

The Link between Monetary Policy, Stock Prices, and House Prices—Evidence from a Statistical Identification Approach*

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This paper revisits the monetary policy–asset price nexus within a medium-sized structural VAR for the United States. With regard to identification, we put a recent approach into the spotlight of the analysis that exploits the uniqueness of linear combinations of non-Gaussian independent components under quite flexible distributional assumptions and at low computational cost. The economic interpretation of statistically identified shocks follows from utilizing informative external shock series. In a comparative analysis the benchmark identification scheme is cast into the context of a handful of alternative identification approaches. Our results indicate that contractionary monetary policy shocks have a mildly negative impact on both U.S. house and stock prices. The effect is less pronounced for equity. Moreover, we find considerable differences in the speed of monetary policy transmission among stock and house prices. Benchmark monetary policy shocks are rather robust for a variety of dynamic systems (and sample periods). Among corresponding estimates from alternative identification schemes, benchmark shocks align soundly with diverse economic underpinnings.

JEL Codes: C32, E44, E52.

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1. Introduction

The role of asset prices in the business cycle and their effects on consumer prices have received considerable attention from academics and policymakers alike. Specifically, several linkages between asset markets and the macroeconomy are likely to amplify the transmission of monetary policy (MP), i.e., the wealth channel of asset prices affecting consumption (Goodhart and Hofmann 2008), policy transmission via investment decisions (Tobin's q), and a credit channel operating via collateral effects on the external finance premium of households and firms (Bernanke, Gertler, and Gilchrist 1999). Furthermore, the crisis of 2008–09 has demonstrated that persistent deviations of asset prices from fundamentals could become an important independent source of shocks. Pointing to policy relevance, the so-called lean against the wind debate revolves around the feasibility and merits of incorporating asset prices into the MP conduct. A minimum prerequisite for the effectiveness of such a strategy is that the monetary authorities are capable of steering asset market developments in the desired direction.

The influence of MP on asset valuation is discussed controversially in the theoretical as well as empirical literature. Theoretically, the conventional view that asset prices respond negatively to surprise hikes in interest rates has been challenged recently by the notion of rational bubbles (see, e.g., Galí 2014). Empirically, the relationship between MP and asset prices has been recurrently investigated by means of structural vector autoregressive models (SVARs). Björnland and Leitemo (2009) have criticized the recursive transmission schemes employed in the earlier literature (e.g., Thorbecke 1997), and detect an active bidirectional linkage between MP and stock prices by imposing specific long-run restrictions within a five-dimensional SVAR for the U.S. economy. Interestingly, adopting an over-identified heteroskedasticity-based identification scheme, Lütkepohl and Netšunajev (2017) argue that the just identifying long-run restrictions in Björnland and Leitemo (2009) are at odds with the data. Galí and Gambetti (2015) even report evidence for a positive response of stock prices to contractionary MP shocks. Apart from using more flexible identification schemes, the literature on linkages between MP and asset markets has also advanced towards multi-asset approaches. Accounting only for the stock

market appears incomplete and might hide important insights into the interdependence between MP and asset prices in general. On the one hand, one can expect market-specific timings of policy effects which differ in particular between equity and housing markets, since house prices tend to react more sluggishly to news than stock prices (e.g., Björnland and Jacobsen 2013; Eickmeier and Hofmann 2013). On the other hand, residential property is the predominant form of household wealth and holds particular relevance for policymakers because of its central role in business cycles (Leamer 2015) and for financial stability (International Monetary Fund 2015). To highlight structural relations among MP and asset prices, the benchmark empirical model in this study is similar to that of Björnland and Jacobsen (2013) and comprises indicators from both equity and housing markets, and thereby copes with information deficits that could originate from the omission of important asset markets.

Seeing contradicting findings with regard to on-impact and dynamic interdependencies, we investigate the MP–asset price nexus in a structural manner by means of the flexible independent component analysis (ICA) toolkit of Matteson and Tsay (2017) that builds upon the uniqueness of linear combinations of non-Gaussian independent components (Comon 1994). Yet, identifying structural information with ICA-based methods has given rise to several alternative approaches (e.g., Moneta et al. 2013; Gouriéroux, Monfort, and Renne 2017; Lanne, Meitz, and Saikkonen 2017). As suggested by Matteson and Tsay (2017), we obtain a fully identified structural model from minimizing the distance covariance statistic of Székely, Rizzo, and Bakirov (2007), which has been designed for testing the null hypothesis of joint independence in a non-parametric (i.e., general) manner. Hence, in the context of SVAR identification, the minimization of this statistic conveniently avoids both the a priori imposition of short-run restrictions (as, e.g., in Moneta et al. 2013) or distributional assumptions in the vein of Gouriéroux, Monfort, and Renne (2017) or Lanne, Meitz, and Saikkonen (2017). Going beyond statistical identification, we enter the long-lasting debate about the implications of weak shock correspondence, especially between SVAR and narrative shock series as initiated by Rudebusch (1998). Accordingly, we corroborate the interpretations of the statistically identified shocks by means of correlation analysis with external shock series in the spirit of the proxy SVAR literature (Stock

and Watson 2012; Mertens and Ravn 2013). Furthermore, we provide an in-depth comparison of the benchmark identification scheme with outcomes from alternative approaches to SVAR analysis that have been used to develop MP models, namely sign restrictions (e.g., Canova and De Nicrolo 2002; Uhlig 2005), the combination of short- and long-run restrictions (Björnland and Leitemo 2009), the supposition of smooth covariance transitions (Lütkepohl and Netšunajev 2017), and a (pseudo) likelihood variant of ICA (Gouriéroux, Monfort, and Renne 2017; Lanne, Meitz, and Saikkonen 2017).

Previewing some core results, we find that MP has a moderately negative impact on real house prices which is sluggish and persistent. Our findings draw a different picture for real stock prices. The effect of interest rate shocks on equity prices is immediate and short-lived with a considerable degree of uncertainty surrounding the point estimates. While our results point to the ability of the Federal Reserve to steer asset valuation in the desired direction, even in the case of discrete MP conduct policymakers have to expect timing frictions and high economic costs of contractionary interventions. Interestingly, historical decompositions of house prices reveal that deviations of the Fed from the (model-implied) policy rule have not contributed considerably to the housing boom preceding the Great Recession. Moreover, our results suggest that the Fed reacts to both asset price shocks but more decisively to stock price shocks. Both shocks imply moderate macroeconomic effects, while the effect of the equity price shock appears more pronounced. From a methodological perspective, our results underline the merits of the proposed identification approach. It suffices to make the slightly stronger but often sensible assumption of non-Gaussian independent components to recover meaningful shocks while avoiding possibly intricate identifying assumptions on the short-run or long-run impact matrices. Moreover, estimation of the structural relations is less computationally demanding compared with the maximization of complicated likelihood specifications in both non-Gaussian iid and heteroskedastic models.

Section 2 outlines the SVAR model and the statistical identification scheme. Section 3 illustrates the ICA-based identification for a multiple asset price model of the U.S. economy, and subjects the structural model to a comparison with other identification schemes. Section 4 discusses structural features of MP asset

valuation linkages. Section 5 provides detailed evidence on the robustness of our empirical results, and Section 6 concludes. Appendix A summarizes external measures of MP shocks that we use to support SVAR identification. Baseline structural estimates are documented in Appendix B. Appendix C complements the robustness results of Section 5.

2. ICA-Based SVAR Identification and Shock Labeling

This section outlines briefly the SVAR model and the intrinsic identification problem. Against the background of an existing variety of identification schemes, we highlight the information content of independent non-Gaussian shocks and describe in more detail our adaptation of the ICA method of Matteson and Tsay (2013). For completeness, the section is explicit on the bootstrap schemes applied for inferential analysis.

2.1 The SVAR Model

We study the $K \times 1$ variable vector of interest $y_t = (y_{1t}, \dots, y_{Kt})'$ in an SVAR model of lag order p , i.e.,

$$y_t = c_t + A_1 y_{t-1} + \dots + A_p y_{t-p} + B \epsilon_t, \quad t = 1, \dots, T, \quad (1)$$

where c_t denotes vector-valued deterministic terms and A_i , $i = 1, \dots, p$, are $(K \times K)$ coefficient matrices containing the autoregressive parameters. We assume the model to be causal, i.e., $\det(A(z)) \neq 0$ for all $|z| \leq 1$ and $A(z) = I_K - A_1 z - \dots - A_p z^p$. The non-singular (impact) matrix B traces the reduced-form residuals $u_t := B \epsilon_t$ back to the underlying structural shocks ϵ_t . The ϵ_t are serially uncorrelated with $E \epsilon_t = 0$ and identity covariance matrix, $\epsilon_t = I_K$. Consequently, the reduced-form residuals fulfill $E u_t = 0$ and $u_t = B B' = \Sigma_u$.

To describe the dynamic response of system variables to the structural shocks impulse response functions (IRFs) obtained from the representation in (1), i.e.,

$$\begin{aligned}
A(L)y_t &= c_t + B\epsilon_t \\
\Leftrightarrow y_t &= A(L)^{-1}c_t + A(L)^{-1}B\epsilon_t \\
&= \nu_t + \Phi(L)B\epsilon_t = \nu_t + \sum_{i=0}^{\infty} \Theta_i \epsilon_{t-i},
\end{aligned}$$

where $\Phi(L) = A(L)^{-1}$ and $\nu_t = \Phi(L)c_t$. The h -step-ahead responses of the system to shocks ϵ_t are collected in $\Theta_h := \Phi_h B$. In particular, $\Theta_0 = B$. The implied long-run impact matrix is

$$\sum_{h=0}^{\infty} \Theta_h = A(1)^{-1}B = (I - A_1 - \dots - A_p)^{-1}B. \quad (2)$$

While reduced-form residuals u_t can be estimated consistently from the data, estimation of the structural shocks ϵ_t depends on the non-unique matrix B and cannot be achieved without further information. Several approaches to identify B have been proposed in the literature drawing on external information which is either of economic-theoretical or statistical nature (see Kilian and Lütkepohl 2017). Popular identification tools resort to a priori theoretical information in the form of short-run exclusion restrictions, such as, for instance, recursive structures (Sims 1980), long-run restrictions along the lines of Blanchard and Quah (1989), or sign restrictions in the spirit of Faust (1998), Canova and De Nicrolo (2002), and Uhlig (2005). Data-based or statistical identification techniques have been developed from observing that (i) specific heteroskedastic residual distributions accommodate identifying information on the structural model (e.g., Rigobon 2003), or (ii) going beyond the orthogonality property ($\epsilon_t = I_K$), assuming independence of non-Gaussian structural shocks provides sufficient information to identify the matrix B (e.g., Moneta et al. 2013; Gouriéroux, Monfort, and Renne 2017; Lanne, Meitz, and Saikkonen 2017). Studying the link between MP, stock, and house prices provides us with specific economic and statistical data characteristics under which several identification techniques appear reasonable.

To support the practical choice from a variety of identification tools under distinct perspectives on data generation, the Monte Carlo analysis in Herwartz, Lange, and Maxand (2019) examines comprehensively efficiency and robustness properties of both

theory- and data-based identification. In a nutshell, they argue in favor of the flexibility and robustness of identification on the basis of the non-parametric independence measures (Matteson and Tsay 2017). As an important focus of the present paper, we subject this identification scheme to a case-study comparison of MP shocks derived from a handful of theory- and data-based alternatives. We next sketch ICA as a promising identification tool, and point to its specific adaptation pursued in our empirical baseline MP model.

