

Has the Fed Responded to House and Stock Prices? A Time-Varying Analysis *

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Abstract

We investigate whether the Federal Reserve has responded systematically to house and stock prices and whether this response has changed over time using a Bayesian structural VAR model with time-varying parameters and stochastic volatility. To recover the systematic component of monetary policy, we interpret the interest rate equation in the VAR as an extended monetary policy rule responding to inflation, the output gap, house prices and stock prices.

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Our results indicate that the systematic component of monetary policy in the U.S. responded to real stock price growth significantly but episodically, mainly around recessions and periods of financial instability, and took real house price growth into account only in the years preceding the Great Recession. Around half of the estimated response captures the predictor role of asset prices for future inflation and real economic activity, while the remaining component reflects a direct response to stock prices and house prices.

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1 Introduction

The length and the severity of the Great Recession generated considerable interest in the evolution of US monetary policy over the period that preceded the economic slump. However, while the financial nature of the Great Recession revived the debate on whether monetary policy should respond directly to asset prices (cf. [Borio and Lowe \(2002\)](#), [Cecchetti et al. \(2002\)](#), [Bernanke and Gertler \(2000, 2001\)](#), [Christiano et al. \(2010\)](#), [Galí \(2014\)](#)), less attention has been devoted to the measurement of the actual response of the Federal Reserve to asset prices in recent years.

In this paper we take an empirical approach and evaluate to what extent the Fed reacted to asset prices over the Great Moderation period until the beginning of the Great Recession. In particular, we consider whether stock prices and house prices entered the Fed's reaction function with a positive and significant coefficient. Our key contribution is in providing time-varying estimates of the monetary policy response to asset prices by using a Bayesian VAR model with time-varying parameters and stochastic volatility (TVP-SV-VAR, henceforth), following [Primiceri \(2005\)](#) and [Cogley and Sargent \(2005\)](#). More specifically, we interpret the interest rate equation in our VAR with five variables (interest rate, inflation, output gap, house price inflation and stock price inflation) as an extended monetary policy rule in the spirit of [Arias et al. \(2019\)](#), [Belongia and Ireland \(2016a,b\)](#), [Canova and Gambetti \(2009\)](#) and [Primiceri \(2005\)](#), among others. This set-up allows us to track the systematic response to house and stock prices over our sample period, which goes from 1975:Q2 to 2008:Q4. As far as we know, the seminal contributions in this literature (cf. [Bernanke and Gertler \(2000\)](#), and [Rigobon and Sack \(2003\)](#)) and the following extensions are all based on models with constant coefficients. We achieve identification by imposing a combination of impact and long-run zero restrictions that preserves the simultaneous interactions between interest rates and stock prices as in [Bjørnland and Leitemo \(2009\)](#).

Our main result is that the Fed responded to stock and house prices only episodically. We identify some 'pockets' of responsiveness that are interspersed with long periods with little or no reaction. The response to stock prices is economically and statistically

significant around the 1987 stock market crash and around recession periods (at the beginning of the 1990s, in 2001 and just before the Great Recession). No response at all is detected between 1994 and 2000 and between 2003 and 2006, two periods characterized by large stock market booms, as identified by [Christiano et al. \(2010\)](#). The estimated response to house price growth is even more episodic. In fact, we detect a positive and significant response only over 2006-2008, a period capturing the very last phase of the housing boom and the initial phase of the following bust. During that limited period, the response to house price growth is rather large, around one half of the response to price inflation.

In a second step, we further dissect our main result and relate it to the debate between the *driver view* and the *predictor view* of the stock market, using the terminology introduced by [Cieslak and Vissing-Jørgensen \(2021\)](#). Under the *predictor view*, the estimated response reflects the forward looking nature of the stock market, thus capturing a response to future inflation and future real economic activity rather than a direct response to the stock market. Under the *driver view*, the estimated response reflects the Fed's view of stock market fluctuations being an independent factor driving the economy (perhaps related to fluctuations in risk aversion). Based on a careful textual analysis of FOMC transcripts, [Cieslak and Vissing-Jørgensen \(2021\)](#) confirm a larger role for the *driver view*. We contribute to this debate by controlling for Greenbook forecasts of standard monetary policy objectives (like inflation and the output gap) but also for forecasts of stock prices and house prices, and a measure of TFP. We find that part of the estimated response to stock prices and house prices in our baseline model reflects the forward looking nature of asset prices. However, around half of the estimated response represents a direct response of the Fed to the stock market, in keeping with the *driver view*.

This paper contributes to two strands of literature. First, we obviously complement previous studies on the monetary policy response to stock prices by highlighting the importance of modeling time variation. [Bernanke and Gertler \(2000\)](#) estimate Taylor-type rules with a GMM methodology for the US and Japan and find evidence of a very small response, always statistically insignificant and in some cases even negative. [Rigobon](#)

and Sack (2003) estimate a VAR identified through heteroskedasticity and conclude that the response of monetary policy to stock prices in the US was positive and significant over the period 1985-1999. The same result emerges in [Castelnuovo and Nisticò \(2010\)](#), in an estimated dynamic stochastic general equilibrium (DSGE) model where monetary policy responds to fluctuations in the stock market, as well as in [Bjørnland and Leitemo \(2009\)](#), in a constant coefficient version of our model. In contrast, a more recent literature argues that the Rigobon and Sack's finding is confined to specific periods (around the 1987 stock market crash in [Furlanetto \(2011\)](#) and more generally around recession periods in [Ravn \(2012\)](#)). While those results rely on various forms of sample splitting, they may highlight some instability in the relationship between monetary policy and stock prices, thus calling for the use of a model with time-varying coefficients. The response of monetary policy to house prices is largely unexplored with the noteworthy exception of [Finocchiaro and von Heideken \(2013\)](#) who estimate a positive and significant response in the US in the context of a DSGE model. [Bjørnland and Jacobsen \(2013\)](#) provide evidence on the (conditional) response of interest rates to shocks originating in the stock market and in the housing sector but do not report the coefficients in the interest rate equation.

We also relate to a second (and more recent) strand of literature that introduces asset prices into TVP-SV-VAR models. [Prieto et al. \(2016\)](#) use data on several financial variables (including house prices and stock prices) to investigate the relative importance of various financial shocks. However, they do not consider the systematic component of monetary policy in their analysis. [Galí and Gambetti \(2015\)](#) study the time-varying response of stock prices to monetary policy shocks and disentangle the response of a bubble component from a fundamental component in stock prices. Like us, [Paul \(2020\)](#) takes into account the interdependence between stock prices and interest rates as he uses high-frequency surprises as a proxy for structural monetary policy shocks. Yet, both [Galí and Gambetti \(2015\)](#) and [Paul \(2020\)](#) focus on the response of asset prices to monetary policy shocks but not on the opposite relationship, namely the historical response of monetary policy to stock prices. Other papers emphasizing the importance of accounting for time-varying parameters include [Boivin \(2006\)](#) and [Coibion and Gorodnichenko](#)

(2011), who estimate Taylor rules with time-varying coefficients but do not include asset prices in their specifications, and [Antolin-Diaz et al. \(2017\)](#) who consider time variation in long-run GDP growth in a dynamic factor model.

