

DO CENTRAL BANKS REACT TO HOUSE PRICES?*

Daria Finocchiaro and Virginia Queijo von Heideken[†]

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Abstract

The substantial fluctuations in house prices recently experienced by many industrialized economies have stimulated a vivid debate on the possible implications for monetary policy. In this paper, we study the response to house prices of the U.S. Federal Reserve, the Bank of England and the Bank of Japan. First, we show that generalized method of moments (GMM) estimates of a Taylor rule augmented with house prices are biased and dispersed. Then, we propose full-information methods as a suitable alternative and estimate the policy rule together with a VAR for the non-policy variables. Also in this case we find that the estimates are downward biased. We therefore propose an alternative approach and estimate a full-fledged DSGE model where house price fluctuations affect firms' and households' balance sheets. We find that house price movements did indeed play a separate role in the reaction functions of these central banks.

Keywords: House prices, monetary policy, DSGE models, Bayesian estimation

JEL codes: E31, E44, E52, E58

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[†]Sveriges Riksbank, Research Division, SE-103 37 Stockholm, email: daria.finocchiaro@riksbank.se and virginia.queijo.von.heideken@riksbank.se

1 Introduction

In the last few decades house prices have undergone major medium-run fluctuations in many industrialized economies. Boom-bust cycles in house prices, coupled with a substantial increase in household indebtedness, have drawn the attention of both policymakers and academics toward the developments in housing markets, their impact on financial stability and the potential implications for monetary policy. A crucial question is whether monetary policy has reacted to house price fluctuations.

In this paper, we study the response to house prices of the U.S. Federal Reserve, the Bank of England and the Bank of Japan. First, we show that generalized method of moments (GMM) estimates of a Taylor rule augmented with house prices are biased and dispersed. Then, we propose full-information methods as a suitable alternative and estimate the policy rule together with a VAR for the non-policy variables. Also in this case we find that the estimates are downward biased. We therefore propose an alternative approach and estimate a full-fledged DSGE model where house price fluctuations affect firms' and households' balance sheets. This enables us to use the cross-equation restrictions implied by the model to identify the parameters of interest. We find that house price movements did indeed play a separate role in the reaction functions of these central banks.

A substantial empirical literature analyzing central banks' reaction functions augmented with asset prices has sprouted in recent years. Following the work of Clarida, Gali, and Gertler (2000), most of these papers estimate Taylor-type rules using GMM.¹ Rigobon and Sack (2003) point out that adding stock prices to Taylor rules creates an endogeneity problem. Moreover, they stress that addressing such a problem through instrumental variables is quite a complex task since it would be difficult to find instruments that affect the stock market that are not correlated with interest

¹See, among many others, Bernanke and Gertler (1999), Cecchetti and Li (2008), Chadha, Sarno, and Valente (2003), Clarida, Gali, and Gertler (1998) and Jondeau, Bihan, and Galles (2004).

rate movements. Relying on the heteroskedasticity of stock market returns, they show that in the U.S. a 5% rise in the S&P index increases the likelihood of a 25-basis-point tightening by about one half. By adopting a different identification strategy, D'Agostino, Sala, and Surico (2005) show that the Fed reacts much more strongly to the stock market index during periods of high asset price volatility. Also Fuhrer and Tootell (2008) emphasize the identification issues related to GMM and, using the actual forecasts examined by the FOMC before each policy decision (the "Greenbook" forecasts), find little evidence that the Fed responds directly to stock values.

We contribute to this literature by proposing a structural approach to deal with the endogeneity problem that arises estimating Taylor rules with asset prices in a univariate setting.

Contrary to the previous literature, we focus on house prices rather than stock returns. Empirically, house and stock prices are highly correlated and swings in both of these assets have been highlighted as key factors behind business cycles.² However, in contrast to most assets, real estate serves two important functions that make the whole economy vulnerable to house price movements. First, houses are durable goods that provide direct services to households. As a result, a big chunk of households' wealth is held in this form and house price fluctuations might potentially have a greater impact on aggregate spending than stock returns.³ Second, a large share of bank assets use housing as collateral. Since bank lending is highly dependent on collateral values, there is a positive relation between credit and house prices (the bank credit channel). Finally, house price inflation, but not stock price inflation, has better predictive content for both inflation and output (e.g. Stock and Watson (2003) and Filardo (2000)).

From a methodological point of view, our paper is closely related to Lubik and Schorfheide (2007), who estimate a small-scale general equilibrium model of a small open economy and compare

²Once we detrend the data, these two series do not exhibit a positive correlation in the U.S. and the U.K. Since we use detrended data in our analysis, this excludes the possibility that our results capture central banks' response to stock prices rather than to house prices.

³See, e.g., Carroll, Otsuka, and Slacalek (2006) and Case, Quigley, and Shiller (2005).

different Taylor rules using Bayesian methods. They use posterior odds tests to investigate whether central banks respond to exchange rates in Australia, New Zealand, Canada and the U.K. We perform a similar exercise in a medium-scale model but instead test for the response to house prices.

On theoretical grounds, we follow Iacoviello (2005), who develops a monetary business cycle model with nominal loans and collateral constraints tied to housing values. In the model, changes in house prices affect the borrowing capacity of borrowers, while movements in consumer prices influence the real value of their nominal debt.

The paper is organized as follows. In section 2 we show that both GMM and FIML-VAR, i.e., maximum likelihood estimators where the dynamics of the rest of the economy are represented by VAR equations, produce biased estimates of the parameters of a Taylor rule augmented with house prices. In section 3 we propose a DSGE model to estimate the monetary rule and show our main results. In section 4 we look into optimal simple rules and try to reconcile our results with policymakers' rhetoric. Section 5 presents our conclusions.

2 Estimating Taylor rules with house prices

2.1 A partial information framework: GMM

Single equation methods produce biased and dispersed estimates of a Taylor rule augmented with house prices. To show this point, we first estimate the monetary policy rule followed by the three countries using GMM on real data. Then, we examine the implications of using GMM methods when the true data generating process is the theoretical model described in section 3. Our results highlight the importance of using a system approach to properly identify the parameters of the monetary policy function.

We estimate the following monetary policy rule:

$$\hat{r}_t = \rho \hat{r}_{t-1} + (1 - \rho) [\Gamma_p E_t \hat{\pi}_{t+1} + \Gamma_y \hat{y}_t + \Gamma_q \Delta \hat{q}_t] + \hat{e}_t,$$

where variables with a circumflex (" ^ ") represent log-deviations from a linear trend, r the nominal interest rate, π the inflation rate, y output, Δq house price inflation and e is an *iid* shock that captures a non-systematic component in the policy rule.

To estimate the policy rules for the U.S. and the U.K., we use quarterly data between 1983:Q1-2008:Q4. We have chosen this period since we can treat the period after 1983 as a single regime in both countries. For Japan, we use data between 1970:Q1-1995:Q4 since after 1995 the nominal interest rate has been close to its zero lower bound. All series were detrended using a linear trend and seasonally adjusted prior to estimation. Table 1 shows the GMM estimates for the three countries and the numbers in parenthesis indicate the 95% confidence interval. To estimate the parameters we use a continuous updating GMM procedure where the long-run covariance matrix is the Newey-West covariance matrix with bandwidth 4. The instrument set was selected by using the moment selection criteria, GMM-BIC and GMM-HQIC described in Andrews (1999). The Hansen J-test validates the moment conditions we use at a 5% level in all three countries. Our choice of instruments is reported in Table 1.

For the three countries, the GMM estimates present large standard errors for all parameters. Moreover, the point estimates for Γ_q are not significant at conventional confidence levels in the case of the U.S. and the U.K. Overall, as shown in the next section, the DSGE model-based posteriors are more concentrated than the GMM estimates. As in Lubik and Schorfheide (2007), the model generates restrictions on the volatility and comovements of the variables to be consistent with the data. This constrains the parameter space and explains why the posterior distributions are more

concentrated.

To assess the small sample performance of GMM in estimating Taylor rules, we simulate the model described in the next section and estimate the monetary policy reaction function using GMM. We simulate two versions of the model, an unrestricted one where $\Gamma_q \neq 0$ and a restricted one where $\Gamma_q = 0$. To perform this exercise we use the estimated means of the parameters for the U.S. shown in Table 3.⁴ The instrument set coincides with the one reported for the U.S. in Table 1. Table 2 reports the median and the 5th and 95th percentile of the point estimates as well as the percentage of point estimates that were statistically significant at a 5% confidence level.

The main observation is that Γ_q is downward biased and insignificant in most of the simulations even though the true parameter value is 0.36. Second, the estimates of Γ_p are also downward biased and inefficient.⁵

In general, estimating the rule on simulated data from the restricted model ($\Gamma_q = 0$) yields similar results, with the exception that now the median of the point estimates for Γ_q is upward biased but still insignificant in most of the simulations. Moreover, in both simulations there is a high probability of obtaining negative estimates of Γ_q .⁶ This shows again that GMM cannot identify the true value of Γ_q .

Summarizing, we have shown that single equation methods are unable to identify the response of monetary policy to house prices. This is in line with research in different contexts showing that GMM estimates may be biased and dispersed in small samples⁷ and with Jondeau, Bihan, and

⁴We simulate the model 10,000 times for 200 periods and we eliminate the first 100 periods to reduce the effects of initial conditions. We remove the estimates that did not converge to a solution and those with extreme values. In the case of $\Gamma_q \neq 0$ we remove 3% of the simulations, while in the case of $\Gamma_q = 0$ we remove 2% of the simulations.