2.2 *Independence-Based Identification*

Because of the indeterminacy of the covariance decomposition $\Sigma_u = BB'$, alternative choices for the matrix B are observationally equivalent in a Gaussian context. In contrast, if at most one of the structural shocks in ϵ_t is Gaussian, the additional assumption of mutual independence of the shocks in ϵ_t implies uniqueness of the full B matrix (up to column signs and ordering, Comon 1994). Moreover, in the presence of multiple Gaussian shocks, the non-Gaussian independent shocks can still be identified (Maxand 2020). Determining independent shocks, i.e., applying principles of ICA, appears to be a natural approach to minimize the mutual information between the structural shocks ϵ_t . To determine B under an independence assumption, Moneta et al. (2013) adopt ICA to rank distinct recursive structural models that correspond to alternative variable orderings. Allowing for non-recursive systems, alternative ICA techniques rely on (i) (pseudo) maximum likelihood ((P)ML) estimation (Gouriéroux, Monfort, and Renne 2017; Lanne, Meitz, and Saikkonen 2017), (ii) GMM estimation (Keweloh 2021; Lanne and Luoto 2021), or (iii) the minimization of non-parametric dependence measures (Herwartz and Plödt 2016). Among these alternatives, minimizing the joint informational content of the shocks based on non-parametric dependence measures is most flexible. In comparison with (P)ML and GMM techniques, it imposes fewer restrictions on the distribution and the existence of higher-order moments of the structural shocks, respectively. Next, we briefly describe this approach in more detail.

The distance covariance, denoted $\mathcal{U}(\epsilon_t)$, is a non-parametric dependence measure introduced by Székely, Rizzo, and Bakirov

(2007).¹ Matteson and Tsay (2017) have suggested the minimization of this statistic as a means for ICA showing precision leads over the minimization of alternative independence statistics in mean squared error sense. Adapting this approach to SVAR identification involves solving a (non-linear) optimization problem conditional on a parameterized space of covariance decompositions. Specifically, this benchmark identification approach (henceforth indicated as “dcov”) proceeds as follows:

- (i) Let D denote an a priori covariance decomposition matrix (a Cholesky factor, say), i.e., $\Sigma_u = DD'$. Moreover, parameterize a space of orthogonal matrices Q ($Q \neq I, QQ' = I$), for instance, by means of Givens rotation matrices with vector-valued rotation angles θ . Then a space of potential decompositions of the reduced-form covariance Σ_u is $\mathcal{B} = \{B | B(\theta) = DQ(\theta)\}$.
- (ii) Solve the non-linear optimization problem $\hat{\theta} = \operatorname{argmin}_{\theta} \mathcal{U}(\hat{\epsilon}_t(\theta))$ and select the estimates $B(\hat{\theta})$ and $\{\hat{\epsilon}_t(\theta) = B(\theta)^{-1}\hat{u}_t\}_{t=1}^T$ as structural matrix and structural shocks, respectively.

Although the shocks detected by means of “dcov” are unique in a statistical sense, they do not necessarily hold an economic interpretation. Accordingly, the issue of so-called shock labeling is an important step of the structural analysis (Herwartz and Lütkepohl 2014). For purposes of shock labeling the analyst can, in general, resort to the following three related tools: estimated contemporaneous relations ($\hat{B}$), IRFs, and forecast error variance decompositions

¹To assess mutual independence, $\mathcal{U}(\epsilon_t)$ quantifies the group-wise distance between the joint characteristic functions and their counterparts under independence (for more details see Székely, Rizzo, and Bakirov 2007). In this work, we apply the function *steadyICA* from the R package *steadyICA* for the computation $\mathcal{U}(\epsilon_t)$ and the associated p -values (Risk, James, and Matteson 2015). The full identification algorithm is part of the R package *svars* (Lange et al. 2021), which also allows for the minimization of the Cramér–von Mises statistic of Genest, Quessy, and Rémillard (2007) as an alternative dependence metric. It is noteworthy that the empirical results obtained from “dcov” and from the minimization of Cramér–von Mises of Genest, Quessy, and Rémillard (2007) are numerically similar and qualitatively (almost) identical.

(FEVDs). A minimum requirement for the existence of a specific shock consists in a quantitatively and statistically significant contemporaneous reaction of the variable it is associated with. For instance, the federal funds rate should respond, at least on impact, to an MP shock (Lütkepohl and Netšunajev 2017). Taking notice of the debate about the implications of weak shock correspondence between SVAR shocks and narrative shock series (Rudebusch 1998) on the one hand, and the partial identification through external information (so-called proxy SVARs, Stock and Watson 2012; Mertens and Ravn 2013) on the other hand, we further support the labeling of MP shocks by highlighting their correlation with instrumental variables that have been suggested in the literature for MP analysis. Table A.1 in Appendix A gives an overview of the considered external shock series which are based either on related SVARs, narrative information, high-frequency identification, or dynamic stochastic general equilibrium (DSGE) models.

2.3 Inference in SVARs

Bootstrap procedures have become a common approach to account for estimation uncertainty in structural analysis. Recently, Brüggemann, Jentsch, and Trenkler (2016) have argued powerfully for moving block bootstrap (MBB) inference in SVARs (see also Li and Madalla 1997 and Jentsch, Paparoditis, and Politis 2014 for core contributions to the MBB in multivariate dynamic models). Unlike other common resampling schemes, e.g., the iid and wild bootstrap, the MBB provides consistent estimates whenever the inferential analysis involves both the covariance estimation or decomposition ($\Sigma_u = BB'$), and the dynamic model parameters ($A_i, i = 1, 2, \dots, p$) jointly.

Inferential analysis in this work relies throughout on MBB techniques as implemented in the R package *svars* (Lange et al. 2021). Bootstrap replications of the data read as

$$y_t^* = \hat{c}_t + \hat{A}_1 y_{t-1}^* + \dots + \hat{A}_p y_{t-p}^* + u_t^*, \quad t = 1, 2, \dots, T. \quad (3)$$

In (3) $\hat{A}_i, i = 1, \dots, p$, and $\hat{c}_t$ are OLS estimates from (1). The bootstrap residuals are obtained from resampling T/l blocks of l consecutive residual estimates $\mathcal{R}_{i,l} = [\hat{u}_{i+1}, \hat{u}_{i+2}, \dots, \hat{u}_{i+l}]$ that are

subsequently put together and centered to obtain a sample of T pseudo residuals $\{u_t^*\}_{t=1}^T$. We follow suggestions of Brüggemann, Jentsch, and Trenkler (2016) and use the integer part of $T/10$ as block size l . It is worth noticing that the empirical analysis in this work is in line with a claim of Brüggemann, Jentsch, and Trenkler (2016) saying that in finite samples inferential results of the moving block bootstrap are similar to those based on the wild bootstrap (Gonçalves and Kilian 2004; Hafner and Herwartz 2009).

3. Independent Component Monetary Policy Shocks

After reviewing the related literature in this section, we illustrate ICA-based identification within a multi-asset MP model. The structural analysis proceeds in two main steps. Firstly, seeing that the statistically unique shocks do not necessarily inherit an economic underpinning, a correlation analysis with established external shocks shows that one of the independent components aligns with the interpretation of an MP shock. Secondly, we compare this shock with outcomes of five alternative identification schemes, and find that the independent component MP shock exhibits a combination of characteristics that cannot be achieved from the adoption of competing identification methods.

3.1 *Related SVAR Literature*

Initial contributions to the interaction between MP and asset prices (Patelis 1997; Thorbecke 1997) report rather modest effects of interest rate news on stock prices. Furthermore, stock prices react only sluggishly to MP shocks, which appears to contradict established financial market theory. These studies, however, might suffer from using recursive identification schemes which imply that a contemporaneous reaction of MP (and most other macroeconomic variables) to asset price signals is ruled out by assumption. Björnland and Leitemo (2009) address potential simultaneity biases by identifying the MP and stock price shocks through a combination of short- and long-run restrictions in a five-dimensional system for a monthly sample from 1983:M1 to 2002:M12. In an otherwise recursive system, they trade the short-run zero restriction which would rule out any contemporaneous systematic MP reaction for a restriction on the

long-run multiplier (see Equation (2)) corresponding to the effect of MP on stock prices. Their results suggest a strong negative initial drop of around 12 percent in stock prices in response to contractionary interest rate signals of 100 basis points which fades out slowly. This is in marked contrast to results from a Cholesky-type impact matrix, where stock prices decline by at most 2 percent to subsequently turn considerably positive. Regarding the reverse relation, Björnland and Leitemo (2009) report a 4 basis point impact increase in the federal funds rate in response to a 1 percent rise in stock returns. The effect peaks during the first year and tapers off within the course of three years. Lütkepohl and Netšunajev (2017) re-investigate the system of Björnland and Leitemo (2009) on an extended sample period (1970:M1 until 2007:M6) by means of a just identified heteroskedasticity-based identification scheme. Subjecting the long-run restriction of Björnland and Leitemo (2009) to statistical testing obtains that the data object significantly against it. The MP shock identified in Lütkepohl and Netšunajev (2017), however, has only transitory effects on stock prices. The response of stock prices is characterized by a negligible initial impact and a considerable drop by 2.3 percent after one year. Imposing a long-run restriction, in contrast, results in a more marked decline of stock prices, especially on impact. In contrast to the conventionally identified stock price shock, Lütkepohl and Netšunajev (2017) do not diagnose a significant reaction of the MP instrument ensuing a stock price shock. Based on its persistent effect on output, the authors argue that the stock price shock bears the interpretation of a “news” shock (Beaudry and Portier 2006), as opposed to the non-fundamental shock detected in Björnland and Leitemo (2009).

In SVAR studies distinct asset markets are either implicitly considered homogeneous or important asset classes are not modeled such that possibly crucial differences remain undetected. The real estate market is likely a prime case in point for this claim due to its expected lower adjustment speed, for instance, in response to policy shocks. Pointing to their high relevance for policymakers (International Monetary Fund 2015; Leamer 2015), real estate valuations have been identified not only as important indicators of financial crisis (alongside the credit-to-GDP ratio) but also as closely tied to business cycle fluctuations. For the embedding of our baseline

six-dimensional model in the literature, it is worth noting that it has a similar scope as the empirical studies of Eickmeier and Hofmann (2013); Alessi and Kerssenfischer (2019); and Björnland and Jacobsen (2013), who investigate the link between MP and asset prices and consider more than one asset class.² Eickmeier and Hofmann (2013) provide evidence for the interaction between MP and several asset prices by means of a factor-augmented VAR (FAVAR) model estimated for quarterly U.S. data (1987:Q3–2007:Q4). Their results point to a missing transmission channel for a number of stock price indices but simultaneously to a quite active channel with regard to property prices. Alessi and Kerssenfischer (2019) further advance the econometric approach of Eickmeier and Hofmann (2013) by considering a non-stationary dynamic factor model for U.S. and euro zone data. The monetary policy shock is identified by exploiting instrumental information. Comparing their results with those of a standard proxy SVAR, the authors document a markedly stronger response of both house and stock prices, where the speed of transmission is considerably slower for real estate. Björnland and Jacobsen (2013) estimate a model incorporating house and stock prices for quarterly U.S. data spanning the period from 1983:Q1 to 2010:Q1. Unlike Eickmeier and Hofmann (2013) and Alessi and Kerssenfischer (2019), they also investigate the reverse causation from asset price shocks to systematic MP responses. Adopting identifying assumptions in the spirit of Björnland and Leitemo (2009), they find remarkably distinct roles of house and stock markets for MP transmission. In contrast to stock prices, shocks stemming from the housing market move output and prices considerably, but the monetary authority seems to respond with a significant delay of about two quarters to these shocks. Finally, Paul (2020) expands insights into the link between MP and asset prices by allowing for time variation. His findings suggest that responses of stock and particularly house prices co-move considerably with the price level, i.e., are more responsive when prices are low and vice versa.

²Important studies which focus on the transmission of MP through house prices only are, for instance, Iacoviello (2005), Del Negro and Otrok (2007), and Musso, Neri, and Stracca (2011). With regard to identification, the dominant strategy in most studies is to assume a recursive ordering of variables.