The paper proceeds as follows. Section 2 lays out the model and the details of the estimation. Section 3 presents our results. Section 4 discusses the role of asset prices as drivers or predictors of the economy. Section 5 presents a sensitivity analysis. Finally, Section 6 concludes.

2 Econometric Model

To study how the Fed responded to asset prices in the pre-Great Recession period, we use a Bayesian TVP-SV-VAR à la [Primiceri \(2005\)](#) and [Cogley and Sargent \(2005\)](#). The reduced form representation is given by

$$\mathbf{x}_t = \mathbf{c}_t + \mathbf{B}_{1,t}\mathbf{x}_{t-1} + \dots + \mathbf{B}_{p,t}\mathbf{x}_{t-p} + \mathbf{u}_t, \quad t = 1, \dots, T, \quad (1)$$

where \mathbf{x}_t is a $n \times 1$ vector of endogenous variables, \mathbf{c}_t is a $n \times 1$ vector of time-varying coefficients that multiply constant terms (and can be extended to include exogenous controls), $\mathbf{B}_{i,t}$, $i = 1, \dots, p$ are $n \times n$ matrices of time-varying coefficients and $\mathbf{u}_t \sim MVN(0, \mathbf{\Omega}_t)$, where $\mathbf{A}_t \mathbf{\Omega}_t \mathbf{A}'_t = \mathbf{\Sigma}_t \mathbf{\Sigma}'_t$, with $\mathbf{\Sigma}_t$ diagonal and \mathbf{A}_t , the contemporaneous (time-varying) coefficients matrix, lower triangular.¹

In stacked form, the model is equal to

$$\mathbf{x}_t = \mathbf{Z}'_t \mathbf{B}_t + \mathbf{A}_t^{-1} \mathbf{\Sigma}_t \boldsymbol{\varepsilon}_t, \quad \text{where} \quad \mathbf{Z}'_t \equiv \mathbf{I}_n \otimes [1, \mathbf{x}'_{t-1}, \dots, \mathbf{x}'_{t-p}]. \quad (2)$$

¹ We follow the updated MCMC procedures suggested by [Del Negro and Primiceri \(2015\)](#). They retain most of the procedures in [Primiceri \(2005\)](#) except that sampling of stochastic volatilities is preceded by sampling of states for mixture component approximations to errors with log chi-square distributions.

The time-varying parameters evolve according to the following laws of motion:²

$$\mathbf{B}_t = \mathbf{B}_{t-1} + \boldsymbol{\nu}_t, \quad \boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{\zeta}_t, \quad \log \boldsymbol{\sigma}_t = \log \boldsymbol{\sigma}_{t-1} + \boldsymbol{\eta}_t, \quad (3)$$

where $\boldsymbol{\alpha}_t$ and $\boldsymbol{\sigma}_t$ are the time-varying elements of \mathbf{A}_t and $\boldsymbol{\Sigma}_t$, respectively.

It is assumed that the innovations in the model are jointly normally distributed with the following variance-covariance matrix:

$$V \equiv Var \left(\begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \boldsymbol{\nu}_t \\ \boldsymbol{\zeta}_t \\ \boldsymbol{\eta}_t \end{bmatrix} \right) = \begin{bmatrix} \mathbf{I}_n & 0 & 0 & 0 \\ 0 & \mathbf{Q} & 0 & 0 \\ 0 & 0 & \mathbf{S} & 0 \\ 0 & 0 & 0 & \mathbf{W} \end{bmatrix}. \quad (4)$$

The posterior distributions of \mathbf{B}_t , \mathbf{Q} , \mathbf{A}_t , \mathbf{S} and \mathbf{W} are obtained via Gibbs sampling with standard prior assumptions as in Galí and Gambetti (2015):

$$\mathbf{B}_0 \sim N \left(\widehat{\mathbf{B}}_{OLS}, 4 \cdot V \left(\widehat{\mathbf{B}}_{OLS} \right) \right), \quad (5)$$

$$\mathbf{Q} \sim IW \left(k_Q \cdot rows(Q) \cdot V \left(\widehat{\mathbf{B}}_{OLS} \right), rows(Q) \right), \quad (6)$$

$$\mathbf{A}_0 \sim N \left(\widehat{\mathbf{A}}_{OLS}, V \left(\widehat{\mathbf{A}}_{OLS} \right) \right), \quad (7)$$

$$\mathbf{S}_m \sim IW \left(k_S^2 \cdot (m+1) \cdot V \left(\widehat{\mathbf{A}}_{m,OLS-FS} \right), (m+1) \right), \quad (8)$$

$$\log \boldsymbol{\sigma}_0 \sim N \left(\log \widehat{\boldsymbol{\sigma}}_{OLS}, \mathbf{I}_n \right) \quad (9)$$

$$\mathbf{W} \sim IW \left(k_W^2 \cdot (n+1) \cdot \mathbf{I}_n, (n+1) \right), \quad (10)$$

where $\widehat{\mathbf{A}}_{OLS}$ and $\widehat{\mathbf{B}}_{OLS}$ are estimated by OLS over a training sample and $m = 1, \dots, n-1$, $\widehat{\mathbf{A}}_{m,OLS-FS}$ is the m -th row of $\widehat{\mathbf{A}}_{OLS-FS}$, estimated over the full sample.³ Following

² To check the validity of these assumptions we run a rolling window constant parameter VAR model. We find random-walk behaviour in the first difference of the coefficients, a result which substantiates the assumptions.

³ The total number of Gibbs sampling iterations is set to 150,000 with a burn-in of 100,000 draws and convergence is checked by means of rolling variances plots. We keep the remaining 50,000 draws and use every 100th for inference. The results are basically identical if, more conservatively, we kept every 20th draw instead. Also, results are unaffected if we do or we do not truncate the autoregressive matrices to yield stationary draws. In all exercises, the number of stationary draws is always above 2/3.

Primiceri (2005), we use the first 10 years of data as a training sample to calibrate the priors for estimation over the actual sample period, which starts in 1985:Q3.

The selection of the hyperparameters follows Galí and Gambetti (2015) in choosing $k_Q = 0.005$, $k_S = 0.1$ and $k_W = 0.01$.⁴ This choice of priors is conservative for the question we address in the sense that it balances out the amount of potential time variation in the volatility of the model and in the contemporaneous and lagged policy coefficients.