⁵By using an iterative GMM approach we attain qualitatively similar results but a larger bias.

⁶A negative coefficient on asset prices is observed, for instance, in Bernanke and Gertler (1999). They apply GMM methods to estimate Taylor-type rules for the Federal Reserve and the Bank of Japan. Their estimated response coefficient on asset prices is not significant over the period 1979-1997, neither for the U.S. nor for Japan. However, according to their estimates, the Bank of Japan reinforced the asset price boom by strongly reacting to stock returns with a negative coefficient during the bubble period (1979-1989) and attempted to stabilize the stock market after that date, reacting with a positive coefficient.

⁷See, for instance, Fuhrer, Moore, and Schuh (1995) and Lindé (2005).

Galles (2004), who find that GMM and maximum likelihood yield substantially different parameter estimates of Taylor rules.

2.2 A full information approach: ML with VAR equations

Having shown that GMM methods are unsuitable for estimating Taylor rules with house prices, full information methods seem to be the natural alternative. In practice, full information methods require us to, a priori, specify an equation for each endogenous variable of the system. The resulting restrictions help in identifying the parameters of interest. On the downside, specifying a system of equations opens the door to potential misspecification. In this respect, much of the appeal of VARs lies in their model-independent restrictions, often judged to be less tight and less prone to misspecification than a DSGE model. However, here we show that estimating Taylor rules with ML while modeling other variables with a VAR produces biased estimates, and we argue that the full structure of a DSGE model is indeed crucial for our purpose, i.e., to obtain proper estimates of Γ_q .

To illustrate this point, we estimate the monetary policy rule on actual and simulated data using maximum likelihood methods combined with a pre-estimated VAR for the non-policy variables.⁸ More specifically, we estimate the coefficients in the policy rule using maximum likelihood and use a reduced-form VAR representation for the dynamics of inflation, output and house price inflation.⁹ Table 1 and Table 2 present the results.

As shown in Table 1, contrary to the GMM results of the previous subsection, the ML estimates of the monetary response to house prices are less dispersed, positive and significant for the U.S.

⁸See Fuhrer and Moore (1995) for the same type of exercise in a different context.

⁹The VAR equations include four lags of the non-policy variables and of the nominal interest rate. We keep the coefficients in the VAR equations fixed at their OLS estimates in order to minimize the number of estimated parameters. We impose that the $\hat{\epsilon}$ innovations in the Taylor rule are truly structural and orthogonal to the other innovations of the model which are, in reduced-form, contained in the VAR residuals. Under this assumption, the only structural shock that is identified in the model is the shock to the Taylor rule.

and Japan while the coefficient is not significant in the case of the U.K. On the other hand, the estimated response to inflation in the U.S. is larger than the value typically found in other studies and has a large confidence interval. Moreover, the estimation of the same parameter in the U.K. is problematic, since the likelihood is decreasing in Γ_p . Using the same unrestricted maximization algorithm we used for the other two countries, we attain a negative point estimate for Γ_p . By re-estimating the model imposing the restriction $\Gamma_p > 1$, the ML estimate takes the value 1.0009.

We next estimate the model on simulated data generated by the model developed in section 3 for the two alternative specifications of the monetary policy rule: unrestricted ($\Gamma_q \neq 0$) and restricted ($\Gamma_q = 0$). Table 2 reports the results.

As in the GMM case, ML estimates of Γ_q are downward biased. Even though they are less disperse than GMM, the true value is outside the 95% simulated interval. Moreover, when the true parameter is zero, the median of the point estimates is negative. Extending the sample size to 1,000 periods or increasing the lag length in the VAR from 4 to 8 does not reduce the bias.¹⁰

3 DSGE model estimation

The results in the previous section show that neither GMM nor FIML-VAR are appropriate to estimate a monetary policy rule augmented with house prices. Here, we propose an alternative approach to overcome the problem. We estimate a full-fledged DSGE model where house price fluctuations affect firms' and households' balance sheets. This enables us to use the cross equation restrictions implied by the model to identify the parameters of interest. In what follows we briefly describe the model we use and present our estimation results.

¹⁰The results from both robustness tests are available upon request.

3.1 The model

The model we estimate follows the work of Iacoviello (2005), which incorporates nominal loans and collateral constraints into a monetary business cycle model. The presence of nominal debt contracts and a borrowing constraint are at the heart of debt deflation and collateral effects, which enrich the transmission mechanism of the model. Changes in house prices affect the capacity to borrow (collateral effect), while movements in consumer prices influence the real value of their debt (debt deflation).

The economy is populated by three kinds of agents: entrepreneurs, patient households and impatient households. These agents discount future utility at different rates and borrow using housing as collateral. Entrepreneurs consume nondurable final goods and produce intermediate goods combining capital, real estate and the labor of both kinds of households. Households consume nondurable goods, own real estate and work for the entrepreneurs in a monopolistically competitive labor market. Real estate is in fixed supply. The central bank manages monetary policy using a Taylor-type interest rate rule.

3.1.1 Patient and impatient households

There are two kinds of households, patient ("P") and impatient ("NP"). Each group has a continuum of agents indexed by $i \in (0, 1)$. Impatient households discount the future more heavily than patient ones ($\beta^{NP} < \beta^P$). Both groups maximize a lifetime utility function given by:

$$E_0 \sum_{t=0}^{\infty} z_t (\beta^A)^t \left(\ln (c_{i,t}^A - \zeta C_{t-1}^A) + j_t \ln h_{i,t}^A - \frac{(l_{i,t}^A)^\eta}{\eta} \right), \text{ for } A = P, NP,$$

where c is consumption, h housing, l hours of work and ζ the degree of habit formation with respect to aggregate consumption of each group (C). The variables z and j represent exogenous shocks to

aggregate demand and housing demand that follow AR(1) processes. The housing preference shock might capture either a simple taste shock (see Iacoviello and Neri (2010)) or some unmodeled features of housing demand and credit markets, such as financial innovations or credit market deregulation (see Liu, Wang, and Zha (2010)).

Households are price setters in the labor market. Wages can only be optimally readjusted with probability $1 - \theta_w$. Wages of households that cannot reoptimize are fully indexed to past inflation. Workers set nominal wages maximizing their objective function subject to the intertemporal budget constraint and the following labor demand equation:

$$l_{i,t}^A = \left(\frac{w_{i,t}^A}{w_t^A} \right)^{\frac{\lambda_t}{1-\lambda_t}} L_t^A, \text{ for } A = P, NP,$$

where λ is a time-varying wage markup, w nominal wages and L the aggregate labor supply of each group.

Households face the following budget constraint:

$$c_{i,t}^A + q_t \Delta h_{i,t}^A + \frac{R_{t-1}}{\pi_t} b_{i,t-1}^A = b_{i,t}^A + \frac{w_{i,t}^A}{P_t} l_{i,t}^A + F_{i,t}^A + T_{i,t}^A, \text{ for } A = P, NP \text{ and } F^{NP} = 0,$$

where q denotes real house prices, π gross inflation rate, R gross nominal interest rate, b real debt (loans if b is negative),¹¹ F lump-sum profits received by patient households from retailers and T net cash inflows from participating in state-contingent security markets.¹²

¹¹We assume loan contracts with a duration of only one period. This implies adjustable interest rates on loans. Even though this is a reasonable assumption for the U.K., where mortgage loans are primarily extended on a floating rate basis, it is not the case in the U.S. where fixed rate contracts are more widely used. In Japan, interest rates are mainly tied to market rates or fixed between one and five years.

¹²Following Christiano, Eichenbaum, and Evans (2005), we assume that households buy securities with payoffs contingent on whether they can reoptimize their wages. This ensures that, in equilibrium, households within each group are homogeneous in consumption and asset holdings.

Impatient households can borrow up to a limit defined by the following borrowing constraint:

$$b_{i,t}^{NP} \leq m^{NP} E_t \left(q_{t+1} h_{i,t}^{NP} \frac{\pi_{t+1}}{R_t} \right),$$

where m is the maximum loan-to-value ratio.¹³

3.1.2 Entrepreneurs and retailers

Entrepreneurs combine labor (L), capital (K) and real estate (h) to produce an intermediate good.¹⁴

Entrepreneurs are risk averse and maximize their discounted utility:

$$E_0 \sum_{t=0}^{\infty} \gamma^t \log c_t,$$

subject to a Cobb-Douglas production function, the flow of funds and borrowing constraint:

$$Y_t = a_t K_{t-1}^{\mu} h_{t-1}^{\nu} L_t^{P\alpha(1-\mu-\nu)} L_t^{NP(1-\alpha)(1-\mu-\nu)},$$

$$\frac{Y_t}{X_t} + b_t = c_t + q_t \Delta h_t + \frac{R_{t-1}}{\pi_{t-1}} b_{t-1} + \frac{w_t^P}{P_t} L_t^P + \frac{w_t^{NP}}{P_t} L_t^{NP} + \frac{I_t}{s_t} + \psi \left(\frac{I_t}{K_{t-1}} - \delta \right)^2 \frac{K_{t-1}}{2\delta s_t},$$

$$K_t = (1 - \delta) K_{t-1} + I_t,$$

$$b_t \leq m E_t \left(q_{t+1} h_t \frac{\pi_{t+1}}{R_t} \right),$$

where a represents an AR(1) technology shock, X denotes the markup of the final over intermediate good ($X \equiv \frac{P}{P^w}$), s is an investment-specific technological shock that follows an AR(1) process and

¹³Given that $\beta^{NP} < \beta^P$, this constraint holds with equality in the steady state. As in Iacoviello (2005), we assume that uncertainty is sufficiently small to make the borrowing constraint always bind in the log-linearized model.

