \( j \) at time \( t \) can then be obtained from the ratio of their two responses \( \frac{A_{i,j}}{A_{j,j}} = \frac{A_{i,j}}{A_{j,j}} = \tilde{\zeta}_{i,j} \) (see equation [12]).

\(^{31}\)Figure 14 in appendix A.15 shows that stock prices always respond more strongly than fundamentals imply. Again, an increase in risk premia can explain this difference. Quantitatively, the time-varying response of stock prices is largely due to the time-varying response of risk premia; both show a very similar pattern over the whole sample.
Figure 3.—Time-Varying Impulse Responses

Cumulative impulse responses to a monetary tightening. y-axis: Percentage change. x-axis left: Months (Horizon IRF). x-axis right: Years.

Graph shows that stock prices are not very responsive during the 1990s stock market growth period. However, around this time, their response is changing in the opposite direction as the underlying index. During the stock market crash in the early 2000s, stock prices are strongly responsive, but this pattern changes again afterward, interrupted by a slight uptick in the response during the Great Recession. Over most of the sample, the response of house prices follows a clear pattern with respect to the house price index: house prices are less responsive to monetary policy shocks when house prices are high and more responsive when prices are low. For selected time periods of strong and weak asset price responses, figures 17 and 18 in appendix A.15.1 show that these differences in the response of house and stock prices are mostly significantly different from 0, but only at a smaller confidence level than typically used.  

32In particular, for most differences, around two-thirds of the responses lie either above or below 0 (equivalent to the mass of a 1 SD interval under normality).
Next, similar to the sacrifice ratio (Ball, 1994), which is defined as the percentage loss of output per percentage change in a broad price index, I define sacrifice ratios for stock and house prices, substituting the broad price index response with the response of either house or stock prices. Figure 5 shows the sacrifice ratios for different horizons (left axis) and again compares them with the associated price index in log levels.

The upper graph illustrates that the sacrifice ratio for stock prices was particularly high around the Great Recession. At this time, the response of output, measured by IP, increased, while the response of stock prices did not change much. After the crisis, the sacrifice ratio remained at a relatively elevated level. Overall, there is no consistent relation between the sacrifice ratio for stock prices and the stock market index.
In contrast, the sacrifice ratio for house prices and the house price index nearly perfectly comove. Moreover, the time variation in the sacrifice ratio for house prices is substantial. While a 1 percentage point decrease in house prices in the mid-1990s is associated with a similar percentage change in output, this number increases four to eight times around the peak of the housing boom prior to the Great Recession. Around this time, the response of output was historically high, while the opposite was the case for house prices. After the Great Recession, the sacrifice ratio declined again while house prices recovered. In comparison, the constant parameter VARX in section IVB gives a constant sacrifice ratio for house prices of about 1.5 after three years and therefore masks the sizable time-varying trade-off. Comparing the periods 1995 M1 and 2007 M12, figure 19 in appendix A.15.1 shows that these differences in the response of the sacrifice ratios for house and stock prices are significantly different from 0, but generally at a lower confidence level than typically used.33 Overall, these findings suggest that it would have been difficult for the Federal Reserve to lean against the house price boom before the Great Recession. A monetary tightening with the goal to elicit a response in house prices would have come at the exact time when house prices were least responsive. Instead, such attempts would have come with the risk of deviating from the Federal Reserve’s output target, since IP was quite responsive around this time.

D. Sensitivity Analysis

This section checks the robustness of the results obtained with the time-varying parameter VARX. Figures are shown in appendix A.16.

Priors. Regarding the training sample, I find that the results are unaffected for training samples that start earlier or end later. In this regard, I consider the 1975 M11–1990 M12 and 1978 M11–1994 M12 training samples. Moreover, I check the robustness of the results for different calibrations of $\kappa_0$, since Primiceri (2005) finds that the results may be sensitive to this parameter. Figures 20 to 22 in appendix A.16 show the results for $\kappa_0 = 0.01$. While the results are qualitatively unchanged, setting $\kappa_0$ to a lower value decreases the time variation in the coefficients $B_t$, which is reflected in less time variation in some of the impulse responses. However, the time variation of house prices remains substantial. Setting $\kappa_0$ to a higher value has the opposite effect, increasing time variation. For $\kappa_0 = 0.02$, the shape of the impulse responses and parameter convergence remain much the same.