In our baseline specification, we consider quarterly data from 1975:Q2 to 2008:Q4. The vector $\mathbf{x}_t = [\Pi_t \quad \tilde{Y}_t \quad \Delta H_t \quad \Delta S\&P_t^{500} \quad R_t]'$ consists of Π_t , year-over-year percentage changes in the deflator for personal consumption expenditures (excluding food and energy), \tilde{Y}_t , the output gap measured as the percentage-point difference between actual real GDP and the US Congressional Budget Office estimate of real potential GDP, ΔH_t , the percentage growth of the real Freddie Mac House price index, $\Delta S\&P_t^{500}$, the percentage growth of the real S&P 500 index, and R_t , the federal funds rate. Asset prices are deflated by core PCE. All raw series are drawn from the publicly available FRED database.

Our identification scheme is twofold. First, we assume a triangular structure for the block of inflation and the output gap, which are thus assumed to respond to monetary policy shocks only with a lag. As to the financial variables, we follow Bjørnland and Leitemo (2009) and Bjørnland and Jacobsen (2010) in that we impose that monetary policy shocks have no long-run impact on both the level of real stock prices and the level of real house prices; and that house price inflation does not react simultaneously to a shock to stock price inflation. This scheme preserves the simultaneous interdependence between interest rates and stock prices without imposing any contemporaneous restriction on the behavior of the two variables. The restrictions are imposed at each point in time

⁴ In contrast to Primiceri (2005), this prior disciplines the time variation in the autoregressive parameters \mathbf{B}_t by setting $k_Q = 0.005$ (as opposed to $k_Q = 0.01$) and in the contemporaneous coefficients by tuning the prior variance of \mathbf{A}_t to $4\mathbf{I}_n$ instead of \mathbf{I}_n and by using in the prior mean of \mathbf{S}_m the full-sample estimate $V(\hat{\mathbf{A}}_{m,OLS-FS})$ instead of the training sample estimate $V(\hat{\mathbf{A}}_{m,OLS})$. Another subtle difference is that in the prior for \mathbf{Q} it uses the number of rows of \mathbf{Q} instead of the training sample size. This choice has no meaningful consequences.

t .

A lag length of $p = 1$ is suggested by the BIC criterion obtained from OLS estimation of the constant parameters version of our model. This lag order has the fortunate by-product of facilitating the comparison with the macroeconomic literature on Taylor rules with interest rate smoothing. A specification with two lags is discussed in Section 5.

Let us now recall the reduced form of our model:

$$\underbrace{\begin{bmatrix} \Pi_t \\ \tilde{Y}_t \\ \Delta H_t \\ \Delta S\&P_t^{500} \\ R_t \end{bmatrix}}_{\mathbf{x}_t} = \underbrace{\begin{bmatrix} b_{11,t} & b_{12,t} & b_{13,t} & b_{14,t} & b_{15,t} \\ b_{21,t} & b_{22,t} & b_{23,t} & b_{24,t} & b_{25,t} \\ b_{31,t} & b_{32,t} & b_{33,t} & b_{34,t} & b_{35,t} \\ b_{41,t} & b_{42,t} & b_{43,t} & b_{44,t} & b_{45,t} \\ b_{51,t} & b_{52,t} & b_{53,t} & b_{54,t} & b_{55,t} \end{bmatrix}}_{\mathbf{B}_{1,t}} \underbrace{\begin{bmatrix} \Pi_{t-1} \\ \tilde{Y}_{t-1} \\ \Delta H_{t-1} \\ \Delta S\&P_{t-1}^{500} \\ R_{t-1} \end{bmatrix}}_{\mathbf{x}_{t-1}} + \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ ai_{21,t} & 1 & 0 & 0 & 0 \\ ai_{31,t} & ai_{32,t} & 1 & 0 & ai_{35,t} \\ ai_{41,t} & ai_{42,t} & ai_{43,t} & 1 & ai_{45,t} \\ ai_{51,t} & ai_{52,t} & ai_{53,t} & ai_{54,t} & 1 \end{bmatrix}}_{\mathbf{A}_t^{-1}} \underbrace{\begin{bmatrix} \varepsilon_{\pi,t} \\ \varepsilon_{Y,t} \\ \varepsilon_{H,t} \\ \varepsilon_{SP,t} \\ \varepsilon_{R,t} \end{bmatrix}}_{\boldsymbol{\varepsilon}_t}. \quad (11)$$

The systematic component of monetary policy can be recovered from its structural form

$$\mathbf{A}_t \mathbf{x}_t = \mathbf{A}_t \mathbf{c}_t + \mathbf{A}_t \mathbf{B}_{1,t} \mathbf{x}_{t-1} + \boldsymbol{\Sigma}_t \boldsymbol{\varepsilon}_t, \quad (12)$$

which, omitting constant terms and normalizing the variance of ε_t to unity (i.e., $\Sigma_t = \mathbf{I}$), is

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21,t} & 1 & 0 & 0 & 0 \\ a_{31,t} & a_{32,t} & 1 & a_{34,t} & a_{35,t} \\ a_{41,t} & a_{42,t} & a_{43,t} & 1 & a_{45,t} \\ a_{51,t} & a_{52,t} & a_{53,t} & a_{54,t} & 1 \end{bmatrix}}_{\mathbf{A}_t} \underbrace{\begin{bmatrix} \Pi_t \\ \tilde{Y}_t \\ \Delta H_t \\ \Delta S\&P_t^{500} \\ R_t \end{bmatrix}}_{\mathbf{x}_t} = \underbrace{\begin{bmatrix} ab_{11,t}^1 & ab_{12,t}^1 & ab_{13,t}^1 & ab_{14,t}^1 & ab_{15,t}^1 \\ ab_{21,t}^1 & ab_{22,t}^1 & ab_{23,t}^1 & ab_{24,t}^1 & ab_{25,t}^1 \\ ab_{31,t}^1 & ab_{32,t}^1 & ab_{33,t}^1 & ab_{34,t}^1 & ab_{35,t}^1 \\ ab_{41,t}^1 & ab_{42,t}^1 & ab_{43,t}^1 & ab_{44,t}^1 & ab_{45,t}^1 \\ ab_{51,t}^1 & ab_{52,t}^1 & ab_{53,t}^1 & ab_{54,t}^1 & ab_{55,t}^1 \end{bmatrix}}_{\mathbf{A}_t \mathbf{B}_{1,t}} \underbrace{\begin{bmatrix} \Pi_{t-1} \\ \tilde{Y}_{t-1} \\ \Delta H_{t-1} \\ \Delta S\&P_{t-1}^{500} \\ R_{t-1} \end{bmatrix}}_{\mathbf{x}_{t-1}} + \underbrace{\begin{bmatrix} \varepsilon_{\pi,t} \\ \varepsilon_{Y,t} \\ \varepsilon_{H,t} \\ \varepsilon_{SP,t} \\ \varepsilon_{R,t} \end{bmatrix}}_{\boldsymbol{\varepsilon}_t}. \quad (13)$$