¹⁴We follow Iacoviello and Neri (2010) and assume that the types of labor supplied by the two kinds of households are not perfect substitutes. This simplifying assumption allows us to analytically compute the steady state of the model and disregard the complex interaction between borrowing constraints and labor supply decisions that would otherwise arise.

the last term in the flow of funds represents adjustment costs for capital installation.¹⁵

Nominal rigidities are introduced by assuming that the intermediate good is transformed into a composite final good by a continuum of retailers indexed by n . Each retailer buys the intermediate good Y_t from the entrepreneurs at a price P_t^w and transforms it without costs into differentiated goods $Y_t(n)$, which are sold at a price $P_t(n)$. The differentiated goods are then aggregated into a final good Y^f according to a Dixit-Stiglitz aggregator:

$$Y_t^f = \left[\int_0^1 Y_t(n)^{\frac{1}{u_t}} dn \right]^{u_t},$$

where u is a time-varying gross markup. The retail sector is monopolistically competitive and prices are sticky. With probability $1 - \theta$, the price of an individual firm can be optimally adjusted and the prices that are not reoptimized are fully indexed to past inflation.

3.1.3 Monetary policy

Monetary policy is conducted according to a Taylor-type rule of the same type described in section 2:

$$\hat{r}_t = \rho \hat{r}_{t-1} + (1 - \rho) [\Gamma_p E_t \hat{\pi}_{t+1} + \Gamma_y \hat{y}_t + \Gamma_q \Delta \hat{q}_t] + \hat{e}_t.$$

¹⁵Since by assumption $\gamma < \beta^P$, the borrowing constraint holds with equality in steady state. As in the case of impatient households, we assume the constraint to always be binding even outside the steady state.

3.1.4 Market equilibrium and shock structure

Market equilibrium implies that all the optimality conditions corresponding to the above maximization problems are satisfied. In addition, real estate, goods and loan markets clear:

$$\begin{aligned} H &= h_t + h_t^P + h_t^{NP}, \\ Y_t &= C_t + C_t^P + C_t^{NP} + \frac{I_t}{s_t} + \psi \left(\frac{I_t}{K_{t-1}} - \delta \right)^2 \frac{K_{t-1}}{2\delta s_t}, \\ b_t + b_t^P + b_t^{NP} &= 0, \end{aligned}$$

where H is the fixed supply of housing.

There are seven structural shocks in the economy: productivity, investment, housing demand, preferences, monetary, price markup and wage markup. The first four shocks follow AR(1) processes, while the two markup shocks and the monetary shock are *iid*. The variance of a ε_v shock is denoted by σ_v^2 .

3.2 Estimation

We estimate the model described in the previous subsection using Markov chain Monte Carlo (MCMC) simulation methods. The model is loglinearized around its deterministic steady state and solved numerically using the methods described in Sims (2002).¹⁶ After estimating the posterior mode through numerical optimization methods, we generate a sample representative for the posterior using the random walk Metropolis algorithm.¹⁷

The data used for the estimation corresponds to seven variables in the model: real consumption, real investment, hours worked, real wages, real house prices, inflation and nominal interest rates.¹⁸

¹⁶Appendix A reports the whole system of loglinearized equations.

¹⁷To check convergence, we run five different chains with a total of 100,000 draws each. We initialized the MCMC procedure using importance resampling. Convergence was monitored calculating the potential scale reduction as described in Gelman, Carlin, Stern, and Rubin (2004) and plotting each chain.

¹⁸For house prices, we use data on residential house prices. Since housing is also used by entrepreneurs in the

A detailed description of the data can be found in Appendix B.

The model has a total of 32 free parameters. Nine of these are calibrated, because they cannot be identified from the detrended data. The discount factors β^P , β^{NP} and γ are set at 0.9925, 0.97 and 0.98, respectively. The choice of the discount factor for patient households, β^P , implies that the annual real interest rate in the steady state is 3%. The steady-state rate of depreciation of capital, δ , is set equal to 0.03, which corresponds to an annual rate of depreciation of 12%. The steady-state price and wage markups are calibrated at 20%, while the coefficients in the production function μ and ν are set to 0.35 and 0.035. Last, we fix the average housing weight in the utility function, j , to calibrate steady-state ratios of commercial and residential real estate to annual output around 70% and 145%, respectively, in line with the data.

The priors for the remaining 23 parameters (Table 3) are relatively loose, in line with the previous literature, and are set equal for the three countries.

Since Bayesian hypothesis tests are often criticized because of their dependence on prior distributions, for the main parameter of interest, the response of the interest rate to house prices, Γ_q , we postulate a rather loose prior centered around our null hypothesis value: a normal distribution with mean 0 and standard deviation 0.5.

3.2.1 Posterior distribution

In what follows, we present the estimation results focusing on the parameters of the policy rule. Table 3 shows the mean and the 5th and 95th percentiles of the posterior distribution for the benchmark model ($\Gamma_q \neq 0$) and the restricted one ($\Gamma_q = 0$) for the U.S. In both cases, the nominal interest rate shows a standard smoothing component. The mean reaction to expected inflation is higher in the unrestricted model ($\Gamma_\pi = 2.22$) compared to the restricted one ($\Gamma_\pi = 2.09$), while the model, an aggregated index computed of both residential and commercial house prices could also be used. However, using residential house prices is a good approximation since this series is highly correlated with commercial house prices when considering detrended data.

mean reaction to output is slightly higher under the assumption $\Gamma_q = 0$. In the model where the interest rate reacts to house prices, the posterior mean of Γ_q is 0.36. The estimation of the other structural parameters is robust to both specifications of the monetary policy rule and, in general, is in line with the previous literature. While all shocks are very persistent, housing preference shocks are more volatile than the rest.

The results for the U.K. are presented in Table 4. According to our estimates, the Bank of England has reacted less aggressively to output, expected inflation and house price inflation than the Fed. The mean value of Γ_q is 0.16. The estimates of the other structural parameters are, in general, similar to those in the U.S. However, there are some exceptions. Prices and, in particular, wages adjust more often in the U.K. and adjustment costs in capital are larger. Our results are in line with those of Nelson and Nikolov (2004) and DiCecio and Nelson (2007), who also find less wage and price rigidity in the U.K. compared to the U.S. Last, housing shocks are large and very persistent.

Finally, Table 5 reports the results for Japan. Overall, the estimates of the structural parameters for Japan are close to those for the U.K., while the estimated monetary policy rules are similar to the U.S. Like in the U.S., the mean reaction to expected inflation is slightly higher in the unrestricted model compared to the restricted one, and the mean reaction to house price inflation is 0.26. As to the other structural parameters, consistent with other studies,¹⁹ we find that prices and wages adjust more often than in the U.S. Finally, housing shocks are more volatile in Japan.

3.3 Model comparison

To investigate whether the Fed, the Bank of England and the Bank of Japan responded to house price inflation over the sample periods, we calculate the log marginal data density for the two model

¹⁹See Iiboshi, Nishiyama, and Watanabe (2007).

specifications when $\Gamma_q = 0$ and $\Gamma_q \neq 0$, and compute posterior odds ratios.

Table 6 reports the log marginal data density and posterior odds ratios for the three countries. The main result that emerges from this table is that the Federal Reserve, the Bank of England and the Bank of Japan did react to house price inflation in the sample periods. The marginal data densities are larger when Γ_q is positive, and the posterior odds ratios of the hypothesis $\Gamma_q = 0$ against $\Gamma_q \neq 0$ are $3e^{-5}$, $5e^{-4}$ and 0.015, respectively, which indicates clear evidence in favor of the unrestricted model.

3.4 Impulse response functions

Figures 1 through 3 show the impulse response functions of some key variables to different shocks under the two monetary policy rules: $\Gamma_q = 0$ and $\Gamma_q \neq 0$.

After a tightening of monetary policy, aggregate demand, house prices and inflation fall. The propagation mechanism is qualitatively similar for the three countries and is not affected by the inclusion of house prices in the monetary policy rule. However, the impact response to monetary policy of inflation is larger in Japan, despite the fact that the estimated magnitude of the shock is similar to the one in the U.K. This result is not surprising given that Japan has a higher degree of wage flexibility, which causes a larger decrease in marginal costs on impact.

Housing preference shocks are equivalent to house price shocks since the supply of housing is fixed in the model. A positive house price shock increases the spending capacity of borrowers, relaxing their borrowing constraint. This has a positive impact on consumer prices, which reinforces the initial effect through a debt deflation mechanism. As inflation goes up, the central bank raises the nominal interest rate, thereby dampening the initial increase in inflation and output. The increase in the nominal interest rate is significantly larger when monetary policy reacts to house prices. This last feature is crucial in order to identify monetary policy's response to house price inflation. In

the U.S. and Japan, where the monetary authority's response to house prices is stronger, the larger increase in interest rates when Γ_q is positive counterbalances the debt deflation and collateral effects for the household sector. This mechanism causes a fall in consumption for impatient households. In this case, a substitution effect²⁰ between housing and consumption dominates, causing a negative response of consumption to house prices. Interestingly, after a housing shock, the three countries show a smaller response of output and inflation in the model where the central bank responds to house prices.