3.2 *An Independent Component Monetary Policy Model*

3.2.1 *The Reduced-Form Model and a Case for ICA*

Taking into account asset market heterogeneity and the prominent role of real estate markets, we consider subsequently a six-dimensional ($K = 6$) VAR as in (1). Almost throughout, our empirical analysis conditions on monthly U.S. data covering the period from 1975:M2 until 2015:M8. To a large extent the empirical analysis in this study relies on the R package *svars* (Lange et al. 2021) that comprises reduced-form model estimation and diverse data-based identification techniques. As we complement the identification step of the analysis with correlations between detected shocks and external instruments that are partly only available at the quarterly frequency, we have also implemented our baseline SVAR with quarterly data.³ The composition of y_t is inspired by the single-asset models of Björnland and Leitemo (2009) and Lütkepohl and Netšunajev (2017), and includes in analogy to these reference studies a linearly detrended log industrial production index (q_t), the annual change in log consumer prices (Δp_t), the annual change in the log of the World Bank (non-energy) commodity price index ($\Delta comp_t$), and the log differences of the S&P 500 Composite Index deflated by the consumer price index as monthly real returns (Δsp_t).⁴ Unlike the reference models, y_t comprises the federal funds shadow rate (ffr_t) of Wu and Xia (2016) and, taking a multi-asset perspective, the log returns of the (CPI deflated) Case-Shiller house price index (Δhpi_t).⁵ As suggested by the Akaike information criterion

³The results of the quarterly model are not shown, but available upon request.

⁴The use of an output gap measure has theoretical appeal, since this indicator of economic activity is closely monitored by central banks and, e.g., in New Keynesian DSGE models the output gap plays a central role for model dynamics. Moreover, we emphasize that key conclusions drawn in this paper neither rely on including an output gap measure nor on the specific type of output gap indicator, i.e., modeling potential output as a linear trend process. For more details on the robustness of our results regarding the output variable, the reader is referred to Appendix C.

⁵The availability of the Case-Shiller index determines the sample period. We opt for the shadow rate, since interest rates have been at the zero lower bound since the end of 2008. Before 2008 the federal funds rate used in Björnland and Leitemo (2009) and Lütkepohl and Netšunajev (2017) and the shadow rate are identical. The shadow rate is available at <https://www.frbatlanta.org/cqer/>

(AIC), the lag order is $p = 3$, and deterministic terms enter in the form of a linear trend, i.e., $c_t = \gamma_1 + \gamma_2 t$ in (1), where significantly negative trend coefficient estimates indicate a slowdown of growth rates over recent decades for detrended log-industrial production (q_t) and house price returns (Δhpi_t). We apply least-squares estimation and extract reduced-form residuals u_t for the subsequent structural analysis.

The potential of ICA to uncover structural shocks relies crucially on the assumptions of non-Gaussianity and causality. To address these requirements in a diagnostic manner, we firstly evaluate the number of non-Gaussian components as suggested by Nordhausen et al. (2017) and implemented in R package *ICtest*. The null hypothesis of k_1 Gaussian components and $K - k_1$ non-Gaussian components can be rejected for $k_1 = 1$ with 1 percent significance. Component-wise Jarque-Bera tests confirm the strong evidence against the supposition of normally distributed residuals. Secondly, we test the null hypothesis of fundamentalness (Sahneh 2015).⁶ As it turns out, the reduced-form residuals u_t can be considered as a martingale difference sequence pointing to fundamentalness of the underlying structural shocks (p -values ≥ 0.14). With regard to the choice of a specific identification scheme, ICA might proceed in the form of a fully parametric distributional model (e.g., Gouriéroux, Monfort, and Renne 2017; Lanne, Meitz, and Saikkonen 2017). Following a (pseudo) ML approach requires a (non-normal) iid distribution of the structural shocks, which might be in conflict with the data in longer samples. Subjecting disjoint subsamples of reduced-form residuals u_{kt} to Kolmogorov-Smirnov (KS) tests sheds doubts on such an assumption. For instance, dividing the whole sample into a pre- (1976 until 2008) and post-crisis subsample obtains KS p -values for residuals u_{1t} to u_{6t} of .440, .203, .053, .711, .003, and .087. Hence, with conventional significance the a priori assumption of an underlying iid

research/wu-xia-shadow-federal-funds-rate. All other time series have been obtained from the Federal Reserve Bank of St. Louis's Federal Reserve Economic Database (FRED).

⁶We thank Mehdi Hamidi Sahneh for providing his MATLAB code. Since the size properties of the test could be sensitive to the lag order choice, we conducted it for lag orders up to eight.

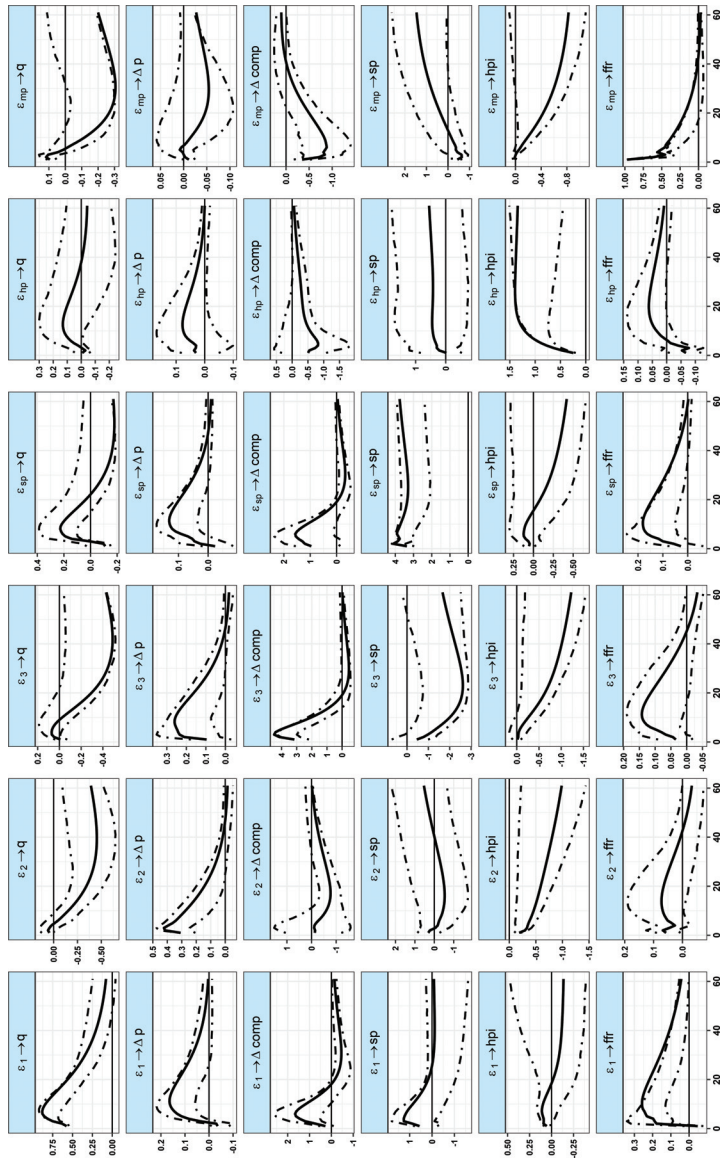
distribution of structural shocks ε_t is at odds with KS diagnostics. Summarizing the diagnostic outcomes on non-Gaussianity, fundamentalness, and distributional heterogeneity, we adopt ICA techniques as suggested by Matteson and Tsay (2017) to develop our benchmark MP model.

3.2.2 Detecting Independent Component MP Shocks

Benchmark estimates (“dcov”) of the structural impact matrix $\hat{B}$ are shown in Appendix B. Figure 1 and the left-hand side of Figure 2 display the corresponding IRFs and FEVDs, respectively. Only one shock, i.e., the one associated with the responses shown in the sixth column of Figure 1 (ϵ_6), invokes a noticeable and statistically significant increase in the federal funds rate on impact, which is considered as a stylized fact of MP shocks in the tradition of Christiano, Eichenbaum, and Evans (1999). Similar to common findings of the MP SVAR and DSGE literature (e.g., Jarocinski and Smets 2008), this shock contributes almost 100 percent to the variance of the federal funds rate on impact and more than 50 percent at medium horizons. Moreover, noticing that this shock is unique to invoke sizable and opposite impact effects on prices and the federal funds rate, we consider ϵ_6 as a potential MP shock.

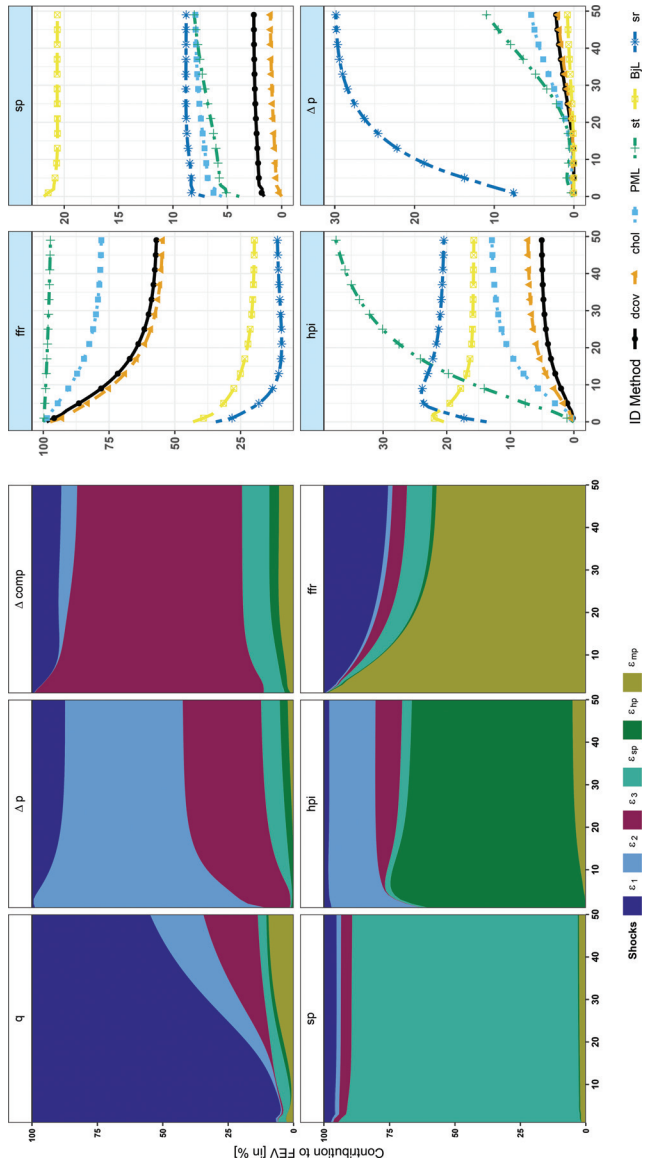
Additional support for assigning ϵ_6 the label of an MP shock obtains from evaluating its correlations with external shock series as documented in Table 1. First of all, we observe that each external MP measure shows stronger (positive) correlation with ϵ_6 in comparison with the remaining (non-MP) shocks ($\epsilon_1, \dots, \epsilon_5$). Particularly, the MP shocks of Sims and Zha (2006) (*sz mps*, $\hat{\rho} = 0.54$) and the narrative shock series of Romer and Romer (2004) (*R&R*, $\hat{\rho} = 0.33$) correlate sizably with our MP shock. Putting the latter correlation estimate into perspective, it is worth recalling that the R&R shock and ours have been estimated conditional on very different sample periods. Despite this fact, our result is of similar magnitude as the corresponding 0.36 correlation reported by Kliem and Kriwoluzky (2013), who condition their SVAR on the same sample period considered in Romer and Romer (2004) and adapt further specification details of the narrative analysis. Turning to the high-frequency policy surprise series, the instrument by Miranda-Agrippino (2016) (*MA hf*) stands out. This surprise series appears

Figure 1. Impulse Responses to a Unit Shock for the Identification Scheme “dcov”



Note: Solid lines indicate point estimates. Dashed lines limit 68 percent confidence bands based on 1,000 bootstrap replications. Impulse responses for real stock and real house prices show accumulations of effect estimates for Δsp and Δhpi , respectively. Instead of a numerical labeling, the shocks in the right-hand side are already indicated with their ensuing economic characterization, i.e., MP (ε_6), house price (ε_5), and stock price shock (ε_4).