Looking at the fifth row of (13), we have

$$\begin{aligned}
 & a_{51,t}\Pi_t + a_{52,t}\tilde{Y}_t + a_{53,t}\Delta H_t + a_{54,t}\Delta S\&P_t^{500} + R_t \\
 & = ab_{51,t}^1\Pi_{t-1} + ab_{52,t}^1\tilde{Y}_{t-1} + ab_{53,t}^1\Delta H_{t-1} + ab_{54,t}^1\Delta S\&P_{t-1}^{500} + ab_{55,t}^1R_{t-1} + \varepsilon_t^R. \quad (14)
 \end{aligned}$$

Bringing R_t over to the left-hand side yields

$$\begin{aligned}
 R_t & = -a_{51,t}\Pi_t - a_{52,t}\tilde{Y}_t - a_{53,t}\Delta H_t - a_{54,t}\Delta S\&P_t^{500} \\
 & \quad + ab_{51,t}^1\Pi_{t-1} + ab_{52,t}^1\tilde{Y}_{t-1} + ab_{53,t}^1\Delta H_{t-1} + ab_{54,t}^1\Delta S\&P_{t-1}^{500} + ab_{55,t}^1R_{t-1} + \varepsilon_t^R, \quad (15)
 \end{aligned}$$

where the coefficient $ab_{55,t}^1$ captures the degree of interest rate smoothing.

We will focus on the time evolution of the long-run coefficients, which are obtained by dividing the sum of the contemporaneous and lagged coefficients of a given variable by one minus the interest rate smoothing term (e.g., $\frac{-a_{51,t} + ab_{51,t}^1}{1 - ab_{55,t}^1}$ for the inflation rate). This allows us to represent the response of the interest rate to a permanent one percentage-point increase in the variables included in the VAR. The interest on the long-run coefficients fol-

lows the literature on TVP-SV-VAR models, starting with [Primiceri \(2005\)](#) and including [Canova and Gambetti \(2009\)](#), among others. These coefficients are viewed as the correct empirical benchmark for detecting violations of the so-called Taylor principle derived by the theoretical literature. Two additional reasons justify our focus on long-run responses. First, central banks might not observe data from the current quarter and thus rather weight on data from the previous period. The second is that lags of an autoregressive process can compensate each other. Concentrating on a single coefficient would thus be misleading if one seeks to explore a variable's contribution to interest rate dynamics.

3 The Systematic Component of Monetary Policy

In this Section, we present estimates for the time-varying coefficients in the interest rate equation. The coefficients are reported along with the 16 percent and 84 percent credibility intervals for the period ranging from 1985:Q3 to 2008:Q4, as we discard the first 10 years of observations used in the training sample to set up the priors.

Results for the Baseline Model We begin by addressing the main questions of interest to this paper, namely i) whether the Fed responded systematically to stock and house prices and ii) whether this response changed over time. The evidence shown in the left column of [Figure 1](#) provides a positive answer to both questions. Indeed, the long-run real S&P 500 growth coefficient is statistically and economically significant but only episodically. We identify a significant response only in a period of historically high stock market instability around the stock market crash of October 1987 and around recession periods like the beginning of the 1990s, 2001 and 2007, at the very end of our sample, when the Great Recession starts.

In contrast, no response at all is detected between 1994:Q2 and 2000:Q2 and between 2003:Q1 and 2006:Q1, two periods characterized by large stock market booms, as identified by [Christiano et al. \(2010\)](#). During the third boom present in our sample (1982:Q3-1987:Q3), the estimated response is even negative before turning positive at the end of 1986. All in all, we conclude that stock price growth entered the central bank's

reaction function only episodically and almost exclusively during stock market busts or around recessions. A similar pattern is found by [Cieslak and Vissing-Jørgensen \(2021\)](#) who document that since the mid-1990s the Fed has engaged in a sequence of policy easings following large stock market declines between FOMC meetings. They refer to this pattern as a “Fed put”.

We now investigate the Fed’s response to real house price growth, which we plot in the second row of the left column in [Figure 1](#). The estimated coefficient is not significant until 2006 when it starts to steadily increase and reaches the value of 1 at the outset of the Great Recession. The response has been economically significant during 2006 and 2007 when the long-run house price growth coefficient is between one half and one third of the long-run inflation coefficient, plotted in the third row of [Figure 1](#). Notably, [Cieslak and Vissing-Jørgensen \(2021\)](#) document the remarkable absence of mentions of the housing market in FOMC minutes until the mid 2000s when the tendency changes, in keeping with the pattern of our estimated long-run coefficient.

In the left column of [Figure 1](#), we plot also time-varying estimates for the long-run coefficients on standard monetary policy targets, namely core PCE inflation and the output gap. The long-run coefficients show a fair amount of time variation and are of comparable magnitude. The long-run inflation coefficient is estimated on average slightly below 2 while the output coefficient is below 1.5. The posterior median estimates are quantitatively comparable with the estimated long-run coefficients on inflation and output growth in [Canova and Gambetti \(2009\)](#). Finally, in the bottom panel of [Figure 1](#) we present the estimate for the coefficient on the lagged interest rate which finds a counterpart in the interest rate smoothing term in a Taylor-type monetary policy rule. Our median estimate fluctuates slightly below 0.8, in line with the value estimated by [Smets and Wouters \(2007\)](#).

Longer Sample Period In our baseline model we focus on the pre-Great Recession period to estimate the systematic component of monetary policy. This choice is motivated by the fact that the federal funds rate is constrained by the zero lower bound between 2009 and 2016 and thus is not an appropriate indicator of the monetary policy stance.

In fact, during that period the Fed has used a series of unconventional measures to fight deflationary pressures and persistently weak levels of economic activity. Using the federal funds rate to capture the systematic component of monetary policy would simply ignore the role of unconventional policies. To overcome this limitation, we follow [Wu and Xia \(2016\)](#) and use their shadow rate indicator as a measure of the monetary policy stance that applies also to binding zero lower bound periods. In the right column of [Figure 1](#), we present the long-run coefficients for the model estimated using data until 2020:Q2 and using the shadow rate as monetary policy instrument for the period in which the policy rate is at the zero lower bound.

Our previous results are confirmed when considering a much longer sample period. Indeed, we still identify an episodic response to stock price growth concentrated in periods of distress and a significant response to house price growth only between 2006 and 2009. Having a longer sample period is useful to briefly discuss the debate on the monetary policy stance in the pre-Great Recession period initiated by [Taylor \(2007, 2009\)](#) who argues that the interest rate was kept too low for too long prior to the crisis. [Belongia and Ireland \(2016b\)](#) estimate a TVP-SV-VAR model and find evidence of a slightly lower response to inflation in recent years, thus weakly supporting the Taylor evidence. Our model can be seen as an extension of their model to include house prices and stock prices in the analysis. We also identify a tiny decrease in the response to inflation and the output gap in the pre-Great Recession period. However, such a pattern is reversed after 2008 when the shadow rate exhibits a strong response to economic fundamentals and reaches its peak in 2013.