When the economy is hit by a supply shock, collateral and debt deflation effects work in opposite directions. For instance, the surge in asset prices caused by a technology shock improves borrowing capacity. On the other hand, the decline in inflation transfers wealth from borrowers to lenders. It turns out that the first effect is dominant and total spending increases. Interestingly, the difference between the propagation mechanisms after a technology shock in the restricted and unrestricted model is more evident in the U.S.; the difference is mainly quantitative, not qualitative.

3.5 Model fit

To assess the empirical performance of the estimated model we report some selected second-order moments. Table 7 reports the empirical moments as well as the 95% probability interval of the simulated moments generated from the model.²¹

Overall the model is able to capture the volatility in the data. Most of the volatilities in the data lie within the 95% probability interval generated by the model. The model can also replicate some of the comovements between the series. For example, the median correlation between house price and consumption is positive for the three countries as in the data.

²⁰ A housing preference shock changes the marginal rate of substitution between consumption and housing.

²¹ The posterior moments were computed for a sample of 500 simulations for 100 periods from 1,000 draws of the posterior. To avoid autocorrelation, the draws from the posterior were picked at fixed intervals.

3.6 Robustness

We check the robustness of our results by reestimating the model using alternative interest rate rules where the monetary authority reacts to contemporaneous rather than expected inflation (Rule 2), expected output growth (Rule 3), and expected output and consumption growth (Rule 4). The last two alternative specifications were chosen in order to address the concern that our estimated positive response on house prices could be just a proxy for an actual response to output forecast.

Table 8 shows the results for the three alternative specifications of the monetary policy rule. Overall, posterior odds tests confirm our result that the Fed, the Bank of England and the Bank of Japan reacted to house price inflation.

There are only two situations where posterior odds tests cannot discern between the constrained and the unconstrained model: Rule 4 for the U.S. and Rule 2 for the U.K. However, in both cases the marginal data density is lower than in the benchmark model, confirming our result that these banks reacted to both future inflation and house price movements.²²

4 Reconciling the rhetoric of central banks

So far, we have shown evidence of a direct monetary policy feedback on house prices in the three countries under study. At first, this conclusion may seem to be at odds with what central banks have been claiming, in some cases even by explicitly denying that they "target" asset prices.²³ However, in this matter it becomes crucial to distinguish between "target variables," i.e., variables that enter directly into the policymakers' loss function, and "indicator variables," i.e., arguments

²²While we cannot discriminate between our benchmark rule and Rule 3 in the U.S. and Japan, in the case of the U.K., Rule 3 has a higher marginal density. However, for parsimony we use a rule where monetary policy does not react to output growth, but rather only to deviations of output from its trend. In any case, both in the benchmark case and in Rule 3, the data prefer a rule where the monetary policy reacts to house price inflation.

²³See for instance, Ben Bernanke (Oct. 15, 2002): *"...the Fed should use monetary policy to target the economy, not the asset markets"* (<http://www.federalreserve.gov/boarddocs/speeches/2002/20021015/default.htm>) and Mervyn King (Nov. 19, 2002): *"I believe that, although there are justifiable concerns about recent movements in asset prices, the policy dilemma can be analysed within the framework of inflation targeting that we have in the UK"* (<http://www.bis.org/review/r021126c.pdf>).

in central banks' reaction functions (see Svensson (1999)). With this distinction in mind, to deny that house prices are an explicit target for monetary policy does not exclude a priori a direct role for asset prices in the monetary policy reaction function.

To clarify this point, we calculate the optimal coefficients in our monetary policy rule using a quadratic loss function with equal weights on output and inflation. Table 9 reports the results.²⁴ For the sake of comparison, the table also reports the welfare calculations for the optimal rule where we restrict the coefficient on house prices to zero.

The optimal response to house price inflation is positive, even when the policymakers are not targeting house prices. This is consistent with Svensson (1997), who shows that even under strict inflation targeting it is optimal to respond both to output and inflation. Moreover, irrespective of whether house prices are included in the monetary rule or not, the difference in the computed losses is negligible.

Nevertheless, to draw normative conclusions from this simple exercise could be misleading since in the particular model used here credit markets are very stylized. In particular, the model abstracts from other sources of inefficiencies in financial markets, besides liquidity constraints, that in reality could involve larger welfare losses.

5 Conclusions

In this paper we investigate whether the Federal Reserve, the Bank of England and the Bank of Japan have reacted to house price inflation. We show that GMM estimates of the policy reaction function are biased and dispersed and that FIML methods combined with pre-estimated VAR equations produce downward biased estimates. These results highlight the importance of using a full information model's cross-equation restrictions to properly identify the parameters of the

²⁴To obtain the results shown in Table 10, we set all the non-policy model parameters as their posterior means in Table 3 and restrict Γ_y between (0, 1).

monetary policy function.

We specify a medium-scale DSGE model based on Iacoviello (2005) enriched by a number of modifications to improve its empirical fit. In this model economy, business cycle fluctuations are amplified because credit-constrained agents borrow using real estate as collateral. We estimate the model with Bayesian methods and employ posterior odds ratios to perform model comparisons. We find that house price movements did play a separate role in the monetary policy reaction functions of the countries in our study. This result is robust to different specifications of the estimated rule.

Finally, we show that even under strict inflation and output targeting, it is optimal to react to house price inflation even though the gains are negligible. Nevertheless, some caution is needed when drawing normative conclusions from such a stylized set-up. Whether central banks should react or not to house prices is still an open question and we leave the answer for future research.

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A The loglinearized model

The model is loglinearized around its deterministic steady state where variables with a circumflex ($\hat{\cdot}$) represent log-deviations from the steady state. The first-order conditions for patient and impatient households’ choice of consumption, real estate and wages are:

$$\hat{z}_t - \hat{c}_t^P + \zeta \hat{c}_{t-1}^P = E_t (\hat{r}_t - \hat{\pi}_{t+1} + \hat{z}_{t+1} - \hat{c}_{t+1}^P + \zeta \hat{c}_t^P)$$

$$\hat{q}_t = \beta^P E_t \hat{q}_{t+1} + (1 - \beta^P) \hat{j}_t + \iota \hat{h}_t + \iota^{NP} \hat{h}_t^{NP} + \frac{\hat{c}_t^P - \zeta \hat{c}_{t-1}^P}{(1 - \zeta)} - \beta' E_t \left(\frac{\hat{c}_{t+1}^P - \zeta \hat{c}_t^{NP}}{(1 - \zeta)} \right) + \beta' E_t (\hat{z}_{t+1} - \hat{z}_t)$$

$$\begin{aligned} \hat{w}_t^{Pr} &= \frac{1}{1 + \beta^P} \hat{w}_{t-1}^{Pr} + \frac{\beta^P}{1 + \beta^P} E_t \hat{w}_{t+1}^{Pr} - \hat{\pi}_t + \frac{\beta^P}{1 + \beta^P} E_t \hat{\pi}_{t+1} + \frac{1}{1 + \beta^P} \hat{\pi}_{t-1} \\ &+ \frac{1}{1 + \beta^P} \frac{(1 - \theta_w \beta^P)(1 - \theta_w)}{\theta_w \left(1 - (\eta - 1) \frac{\lambda}{1 - \lambda}\right)} \left[(1 - \zeta)^{-1} (\hat{c}_t^P - \zeta \hat{c}_{t-1}^P) + (\eta - 1) \hat{l}_t^P - \hat{w}_t^{Pr} \right] + \hat{\lambda}_t \end{aligned}$$

$$\begin{aligned} \hat{q}_t &= \gamma_h E_t q_{t+1} + (1 - \gamma_h) \left(\hat{j}_t + \hat{z}_t - \hat{h}_t^{NP} \right) - (1 - m^{NP} \beta^P) (\hat{z}_t - \omega E_t (\hat{z}_{t+1})) \\ &- m^{NP} \beta^P (\hat{r}_t - E_t \hat{\pi}_{t+1}) + (1 - m^{NP} \beta^P) \left(\frac{\hat{c}_t^{NP} - \zeta \hat{c}_{t-1}^{NP}}{(1 - \zeta)} - \omega \frac{E_t (\hat{c}_{t+1}^{NP} - \zeta \hat{c}_t^{NP})}{(1 - \zeta)} \right) \end{aligned}$$

$$\begin{aligned} \hat{w}_t^{NPr} &= \frac{1}{1 + \beta^{NP}} \hat{w}_{t-1}^{NPr} + \frac{\beta^{NP}}{1 + \beta^{NP}} E_t \hat{w}_{t+1}^{NPr} - \hat{\pi}_t + \frac{\beta^{NP}}{1 + \beta^{NP}} E_t \hat{\pi}_{t+1} + \frac{1}{1 + \beta^{NP}} \hat{\pi}_{t-1} \\ &+ \frac{1}{1 + \beta^{NP}} \frac{(1 - \theta_w \beta^{NP})(1 - \theta_w)}{\theta_w \left(1 - (\eta - 1) \frac{\lambda}{1 - \lambda}\right)} \left[(1 - \zeta)^{-1} (\hat{c}_t^{NP} - \zeta \hat{c}_{t-1}^{NP}) + (\eta - 1) \hat{l}_t^{NP} - \hat{w}_t^{NPr} \right] \\ &+ \frac{(1 - \theta_w \beta^{NP})(1 + \beta^P)}{(1 - \theta_w \beta^P)(1 + \beta^{NP})} \hat{\lambda}_t, \end{aligned}$$

