Liquidity, Inflation and Asset Prices in a Time-Varying Framework for the Euro Area*

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Abstract

In this paper, we investigate how the dynamic effects of excess liquidity shocks on economic activity, asset prices and inflation differ over time. We show that the impact varies considerably over time, depends on the source of increased liquidity (M1, M3-M1 or credit) and the underlying state of the economy (asset price boom-bust, business cycle, inflation cycle, credit cycle and monetary policy stance).

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1 Introduction

To achieve its primary objective of price stability, the European Central Bank (ECB) uses a strategy based on two "pillars". One of these pillars, referred to as the monetary analysis, exploits the long-run link between money and inflation. In particular, to signal its commitment to price stability and to provide a benchmark for the assessment of monetary developments, the ECB announces a reference value for the growth rate of the broad monetary aggregate M3. This prominent role assigned to money has been subject to intense criticism from the very beginning. Besides theoretical motivations for not considering monetary aggregates (e.g. Galí 2003, Woodford 2007), it has been frequently argued that money might be an unreliable indicator in an environment of low inflation (e.g. Estrella and Mishkin 1997, De Grauwe and Polan 2005). Since the introduction of the euro, the annual growth rate of M3 has almost continuously been above its reference value of 4.5% without a corresponding tightening of monetary policy or an acceleration of inflation, which supports doubts about the usefulness of money aggregates as an indicator of risks to price stability. The ECB claims, however, that the analysis of monetary developments goes well beyond the assessment of M3 growth in relation to its reference value. The monetary analysis uses a comprehensive assessment of the liquidity situation based on information about the balance sheet context as well as the composition of M3 growth (ECB 2004). It is intended to shed light on the outlook for price stability and the implications for monetary policy eschewing a mechanical policy response to a monetary aggregate.[1] For instance, the Governing Council has repeatedly stated that some episodes of rapid money growth were due to special factors and shifts in the demand for money arising from e.g. portfolio shifts or changes in the opportunity cost of holding money. As a consequence, such episodes were disregarded and not considered as signalling risks to price stability. On the other hand, there were cases where excess money growth did warrant a tightening of policy, especially when combined with information obtained from the other pillar of ECB's monetary policy strategy, the economic analysis (Gerlach 2007). This illustrates that the link between excess money growth or excess liquidity and future inflation is probably not constant over time and depends on other factors as well, such as the source of increased liquidity and general economic conditions.

In defense of its two-pillar strategy, the ECB also often argues that asset price bubbles could be the result of strong and persistent growth in money and credit aggregates. Since developments of asset prices not in line with fundamentals are not captured by a pure in-

[1] See also Fischer et al. (2008) for a detailed narrative approach about the role of money in the monetary policy decisions of the ECB and how it has evolved over time.

flation forecast, they do not trigger a policy reaction in a traditional Taylor rule framework (Issing 2002).[2] A detailed monetary analysis could therefore provide early information on emerging financial imbalances which could have destabilizing effects on economic activity and inflation. Detken and Smets (2004) indeed show that high-cost booms in asset prices often follow rapid growth in money and credit stocks just before and at an early stage of the boom. Since financial assets are growing in importance and hence, asset price fluctuations increasingly affect the economy, monetary policy could be improved by taking account of the evolution of money and credit aggregates as a signal of financial imbalances (Hildebrand 2008). There are obviously also episodes in history during which money, temporarily growing out of line with fundamentals, did not coincide with asset price bubbles. Accordingly, the information for asset prices contained in these indicators may also vary over time and this suggests that the weight assigned by a central bank to the monetary analysis should be state dependent (Issing 2002).