4 Inspecting the Response to Asset Prices:

Driver View vs. Predictor View

In this Section, we inspect whether the estimated response reflects a direct response to the stock market (driver view) or whether it captures a response to forecasts of standard objectives of monetary policy that are correlated with current values of stock prices (pre-

dicator view). The debate is unsettled in the literature. After controlling for policymakers' forecasts (Greenbook forecasts) in single equation estimation of Taylor rules, [Fuhrer and Tootell \(2008\)](#) find that the Fed responded to stock prices merely to the extent to which they act as good predictors of forward-looking variables like inflation and output. In contrast, [Castelnuovo and Nisticò \(2010\)](#) and [Cieslak and Vissing-Jørgensen \(2021\)](#) find results that support an important role for the driver view.

Controlling for Greenbook Forecasts In a first experiment, we repeat the [Fuhrer and Tootell \(2008\)](#)'s experiment in the context of our model. In particular, we control for one- and two-quarters ahead Greenbook forecasts of the output gap as well as for the forecast of GDP price inflation at $t + 1$ and its average over $t + 1$ and $t + 2$, as in [Coibion and Gorodnichenko \(2012\)](#). Details on the construction of the series are provided in the Online Appendix. The series are added as exogenous variables to our baseline TVP-SV-VAR, with time-varying loadings. In [Figure 2](#), we compare the estimates obtained from this exercise (solid lines) with the estimates from the baseline specification (dashed lines). In the first row, we see that a significant (although still very episodic) response to stock prices and house prices is preserved in the extended set-up. Notably, the magnitude of the long-run coefficients is considerably reduced (almost halved), thus highlighting that our baseline estimates capture at least to some extent the predictor view. Nonetheless, the estimates remain significant, both economically and statistically, in all the episodes identified in our baseline model, in keeping with the driver view.

In a second experiment, we explore the role of the forward-looking component of asset prices by controlling for one- and two-quarters ahead Greenbook forecasts of real stock price and house price inflation, taken respectively from the the Philadelphia Fed and [Gallin and Sherlund \(2018\)](#) (details on the construction of the series are provided in the Online Appendix). We add them as exogenous variables to our baseline model and we plot results in the second row of [Figure 2](#). The response to stock prices and house prices is only marginally affected in this extended set-up, thus showing that the predictor role of asset prices is mainly related to the standard objectives of monetary policy and not to asset prices themselves. Finally, in the bottom panel of [Figure 2](#), we control for both

one-quarter ahead Greenbook forecasts of standard objectives and one-quarter ahead forecasts of stock prices and house prices.⁵ On average, around one half of the baseline estimated response is preserved also in this experiment.

Response to a Proxy for the Driver View One additional way to isolate a direct response to stock prices consists in estimating the response of monetary policy to a proxy that captures fluctuations in risk aversion. In fact, [Cieslak and Vissing-Jørgensen \(2021\)](#) relate explicitly the driver view to shocks to risk aversion or investor sentiment.⁶ One well-known proxy for risk aversion is computed by [Bekaert et al. \(2013\)](#) who decompose the VIX index into a risk aversion component and an uncertainty component related to expected stock market volatility. Therefore, we substitute real stock price growth with the proxy for risk aversion in our baseline model, and estimate the Fed’s response to the risk aversion proxy, a variable that mainly reflects the driver view of the stock market. Since the risk aversion proxy is available only from 1990, we estimate the model over the sample 1990:Q1-2008:Q4.⁷

In [Figure 3](#), we plot the estimate of the negative of the time-varying long-run coefficient of the risk aversion proxy (solid line) in comparison with the estimate of the time-varying real stock price growth coefficient from our baseline model (dashed line). The response to the risk aversion proxy is on average smaller, especially in the first part of the sample, and very often statistically insignificant. However, we still identify some pockets of responsiveness in selected periods, thus showing that some traces of a direct response to stock prices is preserved also in this experiment. Notably, once we control for Greenbook forecasts of standard monetary policy objectives, stock prices and house prices

⁵ We refrain from including both one- and two-quarters ahead forecasts for all variables as 20 additional coefficients with respect to the baseline model would need to be estimated.

⁶ An important role for shocks originating in the stock market emerges from recent papers by [Caballero and Simsek \(2020\)](#) and [Basu et al. \(2021\)](#). Empirical evidence for a causal nexus linking the stock market to various macroeconomic variables is provided in [Chodorow-Reich et al. \(2021\)](#), [Cieslak and Vissing-Jørgensen \(2021\)](#) and [Di Maggio et al. \(2020\)](#).

⁷ Our training sample covers 15 years of data, from 1975:Q1 to 1989:Q4. Since the risk aversion proxy is only available starting in 1990:Q1, we use the negative of stock price growth to tune the priors in the training sample.

(dash-dotted line), the estimated response to the risk aversion proxy is only marginally affected, unlike our baseline response to real stock price growth which is almost halved when controlling for Greenbook forecasts (see Figure 2). This result is consistent with our baseline estimate capturing both the driver and the predictor view while the response to the risk aversion proxy being more directly related to the driver view.

Controlling for TFP A third way to control for the predictor view builds on [Beaudry and Portier \(2006\)](#) who document that surprise movements in stock prices are highly informative about future productivity movements. They show that innovations to stock prices, which are orthogonal to innovations to TFP, and a shock that drives long-run movements in TFP - when isolated separately without imposing orthogonality - are almost perfectly collinear. According to this view, stock prices and TFP are potentially driven by the same shock and our estimated response to asset prices may hide a response to TFP. To account for this, we add the [Fernald \(2012\)](#) utilization-adjusted TFP series as an exogenous variable to our baseline TVP-SV-VAR. In the first row of Figure 4, we see that the response to stock prices and house prices is only marginally affected once we control for TFP.

Disentangling the Response to Credit Spreads Finally, we verify that the estimated response to stock prices and house prices does not reflect a response to credit spreads. This concern is well-founded since [Caldara and Herbst \(2019\)](#) document that the Fed's monetary policy rule reacts systematically to changes in corporate credit spreads. To address this, we substitute house price inflation and stock price inflation, respectively, in our baseline model with quarter-over-quarter changes of the [Gilchrist and Zakrajšek \(2012\)](#) credit spread. In the second and third rows of Figure 4, we show that the significant response to stock and house prices in selected periods is preserved with one important exception: the response to stock prices is not significant anymore at the end of the sample, a period when the response to the credit spread reaches its peak. Interestingly, in both experiments the response to the spread is also episodic, mostly concentrated in the first part of the sample and in the initial phase of the Great Recession.