where

$$\begin{aligned} \iota &= (1 - \beta^P) \frac{h}{h^P}, \\ \iota^{NP} &= (1 - \beta^P) \frac{h^{NP}}{h^P}, \\ \omega &= \frac{(\beta^{NP} - m^{NP} \beta^{NP})}{1 - m^{NP} \beta^P}, \\ \gamma_h &= \beta^{NP} + m^{NP} (\beta^P - \beta^{NP}), \end{aligned}$$

and \hat{w}_t^{Pr} and \hat{w}_t^{NPr} denote real wages. The budget and borrowing constraints for impatient households are:

$$\frac{b^{NP}}{Y} \hat{b}_t^{NP} + s^{NP} (\hat{y}_t - \hat{x}_t) = \frac{C^{NP}}{Y} \hat{c}_t^{NP} + \frac{qh^{NP}}{Y} \Delta \hat{h}_t^{NP} + \frac{Rb^{NP}}{Y} (\hat{b}_{t-1}^{NP} - \hat{\pi}_t + \hat{r}_t)$$

$$\hat{b}_t^{NP} = E_t \left(\hat{q}_{t+1} + \hat{h}_t^{NP} + \hat{\pi}_{t+1} - \hat{r}_t \right).$$

The first-order conditions for entrepreneurs' choice of investment, real estate, and labor are:

$$\begin{aligned} \hat{i}_t - \hat{k}_{t-1} = & \gamma E_t \left(\hat{i}_{t+1} - \hat{k}_t \right) + \frac{1 - (1 - \delta) \gamma}{\psi} E_t \left(\hat{y}_{t+1} - \hat{x}_{t+1} - \hat{k}_t \right) \\ & + \frac{\hat{c}_t - E_t \hat{c}_{t+1}}{\psi} + \frac{\hat{s}_t - (1 - \delta) \gamma E_t \hat{s}_{t+1}}{\psi} - \frac{\hat{z}_t - E_t \hat{z}_{t+1}}{\psi} \end{aligned}$$

$$\hat{q}_t = \gamma_e E_t \hat{q}_{t+1} + (1 - \gamma_e) E_t \left(\hat{y}_{t+1} - \hat{x}_{t+1} - \hat{h}_t \right) - m \beta^P \left(\hat{r}_t - E_t \hat{\pi}_{t+1} \right) - (1 - m \beta^P) E_t \left(\hat{c}_{t+1} - \hat{c}_t - \hat{z}_{t+1} + \hat{z}_t \right)$$

$$\hat{l}_t^A = \hat{y}_t - \hat{x}_t - \hat{w}_t^{Ar} \text{ for } A = P, NP,$$

where

$$\gamma_e = (1 - m) \gamma + m \beta^P.$$

The budget and borrowing constraints for entrepreneurs are:

$$(\hat{y}_t - \hat{x}_t) (1 - s^P - s^{NP}) + \frac{b}{Y} \hat{b}_t = \frac{C}{Y} \hat{c}_t + \frac{qh}{Y} \Delta \hat{h}_t + \frac{Rb}{Y} \left(\hat{b}_{t-1} - \hat{\pi}_t + \hat{r}_{t-1} \right) + \frac{I}{Y} (\hat{i}_t - \hat{s}_t)$$

$$\hat{b}_t = E_t \left(\hat{q}_{t+1} + \hat{h}_t + \hat{\pi}_{t+1} - \hat{r}_t \right).$$

The production technology and capital accumulation are given by:

$$\hat{y}_t = \frac{1}{\mu + \nu} \left(\hat{a}_t + \mu \hat{k}_{t-1} + \nu \hat{h}_{t-1} \right) - \frac{(1 - \mu - \nu)}{\mu + \nu} \hat{x}_t - \frac{(1 - \mu - \nu)}{\mu + \nu} \left(\alpha \hat{w}_t^{Pr} + (1 - \alpha) \hat{w}_t^{NPr} \right)$$

$$\hat{k}_t = \delta \hat{i}_t + (1 - \delta) \hat{k}_{t-1}.$$

Retailers choose prices so that:

$$\hat{\pi}_t = \frac{1}{1 + \beta^P} \hat{\pi}_{t-1} + \frac{\beta^P}{1 + \beta^P} E \hat{\pi}_{t+1} - \frac{1}{1 + \beta^P} \frac{(1 - \theta \beta^P)(1 - \theta)}{\theta} \hat{x}_t + \hat{u}_t.$$

Monetary policy is given by:

$$\hat{r}_t = \rho \hat{r}_{t-1} + (1 - \rho) [\Gamma_p E_t \hat{\pi}_{t+1} + \Gamma_y \hat{y}_t + \Gamma_q \Delta \hat{q}_t] + \hat{e}_t.$$

The market clearing condition is:

$$\hat{y}_t = \frac{C}{Y} \hat{c}_t + \frac{C^P}{Y} \hat{c}_t^P + \frac{C^{NP}}{Y} \hat{c}_t^{NP} + \frac{I}{Y} \hat{i}_t - \frac{I}{Y} \hat{s}_t.$$

The structural shocks are:

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \varepsilon_{zt}$$

$$\hat{s}_t = \rho_s \hat{s}_{t-1} + \varepsilon_{st}$$

$$\hat{j}_t = \rho_z \hat{j}_{t-1} + \varepsilon_{jt}$$

$$\hat{a}_t = \rho_a \hat{a}_{t-1} + \varepsilon_{at}.$$

B The data

The data used for the estimation correspond to seven variables in the model: real consumption, real investment, hours worked, nominal interest rate, inflation, real wages and real housing prices.

All series were detrended using a linear trend and were seasonally adjusted previous to estimation.

Inflation is calculated as the difference in the GDP deflator. Nominal wages and house prices are

converted into real terms using the GDP deflator. When we estimate the Taylor rules using GMM, we also use data on real GDP.

B.1 U.S.

For the U.S., we use data between 1983:Q1-2008:Q4. Data on real personal consumption expenditures (B002RA3), real gross private domestic investment (B006RA3), GDP price deflator (B191RG3) and real GDP (B191RA3) were taken from the Bureau of Economic Analysis at the U.S. Department of Commerce. Data on total hours (PRS85006033) and real hourly compensation (PRS85006153) in the non-farm sector were obtained from the Bureau of Labor Statistics. For house prices, we use the Conventional Mortgage Home Price Index (CMHPI) purchase-transactions only made available by Freddie Mac. The nominal interest rate is the federal funds rate.

B.2 U.K.

The data for the U.K. also cover the period 1983Q1-2008Q4. Data on household final consumption expenditures (ABJR), total gross fixed capital formation (NPQT), GDP at market prices deflator (YBGB), total actual weekly hours of work (YBUS), wages and salaries (ROYJHN) and GDP (YBEZ) were taken from National Statistics U.K. For house prices, we use the price index of all residential properties obtained from the Nationwide Building Society. For the nominal interest rate, we use the quarterly average of the official bank rate (IUQABEDR) of the Bank of England.

B.3 Japan

In the case of Japan, we use data between 1970:Q1-1995:Q4 since after 1995 the nominal interest rate has been close to its zero lower bound. Data on private consumption, private non-residential investment, GDP deflator and GDP were obtained from the Official Cabinet. Aggregate weekly hours of work (non-agricultural industries) were obtained from the Statistic Bureau, Ministry of

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Internal Affairs and Communications. For nominal wages, we use monthly earnings in the private sector from the OECD database. For house prices, we use residential house prices obtained from the BIS database. For the nominal interest rate, we use the call money rate from the IFS database.

C Tables and figures

Table 1: GMM and VAR-FIML estimation

Country	ρ	Γ_p	Γ_y	Γ_q
US				
GMM ^a	0.86*	1.53*	0.23*	-0.09
	(.81,.91)	(.64,2.4)	(.14,.31)	(-.27,.08)
VAR-FIML	0.91*	3.51*	0.04	0.10*
	(.87,.94)	(2.5,4.5)	(-.02,.14)	(.01,.19)
UK				
GMM ^b	0.91*	2.51*	-0.08	0.23
	(.86,.97)	(.60,4.4)	(-.32,.16)	(-.08,.54)
VAR-FIML ^c	0.97*	1.0009	0.54	0.44
	(.94,1.0)	na	(-.14,1.2)	(-.61,1.5)
JPN				
GMM ^d	0.58*	1.59*	-0.02	0.53*
	(.40,.76)	(1.1,2.1)	(-.11,.08)	(.31,.74)
VAR-FIML	0.95*	1.60*	0.27*	0.18*
	(.78,1.1)	(1.1,2.1)	(.18,.35)	(.14,.23)

Note: *Significant at 5% level. 95% confidence intervals in brackets.

^aInstrument set: r, w lags (1-2), y lags (1-4), π, q lags (1-8).