Effective lower bound. A potential caveat is that the sample for the TVP-VARX includes the effective lower bound episode from late 2008 to late 2015. During this period, the surprises with respect to the current month’s federal funds rate were much smaller in absolute size (see figure 1). Hence, there was little information in the data to identify contemporaneous impulse responses over this period. To address this issue, I estimate a TVP-VARX on a sample that ends in 2007 M12, thereby simply excluding the ELB episode. The results are shown in figures 23 to 25 in appendix A.16. The findings are also robust to this variation as the relative responses of output-to-asset prices rise in the run-up to the crisis.34

Timing of policy actions. As Bernanke and Kuttner (2005) pointed out, surprises with respect to the current month’s federal funds futures may only reflect unanticipated changes in the timing of policy actions. I therefore follow Gürkaynak et al. (2005) and construct a target and a path factor from a rotation of the first two principal components across a set of future surprises around scheduled FOMC meetings.35 The target factor moves the MP1 series, but is orthogonal to any surprises with respect to futures that expire after the current month. Based on this new series, the results remain largely unchanged and are shown in figures 26 to 28 in appendix A.16.

Unscheduled meetings. As argued above, the inclusion of monetary policy surprises around unscheduled meetings may distort the impulse responses, since the Federal Reserve is likely to release private information around such meetings by changing interest rates. I check whether that is indeed the case by considering a time-varying parameter VAR and using a series of surprises from the current month’s federal funds futures around scheduled and unscheduled meetings. The results show that dividends and house prices initially increase after a monetary tightening, and the response of the consumer price index is positive throughout the sample, justifying the initial restriction.

Excess bond premium. As for the constant parameter VAR, I check whether the results are robust to including the excess

33To compare responses of sacrifice ratios over time, I condition on negative responses of IP and asset prices to monetary tightenings. That is because a positive response in either IP or asset prices leads to a negative sacrifice ratio. This response cannot only be negative, but also very large in absolute terms if the response of either stock or house prices is small in absolute terms. The considered time variation of sacrifice ratios is still statistically significant without this conditioning.

34To increase the sample size of the estimation, I consider a slightly shorter training sample from 1978 M11 to 1989 M12. In figure 25, I exclude the responses after three years since house prices increase to a monetary tightening around this time (see figure 23). The associated sacrifice ratios therefore flip signs. Moreover, the previously mentioned statistical significance of the time variation in asset prices and sacrifice ratios also remains for this shorter sample.

35The set includes the current month’s federal funds futures (MP1), the three-month-ahead federal funds futures (FF4), and the six-month, nine-month, and year-ahead futures on three-month eurodollar deposits (ED2, ED3, ED4). Based on regression (13), I confirm that the target factor is not strongly confounded by an information release. For example, with respect to scheduled FOMC meetings, $\beta$ in equation (13) is not statistically different from 0 (dependent variable: change in private output forecast over the next year; sample: 1988 M11–2017 M9; see table 2). If unscheduled meetings are included, $\beta$ is positive and statistically different from 0 at the 99% confidence level. The time-varying impulse responses that I report are for $\kappa_0 = 0.01$. 
bond premium by Gilchrist and Zakraje sek (2012). To lower the dimensionality of the model and ensure convergence, I exclude the dividend series. In unreported work, I find that the results are much the same, as well as when ending the sample in 2007 M12.

V. Conclusion

Swings in asset prices can have large effects on economies. During boom periods, rising asset prices can boost an economy that is already running hot. When asset prices reverse, they can amplify a downturn in economic activity. Recent research finds that such movements are important for financial stability: quickly rising stock and house prices are strong early-warning indicators of financial crises and their severity (Jordà et al., 2015; Kiley, 2018; Paul, 2018). To avoid the generally large costs of financial crises, it may therefore be optimal to use monetary policy to lean against asset price booms.

A monetary tightening typically decreases economic activity and asset prices. However, based on US data over the past thirty years, I find that these effects are far from constant over time. Stock and house prices show substantial time variation in their response to monetary policy shocks. The response of house prices strongly comoves with the level of house prices: they are less responsive to monetary policy shocks when house prices are high and more responsive when prices are low. In addition, I find time variation in the relative impact of monetary policy on asset prices and economic activity. The response of stock and house prices, relative to the response of output, was particularly low in the run-up to the Great Recession. Hence, attempts by the Federal Reserve to lean against the house price boom at the time may have been less effective.

These findings are based on the identified responses to unanticipated deviations of monetary policy from a perceived reaction function. Thus, my analysis cannot speak to the question of whether monetary policy should incorporate asset prices into its reaction function and how agents would change their decisions because of that. Finding answers to these important questions is left to future research.

In addition, there are a few other avenues for future research with respect to the methodology developed in this paper. First, it would be interesting to see a thorough analysis of the weak instrument problem for the VARX and the TVP-VARX. Second, a fixed-design wild bootstrap as applied by Goncalves and Kilian (2004) may produce valid confidence bands since the impulse responses with a VARX can be obtained from the estimated coefficients on the controls and the instrument. It would be great to see a formal proof whether such a bootstrap indeed produces valid confidence bands given the critique by Lunsford and Jentsch (2016) with respect to the recursive wild bootstrap. And finally, I think that it be fruitful to extend the TVP-VARX in this paper to allow for time-varying variances along the lines of Primiceri (2005).

REFERENCES