5 The Importance of Modeling Time Variation and Sensitivity Analysis

First, we evaluate the importance of modeling time variation. Figure 5 shows that shutting down time variation in the parameters would lead a researcher to mistakenly infer that the Fed did not care about house and stock prices in its conduct of monetary policy. Notably, time variation in the matrix of contemporaneous coefficients (A_t) is particularly important: a model with no time variation in A_t would not detect any response. A version of the model with no time-variation in the matrices of lagged coefficients $B_{1,t}$ would detect an almost constant response which is particularly biased in the case of stock prices. These results highlight the importance of allowing for time variation in all parameters to detect the pockets of responsiveness to asset prices uncovered in our analysis.⁸

Next, we investigate a different ordering for the variables included in our baseline model. It is well-known that the reduced form parameters of standard time-varying models may depend on the ordering of the variables. This dependence is passed on to the structural parameters when applying identification algorithms, as acknowledged in [Primiceri \(2005\)](#) and [Cogley and Sargent \(2005\)](#). This means that, for a given identification strategy, the ordering of the variables may matter. To check this concern in the context of our model, we report results for the most radical alternative ordering in the third row of Figure 5. Here, the order of the variables is inverted while maintaining the same identification scheme. Not surprisingly, given the previous discussion, the results are slightly affected but the main patterns are confirmed. New methods at the frontier of the literature dealing with this problem are presented in [Bognanni \(2018\)](#), [Liu et al. \(2018\)](#) and [Petrova \(2019\)](#).

Finally, we estimate a version of our model with two lags and we report results on the last row of Figure 5. Not surprisingly, given the larger amount of parameters to be

⁸ In the Online Appendix, we show that a model with time-varying parameters and constant volatility recovers estimates that are similar to our baseline model. In contrast, a model with no stochastic volatility and constant parameters is not able to detect any response to asset prices.

estimated, the coefficients are estimated less precisely. Nonetheless, all our main results are confirmed also in this extended version of the model.

6 Conclusion

The main contribution of this paper is to provide empirical evidence on the time-varying response of monetary policy to stock prices and house prices. We find that the response to stock price fluctuations has been positive but episodic, being economically and statistically significant only around the 1987 stock market crash and around recession periods. No response at all is detected between 1994 and 2000 and between 2003 and 2006, two periods characterized by large stock market booms. The estimated response to house price growth is even more episodic, being concentrated only over the period 2006-2008. The use of a model with time-varying coefficients is crucial to detect these pockets of responsiveness.

Finally, it is important to stress that our analysis has no normative implications for whether such a response to stock prices and house prices was optimal, insufficient or excessive (cf. [Adam and Woodford \(2021\)](#)). Nevertheless, we believe it is interesting to document that it was episodic, rather large in specific periods and totally absent in others.

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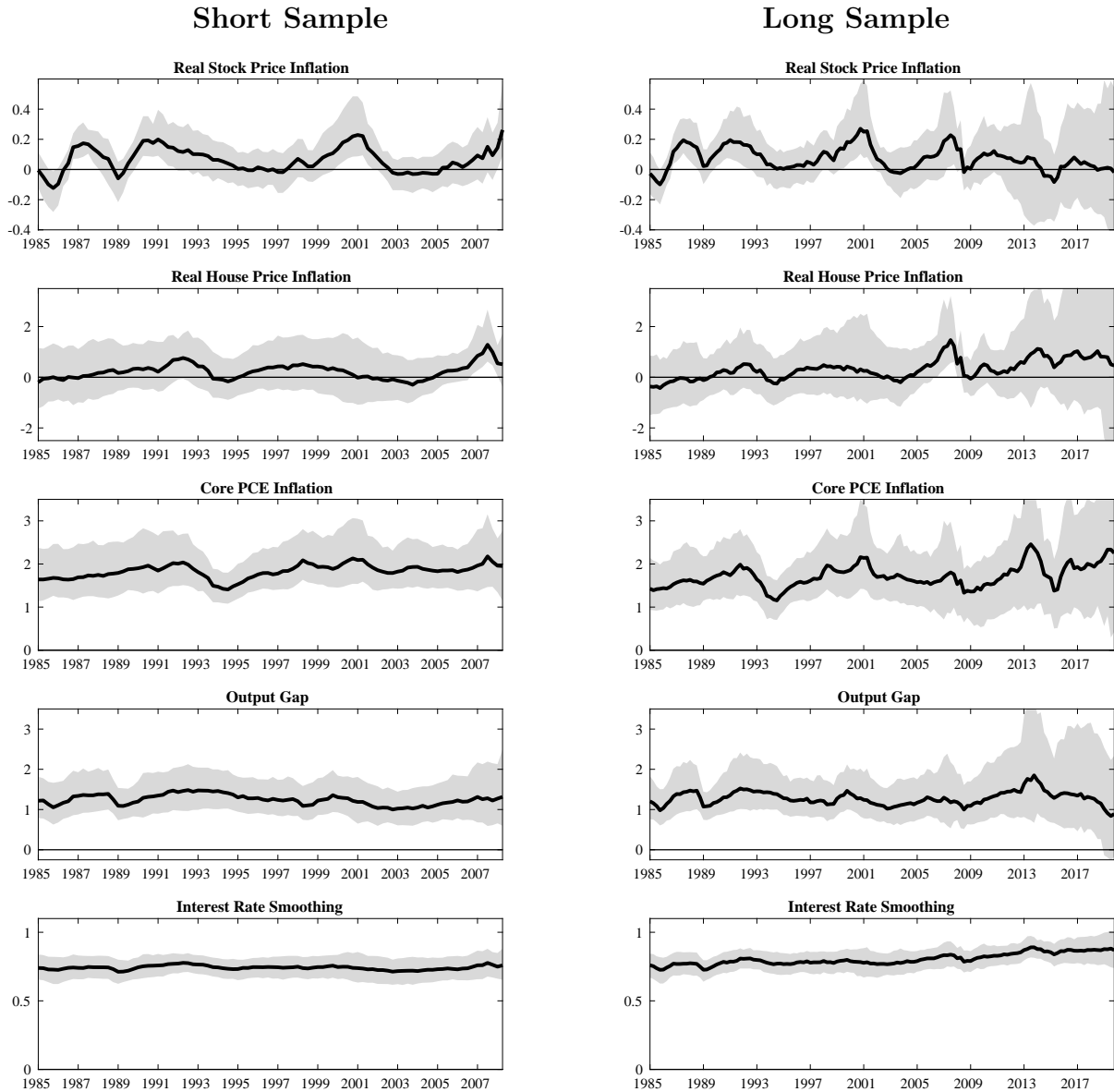
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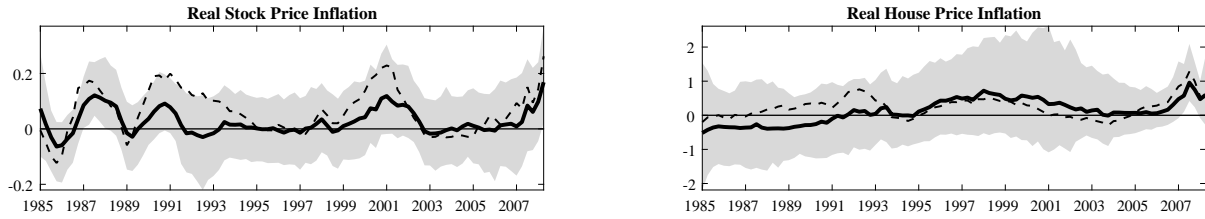
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Figure 1: Long-Run Coefficients and Interest Rate Smoothing.