^bInstrument set: r, w, I lags (1-2), y, C lags (1-4), π, q lags (1-4,6,8).

^cRestricted maximization $\Gamma_p > 1$. Standard errors cannot be calculated using standard methods.

^dInstrument set: r, I lags (1-2), y lags (1-4), π, q lags (1-4,6,8).

Table 2: GMM and VAR-FIML on simulated data

	ρ	Γ_p	Γ_y	Γ_q
$\Gamma_q > 0$				
true value	0.71	2.22	0.02	0.36
GMM ^a				
simulated median	0.74	1.97	0.04	0.10
5-95% simulated interval	(-2.5,.92)	(-.91,5.6)	(-.13,.48)	(-.54,.72)
% of significant point estimates	85	73	33	34
FIML-VAR				
simulated median	0.71	1.32	-0.06	0.13
5-95% simulated interval	(.56, .83)	(.66, 2.5)	(-.13, -.003)	(.04, .26)
$\Gamma_q = 0$				
true value	0.69	2.09	0.06	0
GMM ^a				
simulated median	0.74	1.96	0.08	0.09
5-95% simulated interval	(-2.5,.93)	(-.69,5.2)	(-.13,.47)	(-.44,.84)
% of significant point estimates	88	78	36	38
FIML-VAR				
simulated median	0.71	1.53	-0.03	-0.08
5-95% simulated interval	(.57, .84)	(.93, 2.4)	(-.11, .004)	(-.22, .02)

Note: ^aInstrument set: r , w lags (1-2), y lags (1-4), π , q lags (1-8).

Table 3: U.S. Data

	Dist.	Prior		Posterior $\Gamma_q = 0$			Posterior $\Gamma_q \neq 0$		
		Mean	SD	5%	Mean	95%	5%	Mean	95%
ζ	beta	0.5	0.20	0.03	0.13	0.26	0.07	0.22	0.38
θ	beta	0.7	0.15	0.80	0.83	0.87	0.80	0.83	0.87
θ_w	beta	0.7	0.15	0.64	0.73	0.82	0.64	0.72	0.81
ψ	gamma	2.0	1.00	0.62	0.81	1.02	0.68	0.86	1.06
m	beta	0.8	0.05	0.57	0.64	0.71	0.57	0.65	0.72
m^{NP}	beta	0.8	0.05	0.77	0.83	0.88	0.73	0.81	0.87
α	beta	0.64	0.10	0.42	0.59	0.77	0.67	0.81	0.91
η	normal	2.0	0.75	1.07	2.01	3.13	1.33	2.30	3.39
ρ	beta	0.7	0.1	0.63	0.69	0.75	0.64	0.71	0.77
Γ_p	gamma	1.8	0.4	1.66	2.09	2.61	1.68	2.22	2.88
Γ_y	gamma	0.125	0.1	0.03	0.06	0.11	0.003	0.02	0.04
Γ_q	normal	0	0.5	-	-	-	0.22	0.36	0.53
ρ_a	beta	0.85	0.1	0.954	0.969	0.986	0.960	0.971	0.987
ρ_j	beta	0.85	0.1	0.938	0.962	0.982	0.900	0.928	0.954
ρ_z	beta	0.85	0.1	0.874	0.898	0.919	0.883	0.907	0.929
ρ_s	beta	0.85	0.1	0.863	0.945	0.982	0.918	0.952	0.982
σ_a	gamma	0.05	0.05	0.0050	0.0056	0.0063	0.0051	0.0057	0.0065
σ_u	gamma	0.05	0.05	0.0017	0.0021	0.0024	0.0017	0.0020	0.0023
σ_j	gamma	0.05	0.05	0.0551	0.0930	0.1380	0.1045	0.1508	0.2031
σ_m	gamma	0.05	0.05	0.0015	0.0017	0.0019	0.0015	0.0018	0.0022
σ_z	gamma	0.05	0.05	0.0100	0.0122	0.0148	0.0095	0.0113	0.0134
σ_s	gamma	0.05	0.05	0.0234	0.0284	0.0339	0.0249	0.0296	0.0350
σ_λ	gamma	0.05	0.05	0.0039	0.0045	0.0052	0.0039	0.0045	0.0052

Table 4: U.K. Data

	Dist.	Prior		Posterior $\Gamma_q = 0$			Posterior $\Gamma_q \neq 0$		
		Mean	SD	5%	Mean	95%	5%	Mean	95%
ζ	beta	0.5	0.20	0.009	0.05	0.12	0.01	0.05	0.13
θ	beta	0.7	0.15	0.75	0.79	0.83	0.70	0.75	0.80
θ_w	beta	0.7	0.15	0.39	0.48	0.58	0.37	0.45	0.56
ψ	gamma	2.0	1.00	1.26	1.63	2.03	1.30	1.66	2.08
m	beta	0.8	0.05	0.45	0.52	0.59	0.48	0.55	0.62
m^{NP}	beta	0.8	0.05	0.64	0.72	0.79	0.67	0.74	0.81
α	beta	0.64	0.10	0.48	0.64	0.80	0.53	0.70	0.84
η	normal	2.0	0.75	1.46	2.05	2.80	1.63	2.22	2.99
ρ	beta	0.7	0.1	0.65	0.71	0.76	0.67	0.73	0.79
Γ_p	gamma	1.8	0.4	1.43	1.67	1.97	1.54	1.84	2.28
Γ_y	gamma	0.125	0.1	0.002	0.02	0.04	0.002	0.01	0.03
Γ_q	normal	0	0.5	-	-	-	0.10	0.16	0.24
ρ_a	beta	0.85	0.1	0.939	0.964	0.985	0.930	0.958	0.981
ρ_j	beta	0.85	0.1	0.9814	0.9912	0.998	0.974	0.988	0.996
ρ_z	beta	0.85	0.1	0.869	0.904	0.934	0.859	0.896	0.925
ρ_s	beta	0.85	0.1	0.923	0.962	0.993	0.928	0.972	0.995
σ_a	gamma	0.05	0.05	0.0076	0.0085	0.0096	0.0077	0.0086	0.0098
σ_u	gamma	0.05	0.05	0.0049	0.0055	0.0063	0.0051	0.0058	0.0068
σ_j	gamma	0.05	0.05	0.0473	0.0760	0.1163	0.0578	0.0947	0.1500
σ_m	gamma	0.05	0.05	0.0022	0.0025	0.0030	0.0020	0.0024	0.0028
σ_z	gamma	0.05	0.05	0.0118	0.0148	0.0184	0.0131	0.0160	0.0199
σ_s	gamma	0.05	0.05	0.0277	0.0337	0.0406	0.0285	0.0343	0.0413
σ_λ	gamma	0.05	0.05	0.0048	0.0056	0.0065	0.0049	0.0057	0.0066

Table 5: Japanese Data

	Dist.	Prior		Posterior $\Gamma_q = 0$			Posterior $\Gamma_q \neq 0$		
		Mean	SD	5%	Mean	95%	5%	Mean	95%
ζ	beta	0.5	0.20	0.01	0.03	0.06	0.01	0.02	0.06
θ	beta	0.7	0.15	0.66	0.70	0.75	0.67	0.72	0.76
θ_w	beta	0.7	0.15	0.23	0.32	0.42	0.27	0.37	0.48
Ψ	gamma	2.0	1.00	2.72	3.16	3.63	2.61	3.07	3.56
m	beta	0.8	0.05	0.58	0.63	0.69	0.58	0.64	0.70
m^{NP}	beta	0.8	0.05	0.69	0.74	0.79	0.67	0.73	0.78
α	beta	0.64	0.10	0.47	0.64	0.79	0.55	0.71	0.83
η	normal	2.0	0.75	2.08	2.96	3.92	1.93	2.77	3.75
ρ	beta	0.7	0.1	0.74	0.79	0.83	0.75	0.80	0.84
Γ_p	gamma	1.8	0.4	1.84	2.28	2.80	1.95	2.40	3.00
Γ_y	gamma	0.125	0.1	0.003	0.02	0.05	0.003	0.02	0.06
Γ_q	normal	0	0.5	-	-	-	0.13	0.26	0.41
ρ_a	beta	0.85	0.1	0.932	0.957	0.980	0.932	0.959	0.984
ρ_j	beta	0.85	0.1	0.935	0.959	0.979	0.925	0.950	0.972
ρ_z	beta	0.85	0.1	0.813	0.843	0.870	0.810	0.840	0.871
ρ_s	beta	0.85	0.1	0.907	0.935	0.962	0.906	0.936	0.966
σ_a	gamma	0.05	0.05	0.0109	0.0124	0.0140	0.0109	0.0122	0.0139
σ_u	gamma	0.05	0.05	0.0051	0.0059	0.0068	0.0049	0.0057	0.0067
σ_j	gamma	0.05	0.05	0.0979	0.1617	0.2374	0.1221	0.1879	0.2668
σ_m	gamma	0.05	0.05	0.0022	0.0026	0.0031	0.0022	0.0026	0.0032
σ_z	gamma	0.05	0.05	0.0108	0.0131	0.0158	0.0115	0.0136	0.0164
σ_s	gamma	0.05	0.05	0.0437	0.0514	0.0598	0.0420	0.0497	0.0585
σ_λ	gamma	0.05	0.05	0.0097	0.0114	0.0135	0.0093	0.0109	0.013

Table 6: Posterior Odds

Country	Log marginal data density		Posterior odds
	$\Gamma_q = 0$	$\Gamma_q \neq 0$	
U.S.	2505.7	2516.2	$3e^{-5}$
U.K.	2244.7	2252.2	$5e^{-4}$
Japan	2197.3	2201.5	0.015

Note: Posterior odds of the hypothesis $\Gamma_q = 0$ versus $\Gamma_q \neq 0$.