Figure 2. FEVDs for the Baseline Model



Note: The left-hand side shows FEVDs for all shocks and variables identified by “dcov” (see also Figure 1 for respective IRFs). Specifically, ϵ_{mp} , ϵ_{sp} , and ϵ_{hp} denote the MP shock (light green), the stock price shock (cyan), and the house price shock (dark green), respectively. The right-hand side shows FEV shares of four key variables that can be traced back to MP shocks retrieved from alternative identification schemes (see Section 3.3.1 for a detailed account of the identifying assumptions). (For figures in color, see the online version of the paper at <http://www.ijcb.org>.)

particularly useful, since it has been thoroughly shown to be orthogonal to both central bank forecasts and historically available public information. Among all structural shocks in the system, only the MP shock exhibits a significant positive correlation with the *MA hf* series ($\hat{\rho} = 0.14$). Complementing results for the (monthly) baseline model, it is worth noticing that its quarterly counterpart provides MP shocks that are also corroborative for the suggested label. For instance, at this lower frequency the *R&R* narrative series of Romer and Romer (2004) and the Smets and Wouters (2007) DSGE-based shocks exhibit correlations with the identified MP shock of 0.61 and 0.72, respectively.

3.3 MP Shocks from Alternative Identification Schemes

The literature on identification in SVARs yet comprises several alternative approaches. While to some extent data-based identification schemes offer an opportunity of testing otherwise just identifying assumptions (e.g., restrictions derived from economic theory), ultimately, the decision in favor of a particular identification scheme is often a matter of convenience, and could benefit from a careful comparison of structural models retrieved from alternative identification schemes. Having elicited potential advantages of the non-parametric detection of independent components in Section 2.2, this section provides a critical discussion of alternative schemes to identify MP shocks in the baseline VAR. We first encounter five alternative identification schemes and turn subsequently to a comparative analysis in terms of three (complementary) criteria.

3.3.1 Alternative Identification Schemes

In particular, we apply the following identification approaches (with short comments on their specific implementation; see also Section 3.1).

Recursive Ordering (“chol”). The variables in y_t align with the widespread convention to order slow-moving variables ahead of financial variables and the policy instrument (Christiano, Eichenbaum, and Evans 1999). Hence, using a lower triangular covariance factor for identification implies that the federal funds

rate reacts to all shocks on impact, while surprise interest movements affect remaining variables with a time lag by assumption. As an alternative to formalizing model hierarchies in an a priori manner, Moneta et al. (2013) have suggested ICA-based criteria to rank lower triangular covariance decompositions that obtain from alternative variable orderings. Adopting their so-called LinGAM (linear, non-Gaussian, acyclic model) approach obtains an ordering $y_t = (\Delta hpi_t, \Delta p_t, q_t, ffr_t, \Delta sp_t, \Delta comp_t)'$.⁷

Long-Run Restrictions (“BjL”). In the spirit of Björnland and Leitemo (2009) and Björnland and Jacobsen (2013), we impose two restrictions on the long-run impact matrix (see (2)) such that both stock and house prices are neutral with respect to MP shocks in the long run. Accordingly, we relax two short-run restrictions implied by “chol,” to allow impact responses of stock and house prices to MP shocks.⁸

Smooth Transitions of Covariance (“st”). The identification of heteroskedastic shocks follows Lütkepohl and Netšunajev (2017) and builds upon a smooth logistic transition between two covariance regimes where the time index t serves as transition variable. For better comparability, we standardize the identified shocks to have unconditional variances of unity.

“PML.” The two-step ICA approach of Lanne, Meitz, and Saikkonen (2017) is applied to maximize the log-likelihood of independent components under the assumption of (standardized) t -distributed shocks in ϵ_t .

⁷For computation we apply the VAR-LinGAM R-code provided along with the study of Moneta et al. (2013). The suggested variable ordering captures key features of a monetary policy rule. We refrain from this model, however, for three reasons. First, the suggested ordering deviates from the convention to order slow-moving macroaggregates prior to financial variables. Second, the implied relation among MP measures and asset markets is asymmetric, as the model implies that the federal funds rate responds to surprises in house prices but not to news originating in stock returns. Third, from an unrestricted estimation of the structural model parameters (see Appendix B) we find that house price returns respond significantly to at least two independent components, which is at odds with the model hierarchy implied by VAR-LinGam.

⁸Björnland and Leitemo (2009) impose long-run restrictions on stock prices. Analyzing stock and house prices, Björnland and Jacobsen (2013) impose, in addition, monetary policy neutrality with regard to output as a second long-run restriction.

Sign Restrictions (“sr”). We impose restrictions such that output, inflation, and both asset prices decrease in response to a positive MP shock on impact and the two following months.⁹ To single out particular estimates from the set of admissible models, we report median target results as proposed by Fry and Pagan (2011). Unlike the remaining identification schemes (“dcov,” “chol,” “BjL,” “st,” and “PML”), “sr” focuses on the partial identification of the MP shock.

The following comparison of alternative MP shocks proceeds in basically three directions: (i) a descriptive look at alternative IRFs and FEVDs, and (ii) a correlation analysis of identified MP shocks with direct measures of MP signals. While these criteria refer to the economic properties of alternative MP shocks, (iii) we provide as a further statistical criterion the p -values obtained from testing the null hypothesis of independence by means of the distance covariance of Székely, Rizzo, and Bakirov (2007). Acknowledging that this criterion favors ICA-based identification techniques trivially, it is interesting in its own to observe if the choice for alternative identification schemes comes with significant dependence among implied structural shocks.¹⁰

Before entering the comparison of identification outcomes, it is worth pointing out that all alternative MP shocks show—conditional on the underlying identification scheme—the strongest correlation with the benchmark MP shocks retrieved from “dcov.” Specifically, these (undocumented) correlations are (i) smallest for “sr” and “BjL” (i.e., 0.544 and 0.699, respectively), and (ii) in excess of 0.97 for the three remaining identification schemes. Taking notice of the completely different identification criteria for the shocks, the close

⁹These restrictions are commonly imposed to identify MP shocks, except for those on house and stock prices (e.g., Björnland and Jacobsen 2013; Uhlig 2005; Eickmeier and Hofmann 2013). If we do not impose these additional restrictions, the house price response is counterintuitive. Qualitatively identical results obtain when combining sign restrictions with further exclusion restrictions to formalize that output and prices do not react on impact.

¹⁰The determination of structural IRFs builds upon the notion of isolated unit shocks, i.e., conditional expectations of $E[\epsilon_{it}|\epsilon_{jt} = 1] = 0, i \neq j$. While such expectations apply under independence or multivariate normality of structural shocks, dependent shocks might encounter non-zero conditional expectations $E[\epsilon_{it}|\epsilon_{jt} = 1] \neq 0, i \neq j$, and could subject conventional impact responses (and IRFs) to estimation bias.

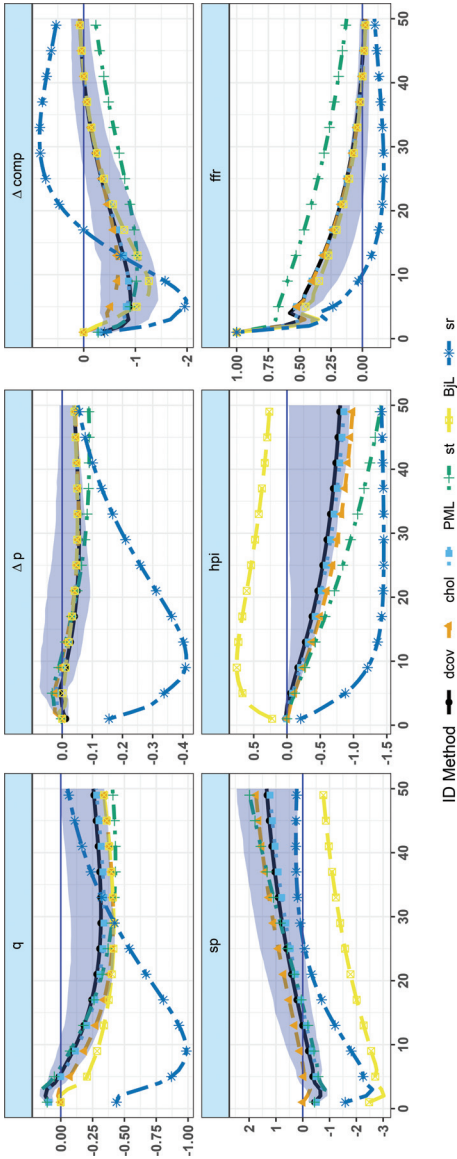
association between the MP shocks supports the MP label of the shocks in general, and of the benchmark shocks (“dcov”) in particular. According to such indications of closeness among identified MP shocks, however, the somewhat smaller empirical correlations of benchmark shocks with outcomes from “sr” and “BjL” could point to notable informational differences.

3.3.2 *Alternative IRFs and FEVDs*

To visualize the effects of alternatively detected (contractionary) MP shocks, Figure 3 and the right-hand side of Figure 2 display, respectively, IRFs and FEVDs. To facilitate the comparative analysis the MP shocks are normalized throughout to invoke an increase of the federal funds rate by 100 basis points. While several identification schemes show IRF patterns that cannot be distinguished from effects of benchmark shocks in statistical terms, we observe that (i) the imposition of sign restrictions (“sr”) obtains shocks with outstandingly strong responses throughout and, in particular, so for output and prices, and (ii) a combination of short and long-run restrictions (“BjL”) comes with the implication of a sizable and counterintuitive increase of house prices in response to contractionary MP shocks. From the displayed dynamic profiles of FEVDs we find that the benchmark model and the supposition of a lower triangular covariance factor (“chol”) are unique in showing both strong short-run and medium long-run effects of MP shocks on the federal funds rate, which aligns with related studies.¹¹ As further implied by the displayed FEVDs at highest horizons, adopting “sr” or “BjL” (“st”) yields an incredibly minor (overly strong) importance of MP shocks

¹¹MP shocks are typically found to contribute substantially in the short run to the federal funds rate (in terms of FEVDs). For instance, on the basis of sign restrictions Uhlig (2005) documents corresponding impact effects of almost 100 percent, while the hierarchical models (“chol”) of Balke and Emery (1994) and Forni and Gambetti (2010) obtain estimates of about 75 percent. Similarly, Smets and Wouters (2007) and Jarocinski and Smets (2008) report at least a 50 percent contribution for estimated DSGE models. While theory lacks sufficient guidance for an exact range of admissible FEV shares accounted for by exogenous MP, marginally low short-term variance shares are certainly at odds with monetary theory. Based on a range of DSGE model types and parameterizations, Canova and Pina (2005) show that these imply in general a variance contribution of MP shocks at medium horizons (four years) of about 60–90 percent.

Figure 3. Impulse Responses to MP Shocks for Alternative Identification Schemes



Note: Lines indicate point estimates from six alternative identification methods (see Section 3.3.1). MP shocks are normalized to impact on the federal funds rate with 100 bps. Based on 1,000 bootstrap replications, shaded areas indicate 68 percent confidence bands for the effects of MP shocks identified by means of the benchmark identification method “dcov.” For corresponding FEVDs, see Figure 2. For further notes, see Figure 1.

for the evolution of the federal funds rate, while “PML” results in assigning a weight beyond 75 percent to MP shocks.