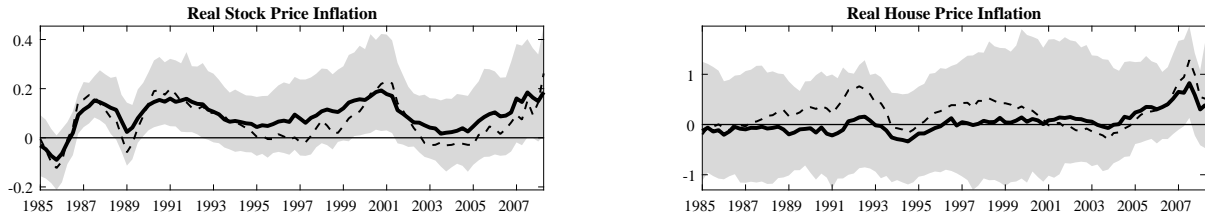


Note: The left panel shows the systematic component of monetary policy for the sample 1985:Q3-2008:Q4. The right panel shows the same results for the sample 1985:Q3-2020:Q2, using the [Wu and Xia \(2016\)](#) shadow interest rate. The top two rows show time-varying long-run coefficients on real stock price growth and real house price growth. The mid rows show time-varying long-run coefficients on core PCE inflation and the output gap. The bottom row shows the smoothing term in a Taylor-type monetary policy rule.

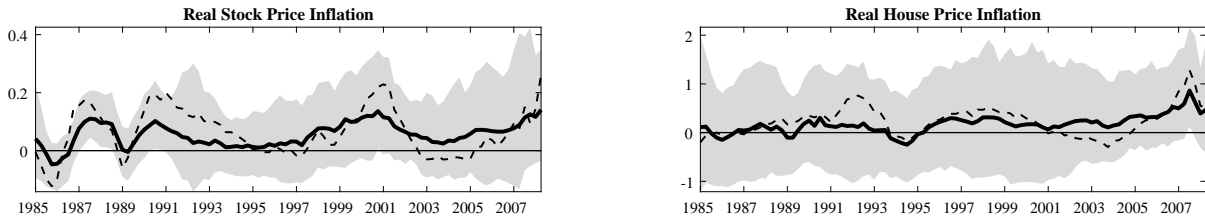
Figure 2: Long-Run Coefficients on House Price and Stock Price Inflation. Controlling for Greenbook Forecasts.



Controlling for Greenbook Forecasts of Standard Objectives



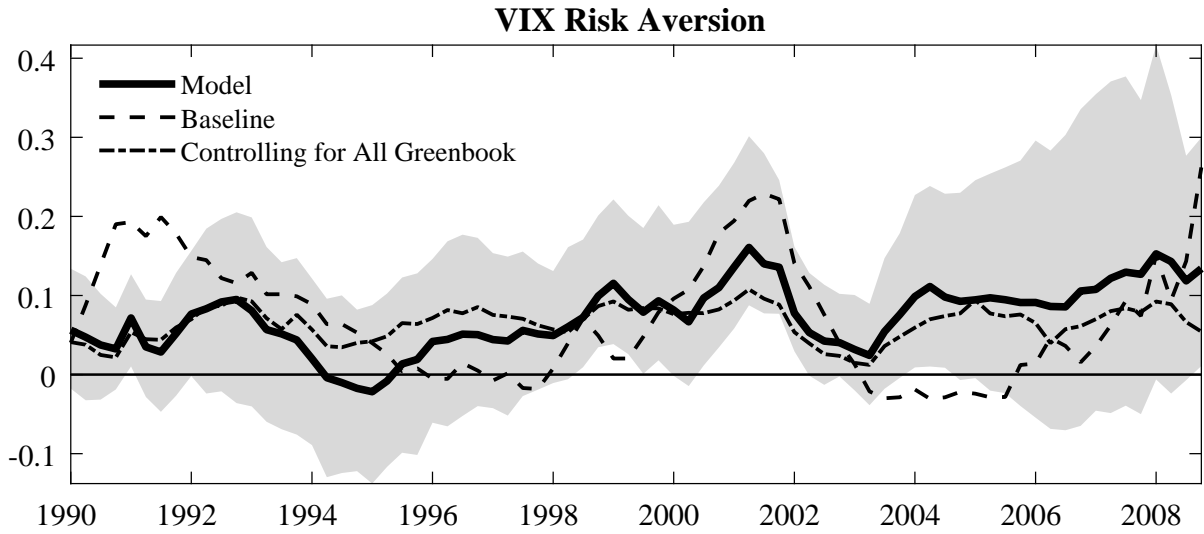
Controlling for Greenbook Forecasts of Real Stock and House Price Inflation



Controlling for all Greenbook Forecasts (1-Step-Ahead)

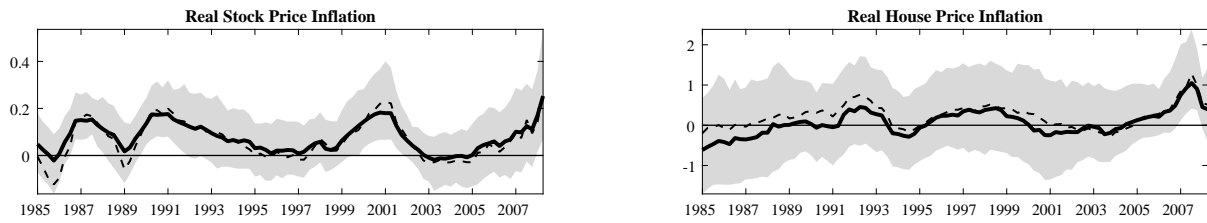
Note: The top panel shows the time-varying long-run coefficients on stock price and house price inflation when we control for one- and two-quarters ahead Greenbook forecasts of inflation and the output gap in our baseline model. The middle panel shows the same exercise with Greenbook forecasts of real stock and house price inflation, while the bottom panel controls for all 1-step-ahead Greenbook Forecasts. The dashed lines represent the coefficients in the baseline specification for the short sample.

**Figure 3: Long-Run Coefficients on Stock Price Inflation.
Risk-Aversion Component of VIX.**

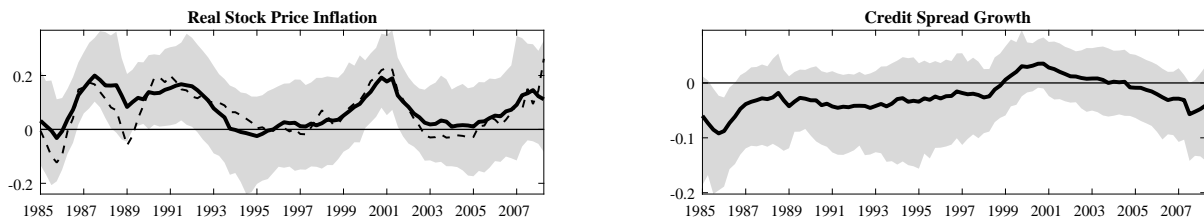


Note: The solid line shows the negative of the time-varying long-run coefficient on the risk aversion proxy. The dashed line represents the coefficient on real stock price growth in the baseline specification for the short sample. The dash-dotted line represents the negative of the risk aversion proxy coefficient for the specification in which we control for 1-step-ahead Greenbook Forecasts of standard objectives and of real stock and house price inflation.