Table 7: Selected Moments

	US ($\Gamma_q > 0$)			UK ($\Gamma_q > 0$)			Japan ($\Gamma_q > 0$)		
	Data	2.5%	97.5%	Data	2.5%	97.5%	Data	2.5%	97.5%
	Standard Deviation (%)								
Consumption	1.93	1.60	4.90	3.21	1.84	5.87	2.97	2.33	6.94
Hours	3.50	2.28	4.65	2.45	1.99	3.70	1.22	1.85	3.44
Inflation	0.24	0.31	0.55	0.62	0.77	1.23	0.92	0.75	1.18
Interest rate	0.54	0.26	0.57	0.54	0.45	0.92	0.65	0.40	0.77
House prices	6.92	2.40	7.33	20.31	5.11	19.71	8.92	3.94	11.55
Investment	10.25	6.17	18.59	6.84	5.02	19.95	12.24	4.11	13.14
Real wages	2.42	1.35	5.23	3.15	1.97	6.70	6.91	2.48	7.35
	Correlations								
C,q	0.49	-0.01	0.91	0.64	-0.52	0.86	0.33	-0.06	0.90
C,I	0.58	-0.11	0.85	0.84	-0.08	0.91	0.05	0.03	0.91
C,w	0.55	0.09	0.93	0.86	0.61	0.96	0.75	0.49	0.94
R,q	0.17	-0.73	0.27	0.38	-0.58	0.50	0.34	-0.68	0.28
q,I	-0.01	-0.08	0.88	0.60	-0.47	0.91	0.71	-0.14	0.90
q,w	0.72	-0.26	0.88	0.51	-0.56	0.85	-0.14	-0.19	0.86
π ,R	0.18	0.27	0.77	0.28	0.45	0.78	0.27	0.36	0.71

Note: For the model, the posterior 95% probability interval is reported.

Table 8: Robustness

	Benchmark		Rule 2		Rule 3		Rule 4	
	$\Gamma_q=0$	$\Gamma_q \neq 0$	$\Gamma_q=0$	$\Gamma_q \neq 0$	$\Gamma_q=0$	$\Gamma_q \neq 0$	$\Gamma_q=0$	$\Gamma_q \neq 0$
US								
ρ	0.69	0.71	0.74	0.63	0.75	0.33	0.76	0.40
Γ_p	2.09	2.22	1.53	2.24	2.16	2.30	1.95	1.14
Γ_y	0.06	0.02	0.09	0.01	0.03	0.04	0.03	0.002
Γ_q	-	0.36	-	1.22	-	0.08	-	0.14
$\Gamma_{\Delta y}$	-	-	-	-	-0.56	1.24	-0.01	-0.83
$\Gamma_{\Delta c}$	-	-	-	-	-	-	-0.88	1.62
Log marg. data density	2505.7	2516.2	2478.2	2496.0	2507.8	2518.7	2509.3	2506.9
Posterior odds	-	$3e^{-5}$	-	$2e^{-8}$	-	$1e^{-4}$	-	11.3
UK								
ρ	0.71	0.73	0.75	0.76	0.66	0.70	0.64	0.40
Γ_p	1.67	1.84	1.39	1.45	1.72	1.27	1.77	1.14
Γ_y	0.02	0.01	0.02	0.02	0.02	0.02	0.03	0.002
Γ_q	-	0.16	-	0.12	-	0.04	-	0.14
$\Gamma_{\Delta y}$	-	-	-	-	0.29	2.23	0.18	-0.83
$\Gamma_{\Delta c}$	-	-	-	-	-	-	0.28	1.62
Log marg. data density	2244.7	2252.2	2236.1	2237.5	2244.7	2265.9	2242.7	2252.4
Posterior odds	-	$5e^{-4}$	-	0.25	-	$1e^{-9}$	-	$6e^{-5}$
Japan								
ρ	0.79	0.80	0.80	0.82	0.79	0.82	0.82	0.86
Γ_p	2.28	2.40	1.54	1.72	2.26	2.32	2.16	1.80
Γ_y	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Γ_q	-	0.26	-	0.37	-	0.33	-	0.47
$\Gamma_{\Delta y}$	-	-	-	-	-0.18	-0.49	-0.11	-0.54
$\Gamma_{\Delta c}$	-	-	-	-	-	-	-0.60	-1.14
Log marg. data density	2197.3	2201.5	2172.2	2180.4	2196.9	2200.9	2195.9	2204.8
Posterior odds	-	0.02	-	$3e^{-4}$	-	0.02	-	$1e^{-4}$

Note: The table reports posterior means of the policy function parameters and posterior odds of the hypothesis

$\Gamma_q=0$ versus the unrestricted model.

$$\text{Rule 2: } \hat{r}_t = \rho \hat{r}_{t-1} + (1 - \rho) [\Gamma_p \hat{\pi}_t + \Gamma_y \hat{y}_t + \Gamma_q \Delta \hat{q}_t] + \hat{m}_t$$

$$\text{Rule 3: } \hat{r}_t = \rho \hat{r}_{t-1} + (1 - \rho) [\Gamma_p E \hat{\pi}_{t+1} + \Gamma_y \hat{y}_t + \Gamma_q \Delta \hat{q}_t + \Gamma_{\Delta y} E \Delta \hat{y}_{t+1}] + \hat{m}_t$$

$$\text{Rule 4: } \hat{r}_t = \rho \hat{r}_{t-1} + (1 - \rho) [\Gamma_p E \hat{\pi}_{t+1} + \Gamma_y \hat{y}_t + \Gamma_q \Delta \hat{q}_t + \Gamma_{\Delta y} E \Delta \hat{y}_{t+1} + \Gamma_{\Delta c} E \Delta \hat{c}_{t+1}] + \hat{m}_t$$

Table 9: Optimal simple rules

	ρ	Γ_p	Γ_y	Γ_q	<i>Loss</i>
$\Gamma_q = 0$	0.81	1.70	0.25	–	0.00201
$\Gamma_q \neq 0$	0.76	1.81	0.25	0.84	0.00195

DO CENTRAL BANKS REACT TO HOUSE PRICES?

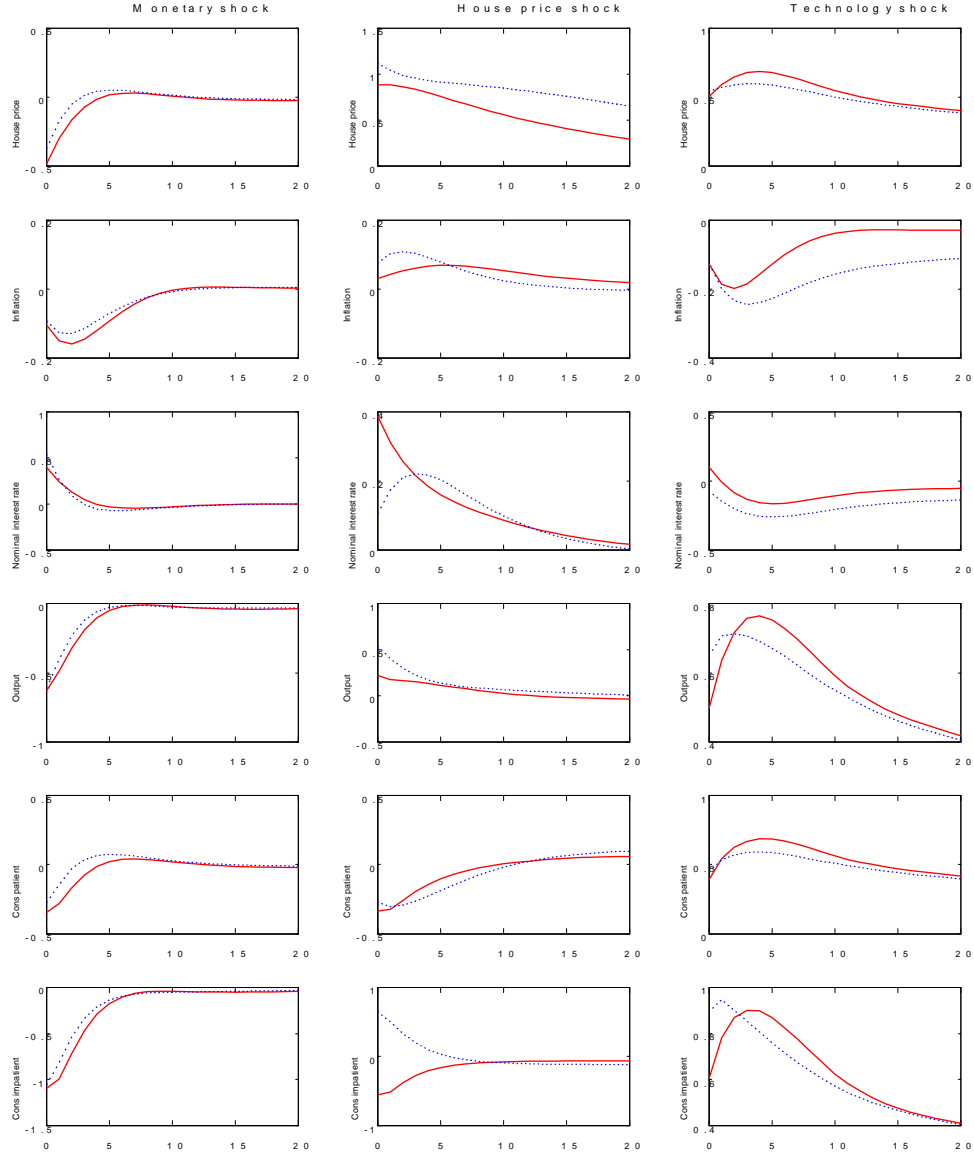


Figure 1: Posterior medians for impulse response functions in the U.S. Dotted line: Taylor rule with $\Gamma_q = 0$. Solid line: Taylor rule with $\Gamma_q > 0$. Responses are presented in percentage points. The shocks are set to one standard deviation.