3.3.3 Correlations with Direct Measures of MP Shocks and Independence Diagnosis

In terms of correlations with direct measures of MP shocks, the results in Table 2 show that several identification schemes provide MP shocks with similar properties as those obtained from “dcov.” However, it is noteworthy that both the application of stylized sign restrictions (“sr”) and the combination of long- and short-run restrictions (“BjL”) result in MP shocks that correlate less strongly with the Sims and Zha (2006) SVAR MP shocks (*sz mps*, $\rho = 0.30, 0.39$) and the narrative shock series of Romer and Romer (2004) (*R&R*, $\rho = 0.16, 0.33$) in comparison with benchmark correlations ($\rho = 0.54$ with *sz mps* and $\rho = 0.33$ with *R&R*). Interestingly, the imposition of sign restrictions obtains MP shocks coming closest to the high-frequency policy surprise series of Miranda-Agrippino (2016) in terms of a linear correlation of 0.19, which is slightly beyond the result for the benchmark model ($\rho = 0.14$).

The upper left panel of Table 2 displays *p*-values of testing the null hypothesis of independence for alternative samples of structural shocks. While the *p*-value attached to benchmark shocks is close to unity (i.e., 0.92), it is worth noticing that this diagnostic results from an optimization procedure and, hence, does not provide strong evidence in favor of the null hypothesis in a conventional manner. Using PML techniques yields shocks of a similar degree of independence (*p*-value of 0.94). Clear violations of the null hypothesis of independence obtain if shocks are retrieved from a combination of short- and long-run restrictions and from an imposition of sign restrictions (with *p*-values of 0.2 percent). Composing structural shocks under a scenario of a smooth covariance transition (*p*-value of 0.09) and a lower triangular covariance factor (*p*-value of 0.13) yields marginal evidence in favor of higher-order dependence.

3.3.4 Summary

Because of their latency, the practical identification of structural shocks in empirical MP models might follow several lines of

reasoning. Unsurprisingly, a clear-cut dominating approach might hardly exist. Nevertheless, our comparative empirical exercises highlight that viewing MP shocks as an independent component has potential to establish a variety of plausible properties, for instance, in terms of implied structural IRFs, FEVDs, and correlations with external and direct MP measures. Among rival ICA approaches, the benchmark approach of Matteson and Tsay (2017) somehow dominates more restrictive (P)ML schemes, which seem to overstress the role of MP for the long-term variance shares of the federal funds rate. In comparison with ICA-based identification schemes, using the informational content of smooth transitions of covariances (“st”) obtains incredibly strong and persistent variance shares in the federal funds rate to result from MP shocks. The imposition of either sign (“sr”) or long-run (“BjL”) restrictions yields orthogonalized shocks that are subject to higher-order dependence. Moreover, the combination of short- and long-run restrictions obtains MP shocks that trigger a counterintuitive increase of house prices. While the median target shocks derived from imposing sign restrictions do not suffer from price or output puzzles by construction, the invoked response profiles can show up as overly strong (see, e.g., price and output effects implied by “sr”). In terms of FEVDs, identification by means of “sr” attributes a quite minor role of MP shocks to the variation of the federal funds rate. While the identification approaches “dcov,” “chol,” “PML,” and slightly less so “st” tend to cross-confirm each other in terms of implied IRFs, “BjL” and “sr” apparently contest the former identification schemes and themselves mutually. Observing that “chol” obtains similar results as data-based identification schemes is a merit of the hierarchical model on the one hand, but also an *ex post* confirmation of the *a priori* hierarchy implied by a particular variable ordering on the other hand. As data-based identification schemes show potential to let the data speak in favor of or against just identifying restrictions, “dcov” shows particular merit, as it operates under quite weak assumptions and is easy to grasp in terms of model complexity and computational effort (for simulation-based evidence, see Herwartz, Lange, and Maxand 2019). On the contrary, theory-based identification (“BjL” and “sr”) could suffer from specific shortcomings, since both identification schemes potentially require controversial choices by the analyst from a theoretical and technical perspective.

For instance, the “sr” approach requires the specification of the horizon for which the restrictions are imposed, and results are eventually not robust to this choice. Accordingly, we had to impose restrictions on the responses of stock and house prices to achieve consensual responses of these variables (i.e., both featuring a negative impact response to contractionary MP shocks). While this comes generally with risks of confusing assumptions and conclusions, it is unclear how far the imposition of specific restrictions is innocent with regard to particular focal structural effects for which the approach claims to be agnostic. Moreover, the combination of long- and short-run restrictions is prone to misidentification due to its reliance on exact unit roots, inflating of biases in autoregressive coefficients, and intricacies that arise from overlooking linkages from shocks to variables in the long run (Kilian and Lütkepohl 2017, chapter 10 and literature therein). Regarding our empirical model, for instance, we observe that results vary considerably for a priori equally plausible long-run restrictions (see also the robustness analysis in Section 5).¹²

4. Macrofinancial Linkages and the Role of Monetary Policy

Having discussed a variety of alternative MP shocks, we turn next to (i) a comparative assessment of model-implied linkages among MP and asset market performance and (ii) the identification of asset valuation shocks that are required to investigate if U.S. monetary policy has been responsive to such surprise information. For the first purpose we put benchmark outcomes for “dcov” into perspectives of both the related literature and outcomes of alternative identification schemes. To address the second issue, our analysis is fully conditional on the benchmark identification scheme (“dcov”) for space considerations. Specifically, we use the benchmark model to identify shocks that originate in equity valuation or house prices and to describe their macroeconomic effects.

¹²If we impose, for example, a long-run restriction on stock prices and output instead on house prices, the FEV share of the MP shock to house prices is close to estimates in Björnland and Jacobsen (2013), with a maximum contribution of 70 percent; however, this result comes with the implication that the FEV share of the federal funds rate explained by the MP shock is $\leq 5\%$ for all horizons.

4.1 The Effects of MP on Housing and Equity

As implied by benchmark identification results (“dcov,” see Figure 1), an unexpected monetary tightening invokes a mildly negative (about -0.5 percent) contemporaneous impact on real equity. The responses turn positive quickly. Point estimators indicate a sizable positive reaction in the medium run, which is, however, not statistically different from zero. Turning to real house prices, we notice that they react more sluggishly to unexpected federal funds rate signals than stock prices. The response of real residential property prices is practically zero during the first quarter, turns negative thereafter, and continues dropping down to -0.75 percent over the entire period of five years.

Figure 3 provides a comparative view at baseline IRFs and outcomes from alternative identification schemes. Except for “BjL”, all identification schemes agree qualitatively on the differences of MP transmission (time lags or adjustment speed) to stock versus house prices. Moreover, data-based identification schemes unravel almost identical shapes of responses for both asset prices. Transmissions implied by “BjL” and “sr” still agree broadly with “dcov” with regard to stock prices, but less so for house prices. The long-run identified shock (“BjL”) leads to an entirely positive response of real house prices, while sign-restricted shocks (“sr”) invoke a more immediate response with achieving a new steady state already after about two years. By construction, employing a recursive identification scheme prohibits stock prices from reacting instantly to a policy surprise.

While our results are at odds with the immediate substantial and quickly rebounding drop of house prices found by Del Negro and Otrok (2007),¹³ similar dynamic transmission characteristics have been documented in the related literature for distinct sample periods, quarterly data and long-run restrictions (Björnland and Jacobsen 2013), recursive models (Musso, Neri, and Stracca 2011), data-rich environments (Eickmeier and Hofmann 2013; Alessi and

¹³A systematic comparison of our results and those in Del Negro and Otrok (2007) is complicated due to substantial differences with regard to the quantification of house prices (they use a sophisticated house price factor extracted from regional U.S. housing indices), a shorter sample period, and the employed econometric approach.

Kerssenfischer 2019), and the time-varying parameter VAR of Paul (2020).

From a theoretical perspective, the detection of distinct transmission profiles for both asset classes is reasonable for at least three reasons. First, the stickiness of house prices can be traced back to imperfections and resulting inefficiencies in the residential property market, such as high transaction and search costs, different timing preferences between buyers and sellers, social norms, and tax considerations (Case and Shiller 1989; Geltner 2015). Second, the heterogeneity of traded assets implies that the market value of houses must be estimated based on historical sales data, which introduces backward-looking behavior into the market (Iacoviello 2010). Third, we conjecture that the slower transmission to house prices in comparison with stock prices partly reflects differences in the financing structure of households and firms. The residential property market is closely tied to long-term mortgage loans which are mostly fixed-rate contracts. An interest rate hike affects mainly new loans, and therefore can be expected to transmit to house prices less rapidly than to stock prices, which adjust more timely due to the discount channel and a presumably larger share of short-term (variable rate) loans in the corporate sector. We conjecture, however, that the double burden faced by households—a rise in debt servicing costs induced by the interest rate hike and a simultaneous worsening of the income situation of households—represents an additional explanation for the persistence of the decline in house prices at longer horizons (from three years onwards).

Besides unravelling asset-specific dynamic transmission patterns, benchmark identification outcomes appear throughout (relatively) small in absolute terms. Two remarks are worth noticing in this regard. First, the detection of minor effects of MP for stock prices is covered by a vast range of stock price responses, including a –10 percent impact in Björnland and Jacobsen (2013) up to a completely insignificant transmission in (Eickmeier and Hofmann 2013). Second, with regard to house prices, benchmark results fall short of outcomes from several studies documenting respective effects between –4 percent and –1 percent (e.g., Iacoviello 2005; Del Negro and Otrok 2007; Björnland and Jacobsen 2013; Eickmeier and Hofmann 2013; Alessi and Kerssenfischer 2019). How far our (upper bound) estimates materialize for the development of actual house prices during

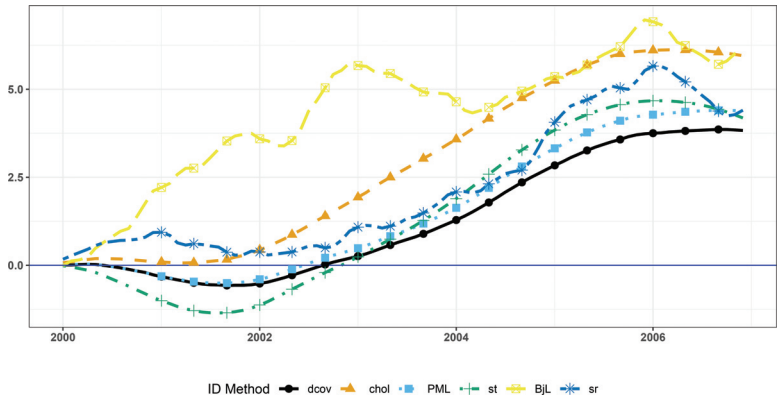
the 2006 housing boom is an interesting concern that will be further addressed below in Section 4.2.

Results displayed in Figures 2 and 3 reveal that disagreement of transmission strength is also reflected among alternative identification schemes. Stock price responses corresponding to “BjL” and “sr” are characterized by considerably stronger short-term and peak effects (between -3.0 percent and -2.5 percent) compared with data-based identification. IRFs implied by “sr” as well as “st” show a more pronounced drop in house prices in the medium and long run. Hence, our results suggest that the stronger response reported in the literature can partly be attributed to the (i) identification method, where impositions of long-run or sign restrictions invoke largest magnitudes, and (ii) the data frequency, where the analysis of quarterly data tends to be associated with larger effects (as we have confirmed in an undocumented quarterly model specification). This accords quite well with the fact that, except for Alessi and Kerssenfischer (2019), all studies mentioned above are conditional on quarterly data. We note that the largest variance contribution of MP to stock prices is associated with the long-run restriction scheme (“BjL”), which points to the particular role of this identification scheme to reflect the largely different conclusions on the role of MP for stock prices as documented in the literature (e.g., Björnland and Jacobsen 2013) and the present study.