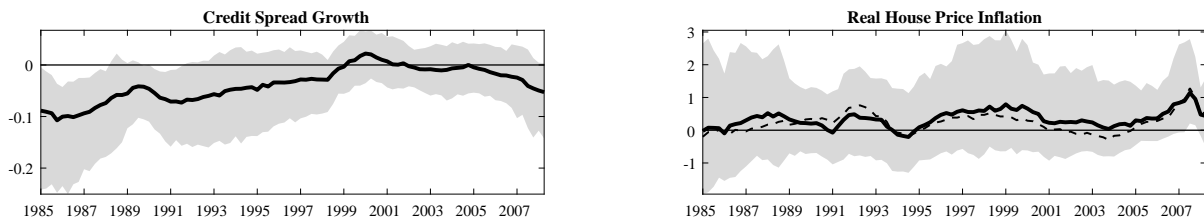
Figure 4: Long-Run Coefficients on House Price and Stock Price Inflation. Predictor vs. Driver View.



Controlling for TFP



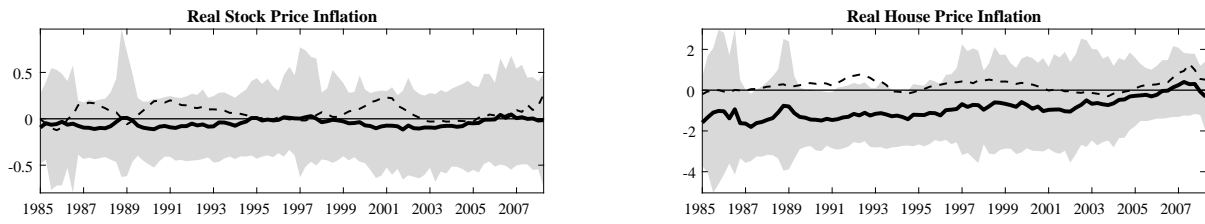
Gilchrist and Zakrajšek (2012) Credit Spread Instead of House Price Inflation



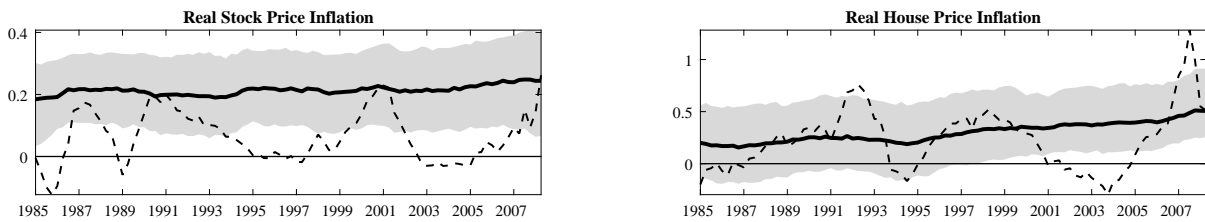
Gilchrist and Zakrajšek (2012) Credit Spread Instead of Stock Price Inflation

Note: The top panel shows the coefficients on stock price and house price inflation when we control for the [Fernald \(2012\)](#) utilization-adjusted TFP series in our baseline model. The middle panel shows coefficients on stock price inflation and the [Gilchrist and Zakrajšek \(2012\)](#) credit spread when we substitute house price inflation with the [Gilchrist and Zakrajšek \(2012\)](#) credit spread in our baseline model. The bottom panel shows coefficients on house price inflation and the [Gilchrist and Zakrajšek \(2012\)](#) credit spread when we substitute stock price inflation with the [Gilchrist and Zakrajšek \(2012\)](#) credit spread in our baseline model. The dashed lines indicate the coefficients in the baseline specification for the short sample.

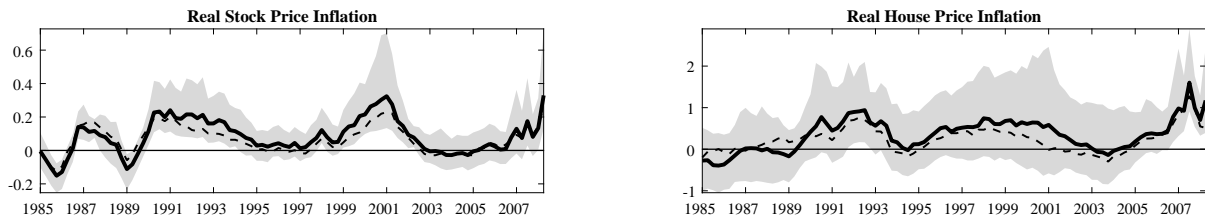
**Figure 5: Long-Run Coefficients on House Price and Stock Price Inflation.
The Role of Stochastic Volatility and Time-Varying Coefficients.**



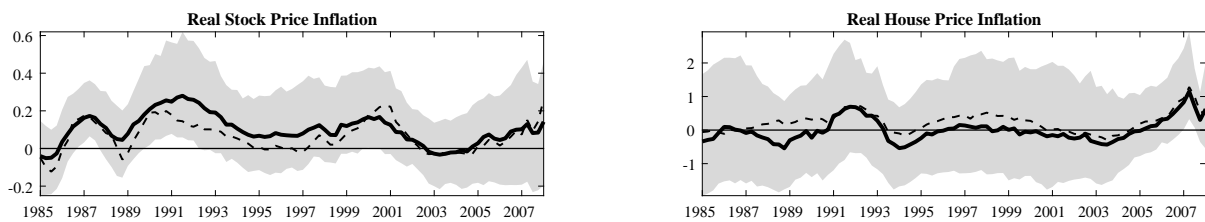
No Time Variation in A_t



No Time Variation in $B_{1,t}$



Inverse Ordering (Identification Unchanged)



VAR Model with 2 Lags

Note: The first two panels show the long-run coefficients on stock price and house price inflation in a model with stochastic volatility and either constant contemporaneous structural coefficients (A_t) or constant lagged structural coefficients ($B_{1,t}$), respectively. The third panel shows the time-varying long-run coefficients on stock price and house price inflation in a model where the order of the standard objectives of monetary policy (inflation and output gap) and of the asset price inflation measures (stock prices and house prices) have been switched. The bottom panel shows the long-run coefficients on stock price and house price inflation in a model featuring two lags. The dashed lines indicate the coefficients in the baseline specification for the short sample.