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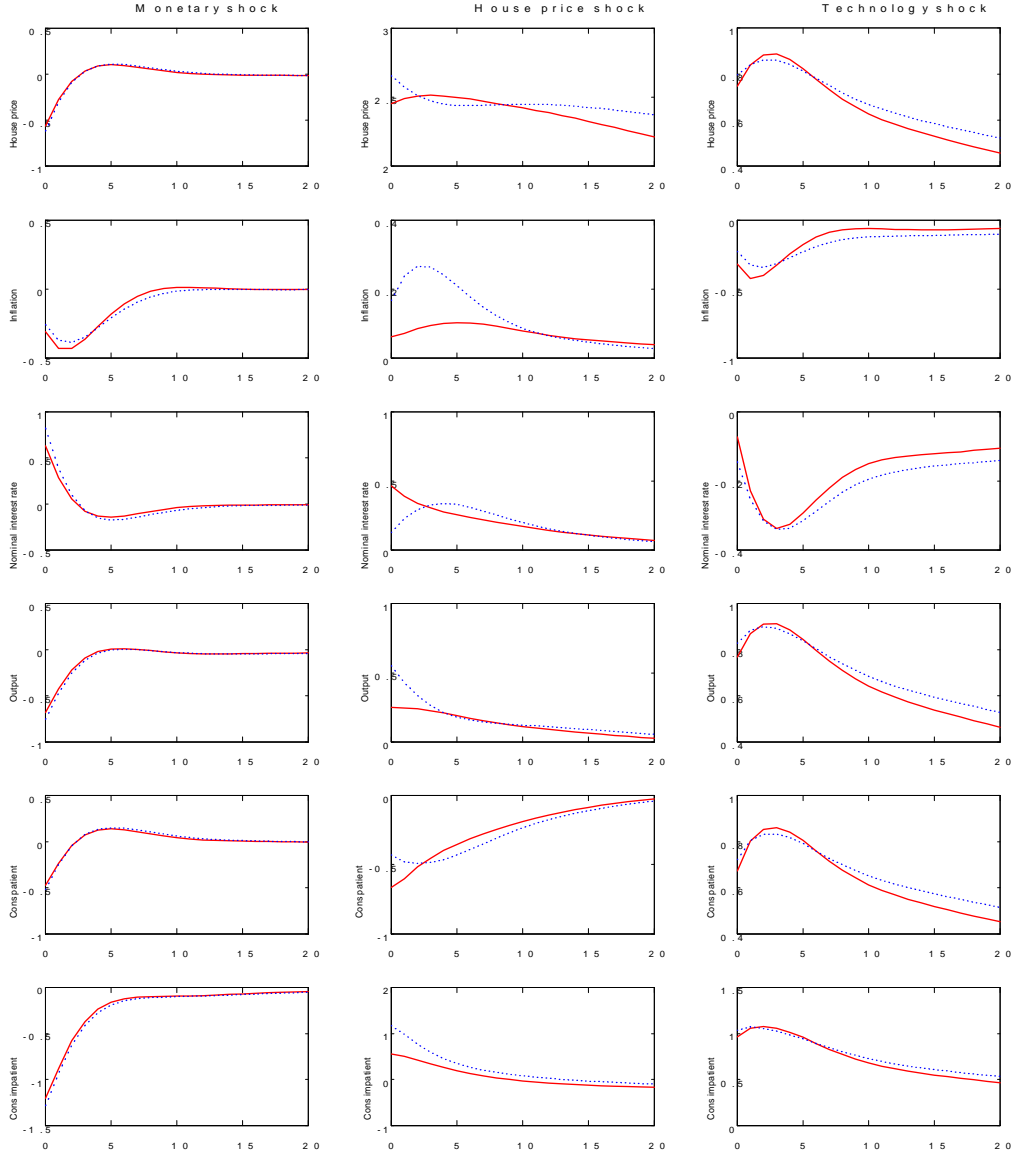


Figure 2: Posterior medians for impulse response functions in the U.K. Dotted line: Taylor rule with $\Gamma_q = 0$. Solid line: Taylor rule with $\Gamma_q > 0$. Responses are presented in percentage points. The shocks are set to one standard deviation.

DO CENTRAL BANKS REACT TO HOUSE PRICES?

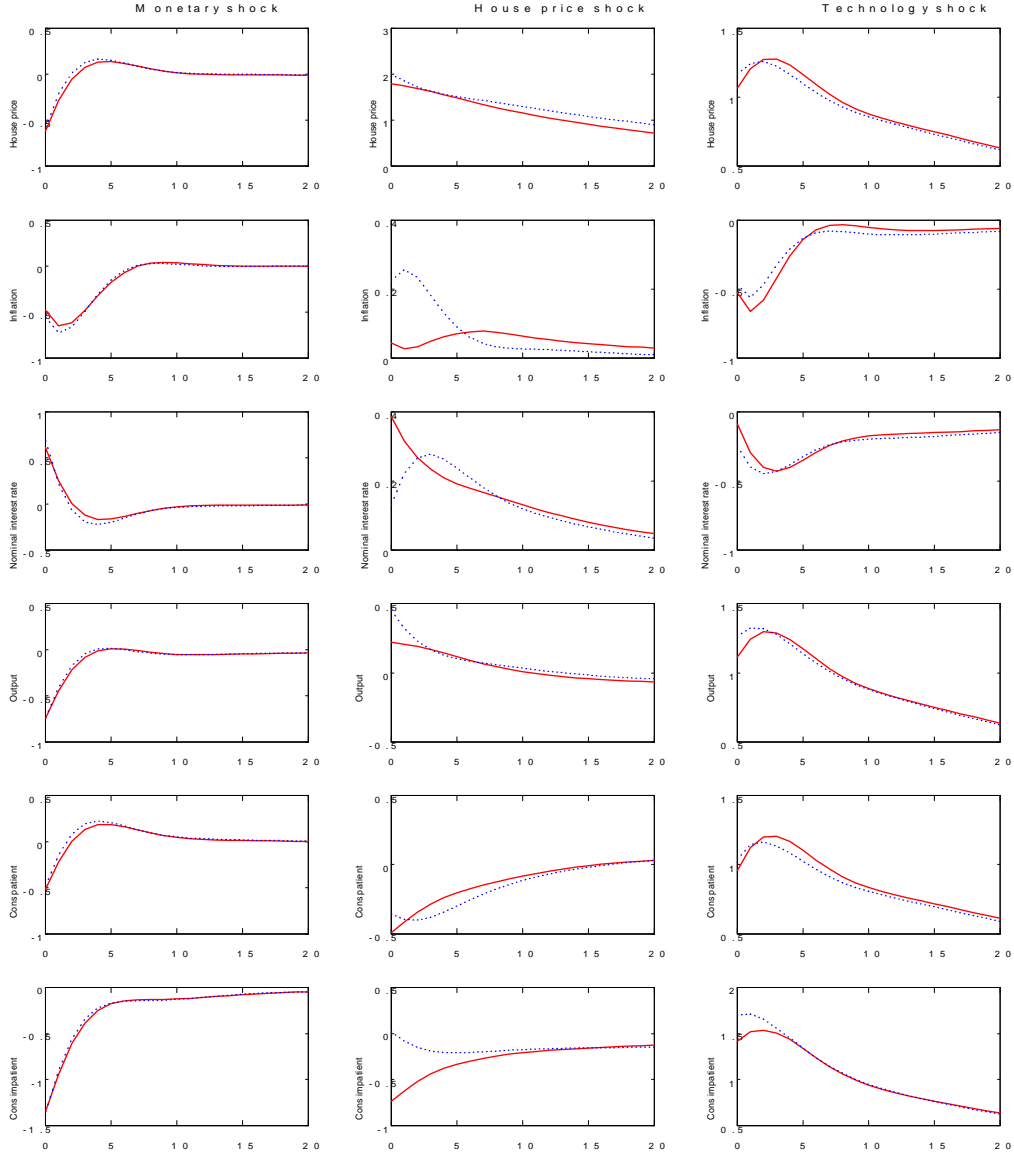


Figure 3: Posterior medians for impulse response functions in Japan. Dotted line: Taylor rule with $\Gamma_q = 0$. Solid line: Taylor rule with $\Gamma_q > 0$. Responses are presented in percentage points. The shocks are set to one standard deviation.