4.2 The Role of MP during the House Price Boom

As a practical exercise, we take up the debate on the role of loose MP—in the sense of downward deviations from the model-implied Taylor-type rule—in the buildup of the price bubble on the real estate markets during the period 2000:M1 until 2006:M12. For this purpose we consider counterfactuals that are based on historical decompositions. Specifically, we compare the actual (trend adjusted) real house prices with their counterparts that obtain from shutting down the effects of MP shocks. All identification schemes agree in providing counterfactual housing return series that are most often (slightly) below actual housing returns. Put differently, deviations from the implied policy rule have mostly exerted a positive effect on house prices during the period under scrutiny. To visualize the role of MP during the house price boom, Figure 4 depicts cumulated

Figure 4. Historical Decomposition-Based Counterfactual



Note: Cumulated difference between actual, i.e., (VAR implied) trend-adjusted real house price index and historical decomposition-based counterfactual excluding the contribution of MP shocks for all considered identification schemes. The considered time frame covers observations beginning in 2000:M1 until 2006:M12.

differentials between counterfactual and actual house price returns. Even though (undocumented) time-specific return differentials are small throughout, the cumulated effect is systematic and not trivial for all identification schemes with “dcov” providing a lower bound of total effect estimates. According to our variety of identification schemes, MP has contributed between 4 (“dcov”) and 7 (“chol” and “BjL”) percentage points to the increase in house prices over the boom period which had its beginning in 2001 and ended early in 2006 (in comparison, house price increases after 2006:M1 appear negligible). Relative to a total increase of 41 percentage points of the detrended real house price series, however, MP has played some minor role in the real estate price boom. This is in line with results of Del Negro and Otrok (2007) and Eickmeier and Hofmann (2013).¹⁴

¹⁴It is noteworthy that Eickmeier and Hofmann (2013) report marked differences in the contribution of MP shocks to house prices, depending on the specific house price index used. We compare our results to theirs for the Case-Shiller house price index.

4.3 *Asset Price Shocks and Their Macroeconomic Effects*

In comparison with the sound labeling of MP shocks, the identification of asset price shocks is more ambiguous by means of IRFs shown in Figure 1, although the fourth (ϵ_4) and the fifth shock (ϵ_5) are suitable candidates for the stock price and the house price shock, respectively. In terms of FEVDs (left-hand side of Figure 2), the fourth shock (ϵ_4) explains about 90 percent of real stock return variation at all horizons. Similarly, the fifth shock (ϵ_5) provides largest contributions to the FEVs of real house returns of about 70 percent on impact and 75 percent at longer horizons. Accordingly, we characterize the fourth shock as “stock price shock” and the fifth shock as “house price shock.” The pronounced share of variance explained by the house price shock is in line with recent estimates from DSGE models. Iacoviello and Neri (2010) report that the long-run contribution of housing demand and housing technology shocks to house price fluctuations amounts to around 60 percent.

Complementing structural IRFs and FEVDs, we consider a variety of external measures to corroborate the interpretation of the asset price shocks. Since these external series are only available at quarterly frequency, we evaluate their correlations with shocks of a quarterly version of the monthly model specification. First, to endorse equity shocks we consider a variety of external measures for technology and credit shocks as investigated, e.g., by Ramey (2016) and Mumtaz, Pinter, and Theodoridis (2018).¹⁵ As an outstanding result, we find that the correlation between the stock price shock in the quarterly model and the news shock of Beaudry and Portier (2006) amounts to 0.82. Hence, there is strong evidence suggesting that the stock price shock identified by means of “dcov” reflects news about fundamentals, i.e., productivity gains that materialize in the future. Second, endorsing the house price shock is distinctly more difficult, since respective external series are scant. Suitable candidates are the housing demand and housing technology

¹⁵The considered shock series are available on Valerie Ramey’s homepage (<https://econweb.ucsd.edu/~vramey/research.html#data>). She has retrieved them either from authors of the original studies or reestimated respective models (e.g., for extended sample periods).

(supply) shocks of Iacoviello and Neri (2010).¹⁶ Resulting correlations with the SVAR house price shock lack significance for both DSGE shocks. This result allows several explanations. On the one hand, one might highlight the mismatch of the scope of the DSGE and SVAR models considered, in the sense that our SVAR does not include enough housing-market-related variables to capture the specific structural sources modeled in Iacoviello and Neri (2010). On the other hand, it is important to recall that the house price shock identified in this work is a noise shock and, as such, is conceptually different from fundamental shocks (preference shifts or technology fluctuations) in the DSGE model. Accounting for the noise explanation, we further analyze the informational content of a housing market sentiment index for the baseline house price shock. More specifically, we use the orthogonalized Housing Market Index (HMI) based on a monthly survey of (around 400) U.S. home builders which reflects the sentiment of the supply side of the single-family housing market.¹⁷ Supporting the suggested interpretation of ε_5 , we find that among the statistically identified shocks in ϵ_t , only the house price shock exhibits a significant correlation with the orthogonalized HMI obtaining a correlation coefficient (p -value) of 0.125 (0.02).

The impulse responses of the federal funds rate to both asset price shocks shown in Figure 1 reveal a similar hump shape, albeit the peak response to a house price shock is slightly more delayed and less pronounced than the responses emanating from an equity shock. The systematic policy response to house price shocks is negative in the short run. In terms of peak effects, the magnitudes of the systematic policy reactions are somewhat weaker than those in Björnland and Jacobsen (2013).

The dynamic response patterns of prices and output are broadly similar for both asset price shocks, albeit the stock price shock

¹⁶The DSGE model can be replicated using the Dynare and MATLAB files provided on Matteo Iacoviello's homepage at <https://www.matteoiacoviello.com/research.htm>.

¹⁷The HMI is published by the National Association of Home Builders (NAHB) and available since 1985:M1; see <https://www.nahb.org/News-and-Economics/Housing-Economics/Indices/Housing-Market-Index>. To measure only the non-fundamental information in the HMI, we regress the HMI on five factors extracted from a large panel of U.S. macroeconomic and financial data to obtain the "orthogonalized HMI."

exhibits stronger macroeconomic effects in terms of both IRFs (Figure 1) and FEVDs (left-hand side of Figure 2). At shortest horizons, the responses of output to both asset price shocks are basically zero (insignificant or even slightly falling), reach a maximum after one year, and turn negative (stock price shock) or vanish (house price shock) in the long term. With regard to the macroeconomic effects, our findings call those of Björnland and Jacobsen (2013) into question, where the stock price shock virtually lacks effects on prices and invokes a relatively weak increase in GDP while the house price shock is characterized by marked effects on both output and prices.

The diagnosed macroeconomic effects might indicate an effective wealth channel which boosts consumption or an effect on investment resulting from an increase in Tobin's q . Alternatively, given the similarity of our stock price shock with the news shock identified in Beaudry and Portier (2006), it might be more plausible to consider the news about technological advances as an original underlying impulse which leads to fundamentals-based investment surge and income improvements. Deciding by the weak instantaneous response of the federal funds rate and the rather strong macroeconomic implications of asset price shocks, it cannot be ruled out that the Fed reacts mainly to the surge in prices and a reduction in the output gap.

5. Robustness

To develop a comprehensive view at the robustness of our empirical results, we evaluate two “families” of further empirical models. On the one hand, we performed a set of robustness analysis for identifying the baseline model by means of “dcov” after conditioning on various choices with regard to variable transformations, lag orders, deterministic terms c_t in (1) and sample periods. Results from these exercises are displayed and discussed in Appendix C, and largely align with outcomes from the baseline model. On the other hand, we reconsider the performance comparison of alternative identification schemes for five modifications of the baseline MP model and discuss respective results in this section. First, we evaluate a model specification (denoted $\mathcal{S}_1$) that conditions the $K = 6$ dimensional model on a sample period covering most recent observations (1975:M1–2020:M6). Second, seeing that related empirical

contributions often focus on single assets, we consider two specifications omitting either real house ($\mathcal{S}_2$) or stock ($\mathcal{S}_4$) returns. Third, for the baseline model the availability of the house price index has been critical for the investigated sample period. Hence, within a $K = 5$ dimensional model including stock returns only, it is possible to modify the sample and cover earlier observations. Using the sample period 1971:M1–2007:M6, specification $\mathcal{S}_3$ allows for a direct comparison with the studies of Björnland and Leitemo (2009) and Lütkepohl and Netšunajev (2017). Finally, from evidence provided in Leeper and Roush (2003), one might assign an important role of including real money within a dynamic system to analyze MP effects. Against this background we also consider a $K = 7$ dimensional model that comprises the real growth of M2 ($\mathcal{S}_5$). We first discuss an overview of core statistics and turn, subsequently, to a more detailed discussion of implied IRFs. A complete documentation of these robustness analysis is available from the authors upon request.

Table 2 documents core comparative outcomes joint with a respective summary for the baseline model ($\mathcal{S}_0$). As it turns out, the results for all modifications are broadly in line with baseline model outcomes. Three observations can be made in particular. First, data-based identification schemes show almost uniformly a lead over “sr” and “BjL” in terms of correlations between identified MP shocks and external measures thereof. Second, going beyond orthogonality, the consideration of structural shocks as independent information is clearly at odds with shocks identified by means of “sr” and “BjL.” With 10 percent significance, moreover, the supposition of lower triangular covariance factors (“chol”) and identification by means of smooth covariance changes (“st”) might result in shocks that exhibit some form of higher-order dependence. For the case of using “PML” estimation to identify the structural VAR with stock prices conditional on an extended sample period ($\mathcal{S}_3$), it is interesting to see that the implied shocks show remaining dependence with 10 percent significance. Third, the benchmark identification scheme (“dcov”) and lower triangular covariance factors (“chol”) are unique in the theory conform assignment (Canova and Pina 2005) of both a strong on-impact contribution (i.e., $> 90\%$) of MP shocks to the FEV of the federal funds rate, and a medium-sized counterpart of 30 percent to 70 percent at longer horizons.

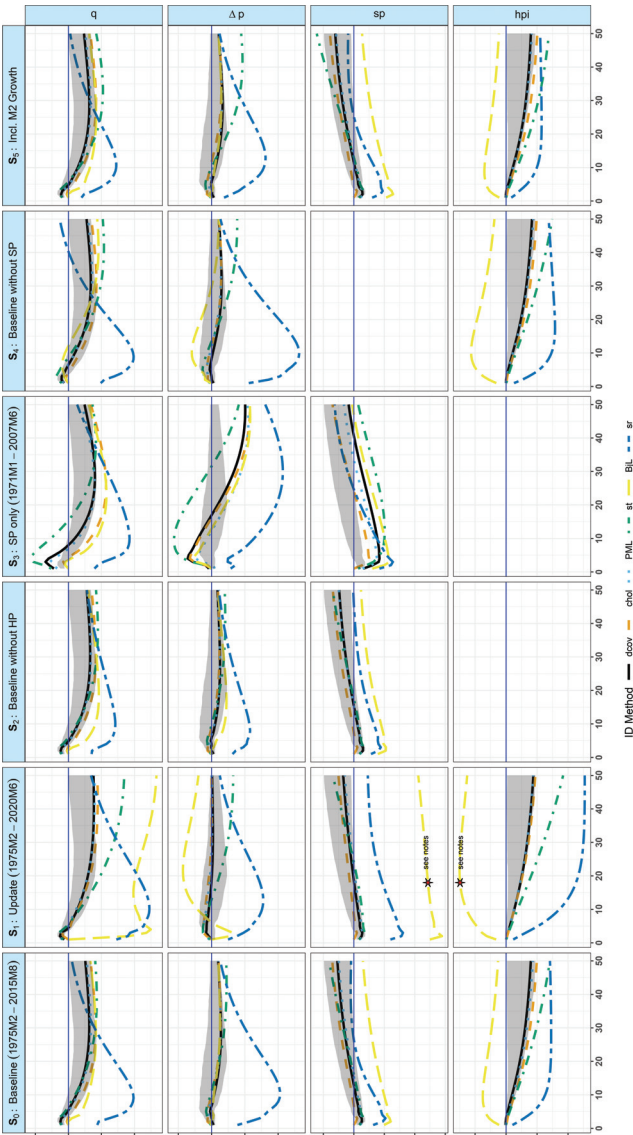
While the results documented in Table 2 indicate robustness with regard to the identified MP shocks, reduced-form model features or structural parameter estimates in B (or estimation biases of B) might give rise to performance heterogeneity at the level of structural IRFs (or FEVDs). Figure 5 displays the IRFs of key variables to an MP shock for six identification schemes and five robustness specifications (for convenience, the baseline results have been added to the plot). While the relative differences in key characteristics among the identification schemes are largely maintained across specifications, “dcov” provides jointly with “PML” and “chol” most robust structural results. Three main comparative findings arise from structural IRFs.

First, the sluggish and persistent response of real house prices appears most robust for all identification schemes (except “BjL”) and across all specifications. This also holds to a lesser degree for the transmission pattern of MP shocks to real stock prices.¹⁸ The immediate reaction of stock markets is almost uniformly confirmed, while systems identified by sign or long-run restrictions (“sr” and “BjL”) show relatively stronger on-impact and peak effects. The recursiveness assumption (“chol”) naturally precludes such instantaneous propagation, which seems less important in the case of house prices but comes as a substantial disadvantage with regard to stock prices. These findings are in line with previous empirical and theoretical evidence in terms of reported response profiles and the role of the different identification schemes (see, e.g., Rigobon and Sack 2004; Castelnuovo and Nistico 2010, for empirical evidence and for theoretical results).

Second, we find that the well-discussed output and price puzzles (Eichenbaum 1992; Uhlig 2005)—an immediate acceleration of output or prices in response to a contractionary MP shock—are ubiquitous, i.e., basically all combinations of model variations and identification schemes show at least one puzzle. For instance, baseline results ($\mathcal{S}_0$, “dcov”) obtain that an unexpected monetary tightening triggers a slight increase in output on impact that is followed by a hump-shaped decline after four to five months. The occurrence of

¹⁸This result also survives further model modifications (e.g., lag length, sample period, output measurement, deterministic terms) undertaken to address robustness of identification by means of “dcov” (see Figure C.1 in Appendix C).

Figure 5. IRFs to MP Shocks for the Baseline and Robustness Specifications and All Considered Identification Schemes



Note: Complementing the baseline model (S_0 , see also Figure 1), the figure shows columnwise results for model specifications S_1 to S_5 (see Section 5). To facilitate robustness assessments, the shaded areas are *identical* in all panels and denote 68 percent confidence bands based on 1,000 bootstrap replications corresponding to the benchmark identification within the baseline model (S_0 , “ $dcov$ ”). The provision of respective confidence bands for “ $dcov$ ” conditional on specifications S_1 to S_5 would result in qualitatively equivalent outcomes. Each panel shows IRFs for all six alternative identification schemes. To keep the IRFs of asset prices shown for S_1 at a reasonable scale, the * indicates that, unlike all other IRFs, these profiles obtain from MP shocks that raise the federal funds rate by only 50 basis points on impact. For further notes, see Figure 3.

output or price puzzles is, however, sensitive to specification changes. In most cases they are not particularly severe and lack statistical significance. Unsurprisingly, “sr” avoids any of the puzzles by definition. More specifically, ranking the magnitudes of both puzzles, we observe that (i) output puzzles are apt to be less pronounced for theory-based identification in the form of “BjL” and “chol,” (ii) smallest price puzzles tend to obtain from “dcov,” and (iii) identification through heteroskedasticity (“st”) is clearly more prone to both puzzles in terms of occurrence frequency and magnitudes. Hence, our results are rather typical for the monetary SVARs literature (e.g., Iacoviello 2005; Musso, Neri, and Stracca 2011; Björnland and Jacobsen 2013; Ramey 2016). Keeping in mind the limited setting of this work, our findings accord with two specific dimensions in which the literature has established the pervasiveness of these puzzles (even though the focus has mostly been on the transmission to prices). On the one hand, the magnitude of the puzzles depends on the sample period, being most severe for the sample that begins the earliest and covers the entire Great Moderation era but not the Great Recession (Coibion 2012; Barakchian and Crowe 2013).¹⁹ We conjecture in accordance with Ramey (2016) that this can be attributed to the ratio of observations belonging to the era of less erratic MP during the Great Moderation to observations with discrete policy (e.g., Volcker chairmanship and Great Recession episodes). On the other hand and confirming similar evidence of Hanson (2004), the inclusion of further variables hardly helps to mitigate the puzzles (e.g., comparing the $K = 5$ dimensional models ($\mathcal{S}_2$, $\mathcal{S}_3$, and $\mathcal{S}_4$), with the baseline model $\mathcal{S}_0$, or baseline $\mathcal{S}_0$ with $\mathcal{S}_5$ including M2 growth). Interestingly, the additional robustness exercises documented in Appendix C for the baseline “dcov” model suggest that modifications of the VAR in its reduced form (e.g., lag length, deterministic terms) shows effects on the prevalence of price or output puzzles. Hence, our results suggest that reduced-form characteristics seem at least as important as identifying assumptions. In this sense

¹⁹Barakchian and Crowe (2013) show that the price puzzle does not disappear for a variety of identification schemes and U.S. data. The robustness analysis in Appendix C highlights that for the case of “dcov” the puzzles depend to a notable extent on lag order choice, which has also been observed in Coibion (2012).

one could characterize price or output puzzles as a stylized feature of (many) SVARs with varying degrees of severeness or magnitude.

Third, the results for the robustness checks which alter the sample period, i.e., employing sample information ranging from 1975 to 2020 ($\mathcal{S}_1$) and the stock prices specification covering 1971–2007 ($\mathcal{S}_3$) hold most diverging observations. On the one hand, it appears that the long-run restriction approach (“BJL”) performs particularly poorly for the updated sample, with no relevance of MP for the movements in the federal funds rate at all (almost zero FEV contribution at all horizons) and implausible price responses. On the other hand, this identification scheme performs quite well for the specification $\mathcal{S}_3$, replicating and corroborating results of Lütkepohl and Netšunajev (2017) and Björnland and Leitemo (2009), respectively. Interestingly, all alternative identification approaches agree especially well for this specification, exhibiting strongest correlations with the external shock series.

6. Conclusions

We revisit the monetary policy–asset price nexus by means of a data-based approach to SVAR identification that builds upon the uniqueness of non-Gaussian independent components. Acknowledging the existence of several rivaling identification techniques, we put the empirical analysis into a comparative perspective that is spanned by a set of six alternative theory- or data-based variants of SVAR identification. For purposes of full system identification, detecting independent components as suggested in Matteson and Tsay (2017) involves the minimization of a non-parametric dependence measure and does not require theoretical a priori restrictions, as is the case for identification by means of Cholesky factors, sign restrictions, or the combination of short- and long-term restrictions. Unlike identification through heteroskedasticity and pseudo maximum likelihood approaches, it avoids the imposition of covariance changes or the assumption of an underlying non-Gaussian iid distribution for the shocks of interest. Moreover, the proposed method economizes substantially on computation time compared with identification schemes that involve the maximization of eventually complicated likelihood functions.

We illustrate the scope of independent component monetary policy shocks for the case of a six-dimensional model including house and stock prices as a natural extension of the single-asset U.S. monetary policy models of Lütkepohl and Netšunajev (2017) and Björnland and Leitemo (2009). Complementing the informational content of statistically unique shocks that are labeled by means of established diagnostics (on-impact effects, IRFs, variance decompositions), we take advantage of the proxy SVAR literature (see, e.g., Stock and Watson 2012; Mertens and Ravn 2013) and further substantiate identification outcomes by means of correlation patterns of identified shocks with external instruments. Among rival estimates from alternative identification schemes, the identified benchmark shocks show a superior and sound alignment with diverse economic underpinnings.

Monetary policy transmits heterogeneously to house and stock markets. In line with the majority of the literature, we find that monetary policy triggers a sluggish but persistent and pronounced decline in real house prices. This finding is robust with respect to alternative choices of the sample period, further modifications of the model specifications, and to a large degree also to the imposition of distinct identifying assumptions. Moreover, supporting similar conclusions of Del Negro and Otrok (2007) and Eickmeier and Hofmann (2013), historical decompositions show that loose MP was not a major factor in the housing boom preceding the Great Recession. The transmission of monetary policy via the stock markets is less clear. We observe an immediate, mildly negative short-lived response to a contractionary MP shock. However, the response of equity turns positive at longer horizons (although insignificantly). Combined with the results from robustness tests, we conclude that interest rate shocks have most likely only a negligible effect on stock prices. In summary, we observe that MP shocks are associated with timing frictions of policy transmission and a disadvantageous cost–benefit ratio, due to substantial costs in terms of output and comparably small effects on asset prices. This suggests the tentative conclusion that a proactive conduct of monetary policy would only be successful if households and market participants adapt to policy changes in a way which would attenuate excessive asset mispricing. Compared with Björnland and Jacobsen (2013), we find less decisive support for a distinct reaction of the central bank to shocks

originating from the asset markets. It appears, however, that the Fed incorporates equity price shocks with a slightly higher weight into the MP rule. Moreover, both asset price shocks imply similar macroeconomic effects qualitatively, whereas the impact of the stock price shock on output is stronger.

Methodologically, this study highlights that the extraction of independent components by means of dependence diagnostics can provide computational merits for the analysis of structural dynamic systems without building upon controversial a priori assumptions. A promising avenue for future research consists in allowing for nonlinearities in the form of potential regime dependence. Such future work would account for the growing evidence that the effectiveness of MP might change under high-volatility/financial stress regimes, or stages of the credit and the business cycle.

Table A.1. Summary of Employed External Monetary Policy Shock Series

Shock/Instrument Name	Type	Source ^a	Sample Period
R&R	Narrative	Romer and Romer (2004)	1969:M1–2007:M12
R&R 83	Narrative	Ramey (2016)	1983:M1–2007:M12
R&R 83b	Narrative	Ramey (2016)	1983:M1–2007:M12
ff1 vr	High Frequency	Ramey (2016)	1988:M1–2012:M12
ff4 vr	High Frequency	Ramey (2016)	1988:M1–2012:M12
ff1 gb	High Frequency	Ramey (2016)	1988:M1–2012:M12
ff4 gb	High Frequency	Ramey (2016)	1988:M1–2012:M12
MA hf	High Frequency	Ramey (2016)	1988:M1–2012:M12
sz mps	SVAR	Miranda-Agrippino (2016)	1990:M2–2009:M12
gss mps	High Frequency	Sims and Zha (2006)	1960:M2–2003:M3
sm mps	DSGE	Gürkaynak, Sack, and Swanson (2005)	1990:Q1–2004:Q4
		Smets and Wouters (2007)	1959:Q1–2004:Q4

^aThe sources stated in the table are the original work suggesting the respective shocks, while most series have been obtained from Ramey (2016).

Note: **R&R** denotes the narrative shock series, constructed as the residuals from a regression of the federal funds *target* rate on Greenbook forecasts for FOMC meeting dates, which has been estimated over an extended sample until 2007:M12 by Ramey (2016). **R&R 83** is the reestimated original R&R series starting in 1983:M1. **R&R 83b** is like R&R 83 but using long-horizon Greenbook forecasts. **ff1/4 vr** denote the monetary surprise series constructed by using the movements in federal funds futures (ff1 current and ff4 three-months-ahead futures) within a 30-minute window surrounding FOMC announcements are are originally from Gertler and Karadi (2015) but have been converted to a monthly basis enveloping the Romer and Romer method by Ramey (2016). **ff1/4 gb** follow the same methodology as ff1/4 vr but have been orthogonalized to the Romer Greenbook variables (Ramey 2016). **MA hf** stands for the monetary surprise series that has been purged of anticipatory effects from monetary surprises, i.e., the reaction of market participants to information revealed by the central bank's monetary decision. In comparison to the ff1/4 gb shocks, the **MA hf** series are orthogonal to both central bank Greenbook forecasts and publicly available data (the former only to Greenbook forecasts). **sz mps** is the Sims and Zha (2006) monetary policy shock from an SVAR specification allowing for regime-dependent volatility. **sm mps** is the monetary policy shock resulting from the Smets and Wouters (2007) DSGE model. All series except for the **MA hf**, **gss mps**, and **sm mps** have been obtained from Valerie Ramey's webpage (<https://econweb.ucsd.edu/~vramey/research.html#data>), while **gss mps** and **sm mps** are available at Mark Watson's webpage (see Stock and Watson 2012). The MA hf monetary surprise is available on Miranda-Agrippino's webpage (<http://silviamirandaagrippino.com/research/>).

Appendix B. Estimated Impact Matrices

The estimated structural impact matrices $\hat{B}$ for baseline empirical model are (jointly with bootstrap means (a) and t -ratios (b) in parentheses (a;b))

$$y = \left(q, \quad \Delta p, \quad \Delta comp, \quad \Delta sp, \quad \Delta hpi, \quad ffr \right)'$$

ϵ_1	ϵ_2	ϵ_3
ϵ_{sp}	ϵ_{hp}	ϵ_{mp}

$$\hat{B} = \left(\begin{array}{ccc} 0.5750 \text{ (0.5642; 29.7921)} & 0.0443 \text{ (0.0598; 0.6476)} & -0.0095 \text{ (-0.0143; -0.1607)} \\ -0.0359 \text{ (-0.0469; -0.9183)} & 0.2723 \text{ (0.2933; 5.3493)} & 0.0962 \text{ (0.0715; 0.8977)} \\ 0.2721 \text{ (0.1938; 0.8082)} & -0.1350 \text{ (-0.0052; -0.1288)} & 3.1523 \text{ (2.7873; 6.3049)} \\ 0.5556 \text{ (0.2712; 1.0651)} & 0.3126 \text{ (0.1986; 0.5019)} & -0.4598 \text{ (-0.1485; -0.5527)} \\ 0.0544 \text{ (0.0468; 1.3681)} & -0.1852 \text{ (-0.1537; -3.0079)} & -0.0147 \text{ (-0.0085; -0.1782)} \\ -0.0474 \text{ (-0.0281; -0.6979)} & 0.0567 \text{ (0.0487; 1.2029)} & 0.0343 \text{ (0.0368; 0.5832)} \end{array} \right)$$

$$\left(\begin{array}{ccc} -0.1104 \text{ (-0.0636; -1.1854)} & -0.0070 \text{ (-0.0021; -0.1070)} & 0.0944 \text{ (0.0831; 2.4763)} \\ -0.0235 \text{ (-0.0292; -0.4204)} & 0.0305 \text{ (0.0162; 0.4231)} & 0.0307 \text{ (-0.0130; -0.7368)} \\ 0.9581 \text{ (0.7997; 1.1869)} & -0.5041 \text{ (-0.3937; -0.6971)} & -0.3480 \text{ (-0.3464; -1.7078)} \\ 3.3165 \text{ (3.0986; 12.7412)} & -0.0235 \text{ (0.1691; -0.0330)} & -0.4346 \text{ (-0.3752; -1.9093)} \\ 0.0551 \text{ (0.0491; 0.8324)} & 0.2443 \text{ (0.2320; 5.9482)} & 0.0163 \text{ (0.0183; 0.7377)} \\ 0.0273 \text{ (0.0047; 0.3714)} & -0.0673 \text{ (-0.0644; -1.0900)} & 0.9694 \text{ (0.9641; 70.0551)} \end{array} \right)$$

The t -ratios are obtained by dividing the parameter estimates by their bootstrap standard deviation (see Section 2.3 for more details on the bootstrap design). The included variables are detrended industrial production (output gap, q), the annualized monthly inflation rate (Δp), the annualized monthly growth rate of commodity prices ($\Delta comp$), monthly S&P 500 log returns (Δsp), monthly log returns of the Case-Shiller house price index (Δhpi), and the interest rate on federal funds (ffr).²⁰ The structural shocks contained in ϵ_t are ϵ_{MP} , the monetary policy shock, ϵ_{SP} , the stock price shock, and ϵ_{HP} , the house price shock, while all shocks with a number index, e.g., ϵ_2 , are left economically uninterpreted. As a side note, based on standard assumptions on the signs of impulse responses and FEVDs, the shock displayed in the first column, ϵ_1 , (second column, ϵ_2) of Figure 1 qualifies as an aggregate demand (supply) shock.

²⁰For more details and data sources, see Section 3.2.1 in the main text.

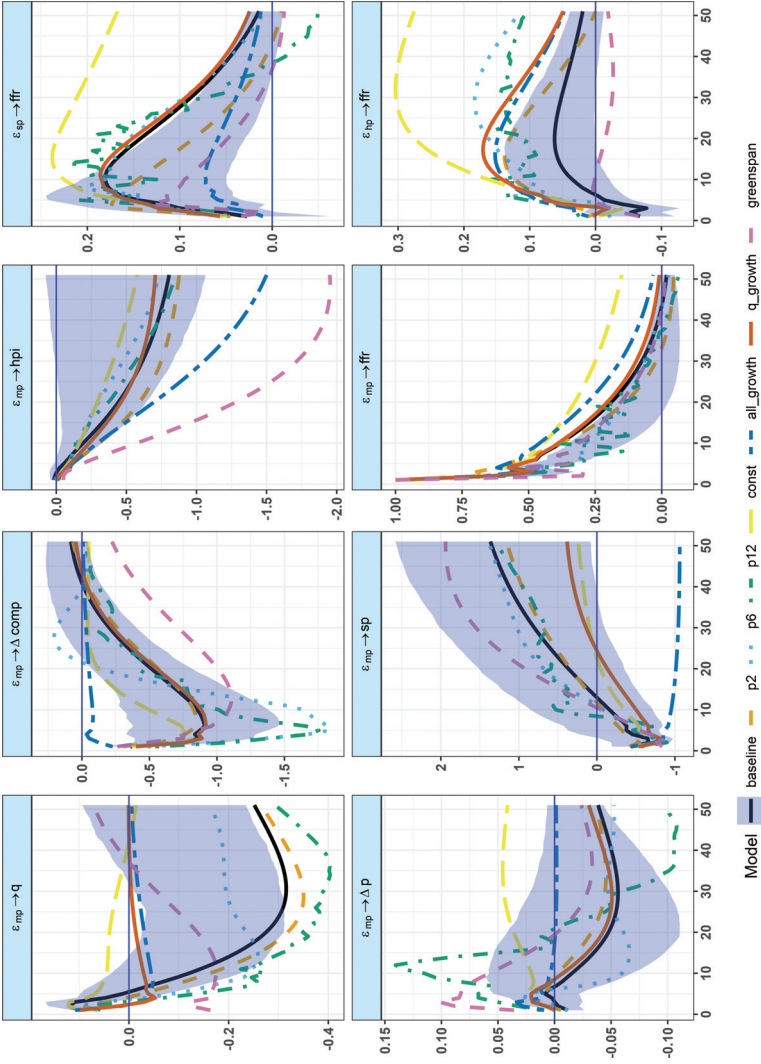
Appendix C. Robustness of “dcov” in Variants of the Baseline Model $\mathcal{S}_0$

With a focus on “dcov,” we have performed several further robustness checks for the baseline model ($\mathcal{S}_0$) with regard to modified sample periods, lag orders, and alternative data transformations. We apply “dcov” to the alternative sample periods 1975:M1–2007:M6 (denoted $\mathcal{RS}_1$), 1980:M1–2010:M6 ($\mathcal{RS}_2$), and 1987:M1–2007:M6 ($\mathcal{RS}_3$) similar to Lütkepohl and Netšunajev (2017), Björnland and Jacobsen (2013), and Eickmeier and Hofmann (2013), respectively. Particularly, $\mathcal{RS}_3$ allows an examination of robustness with regard to variations in the policy regime (“only Greenspan”) and financial deregulation (“abolition of the so-called Regulation Q”). Furthermore, we conduct robustness tests for (i) choices of alternative lag orders (i.e., $p = 2, 6$ and $p = 12$); (ii) including only an intercept term (i.e., $c_t = c$ in (1)); (iii) replacing the industrial production gap with the growth rate; (iv) including CPI and commodity price inflation and industrial production in the form of monthly log changes; (v) an alternative sampling frequency (quarterly) by replacing the industrial production gap with GDP growth; (vi) an alternative output gap, replacing GDP growth in specification (v) with the log percentage deviations of real GDP from the Congressional Budget Office definition of (real) potential GDP; (vii) a model in log-levels (replacing all variables that were in growth rates before); and (viii) specification (vii) for a lag length of $p = 12$. Figure C.1 shows structural IRFs for the encountered model variations (i) to (iv) and sample period variation $\mathcal{RS}_3$.²¹

We cannot find considerable dependencies of the responses of real house and stock prices to MP shocks on the sample period. There is some variation in the strength of the transmission of MP via house prices but not a clear pattern. Moreover, from an overall perspective the exercises (i) to (viii) yield quite robust characteristics of the identified MP shocks. Specifically, linear correlations of the benchmark MP shocks with those obtained from these specifications (i) to (viii) are throughout above 0.87. Similarly, implied MP shocks obtain correlation coefficients with the measures of Sims and Zha

²¹Results for modifications (v)–(viii) are available from the authors upon request.

Figure C.1. IRFs from Robustness Checks for the Baseline Model (S_0 , “dcov”)



Note: The first three columns display responses invoked by MP shocks, while IRFs in column 4 show the reaction of the federal funds rate to asset valuation shocks. Robustness specifications include (i) alternative lag orders “p2”, “p6”, “p12”, (ii) “const”, (iii) “q-growth”, (iv) “all-growth”, and $\mathcal{RS}_3$ (“Greenspan”) as detailed in the text. MP shocks have been scaled to raise the federal funds rate by 100 bps. The stock and house price shocks are standard deviation shocks. Shaded areas denote 68 percent confidence bands for the baseline specification identified by “dcov”. Importantly, the responses of certain variables (e.g., output, “q”, inflation “ Δp ”) are not fully comparable with regard to model variations featuring data transformations from, e.g., year-on-year growth rates to monthly log differences (e.g., “q-growth” (iii)).

(2006) (sz mps) in a range between 0.343 and 0.558, while respective correlations with the narrative shock series of Romer and Romer (2004) (R&R) shocks are between 0.244 and 0.345.

With regard to insights from structural IRFs, we notice that key conclusions from the baseline model remain generally intact for almost all robustness exercises. Some observations are noteworthy. First, the rather sluggish but clearly negative response of house prices to contractionary MP shocks is quite robust over all specifications. Second, the robustness analysis confirms the mild impact of interest rate shocks on stock prices observed for the benchmark model. In almost all specifications there is only a small initial effect followed by a subsequent statistically insignificant positive response. Frequently, a short-run negative effect is insignificant. Third, there tends to be some support for a markedly different systematic reaction of MP to stock and house price shocks. In some models the response of the federal funds rate to house price shocks is statistically insignificant and/or close to zero.²² Fourth, also the main conclusion that the Fed reacts more timely and decisively to stock price shocks is found in most specifications, although the effect differential is eventually subject to mitigation (e.g., for specification (iii)) in comparison with the baseline model. Fifth, some modifications are associated with quite pronounced prize puzzles (specifically, the model estimated with a lag order of 12, the model featuring only a constant (specification (ii)), and the quarterly model(s) (specifications (iv) and (v))). Interestingly, the model estimated over the period 1987:M1–2007:M12 ($\mathcal{RS}_3$, “Greenspan”) exhibits a rather marked price puzzle, lending credence to the conjecture that the great moderation period is particularly linked to counterintuitive price responses (see Section 5). As a final remark, we note that the confidence bands belonging to the baseline model (see Figure C.1) cover a majority of the responses corresponding to the robustness checks, already at the 68 percent confidence level. The responses of house and stock prices are particularly noticeable in this regard. This corroborates our evaluation by pointing to a lack of statistically significant differences among the model variations employed for our robustness analysis.

²²The response is statistically insignificant for the models estimated on data from 1980:M1 to 2010:M6 ($\mathcal{RS}_2$) and 1987:M1 to 2007:M12 ($\mathcal{RS}_3$).

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