In this paper, we focus more extensively on the complex link between money, economic activity, asset prices and inflation. In particular, we investigate the impact of liquidity shocks in a time-varying and state-dependent framework for the Euro area economy. Excess liquidity is identified as the deviation of broad money from an equilibrium value in a structural VAR. We first estimate the impact of a shock to liquidity on a set of macroeconomic variables and asset prices within the VAR framework. This shock has a temporary effect on economic activity and a permanent impact on the price level which is less than proportional. Increased liquidity also creates temporary rises in real equity, property and aggregate asset prices. The economic consequences and the magnitude of the impact however depend heavily on the underlying source of increased liquidity. A 1 percent long-run increase in M1 has a considerable impact on economic activity, asset prices and inflation. The impact on inflation is even proportional. In contrast, a shock in M3-M1 has only minor economic consequences and results more in a permanent long-run increase in the real money stock. We observe that shocks to credit, which is the counterpart of the broad monetary aggregate, have rather similar effects as shocks in M3. Using a simple sample split and more sophisticated Bayesian VARs with time-varying parameters, we also find considerable variation in the dynamic responses over time. On the one hand, inflationary consequences of a liquidity shock are much weaker since the mid-eighties resulting also in a more permanent shift of real money. In more recent times, however, there seems again to be a tendency for an increased impact on inflation. On the other hand, time

[2] Theoretical support is provided by Christiano et al. (2006) who show that when an inflation-targeting central bank and sticky nominal wages are introduced in a standard real business cycle model, a theory of boom-busts emerges naturally, i.e. boom-bust episodes are correlated with strong credit growth.

variation with respect to the effect on output and asset prices is less clear. We find increased responsiveness during some periods but decreased reactions at other points in time. This is not surprising given the growing theoretical and empirical literature (as discussed below and in section 4) that argues that the macroeconomic impact depends on the state of the economy, e.g. asset price boom-busts, credit booms, the business cycle or the monetary policy stance. The final part of the paper analyses this in more detail. More specifically, we estimate the impact of excess liquidity shocks in a single-equation approach allowing the coefficients to differ depending on the state of the economy. We find evidence that liquidity shocks have a stronger impact on economic activity and asset prices during asset price booms and busts, at times of credit booms (which are a proxy for financial innovations) and, to a lesser extent, during periods of tight monetary policy. Negative shocks to liquidity also exert stronger effects on real activity and asset prices than positive ones. While real property prices are much more sensitive to excess liquidity when economic growth is above its trend value, the reaction of output is stronger during recessions. On the other hand, inflationary effects are greater during boom phases of asset prices, economic expansions and credit booms, but smaller when the monetary policy stance is restrictive. In sum, the impact heavily depends on the underlying state of the economy. The estimated differences are also economically important. The reaction of real asset prices to a liquidity shock during an asset price boom is, for instance, three times larger than the average estimated reaction for the whole sample period. Similar conclusions can be drawn for inflation and output growth.

Our paper is linked to several strands of the economic literature. First, some studies find distortions over time of the link between money aggregates and inflation for the Euro area. For instance, Gerlach (2004) shows that the information content of money growth for future inflation in the Euro area differs across sub-periods. Also Hofmann (2006) finds a break in the forecasting performance of M3 in the early years of EMU. Our results show that these deteriorations over time could be due to changes in the growth of the underlying components of broad money, i.e. M1 or M3-M1, or the accompanying state of the economy. Second, several recent studies have discussed the relationship between liquidity and asset prices. In particular, the exact relation could be dependent on the state of some economic variables. One important element of the discussion is to what extent potentially harmful asset price boom-bust episodes are associated with cycles in money and credit aggregates. Borio and Lowe (2002) show that sustained rapid credit growth combined with large rises in asset prices increases the probability of financial instability. Adalid and Detken (2007) and Goodhart and Hofmann (2007) find evidence that liquidity shocks play a more important role in explaining real residential property prices during aggregate asset price booms using a panel of respectively 18 and 17 industrialized countries. We confirm these findings based on a pure time-series approach. However, while Adalid and Detken (2007) observe a weaker impact on consumer price inflation in boom periods, our results indicate the opposite. Another relevant element for the interaction is the role of financial deregulation. For instance, Borio (2006) and Goodhart and Hofmann (2007) argue that financial liberalization can strengthen the link between liquidity and asset prices. The latter has empirically also been confirmed by Borio, Kennedy and Prowse (1994) and Goodhart, Hofmann and Segoviano (2004) who find that the responsiveness of asset prices to credit increases after episodes of financial deregulation. If financial liberalization is at the origin of a credit boom, then this finding is also confirmed by our results, i.e. we find a greater impact on several types of asset prices and economic activity during a credit expansion. Finally, the results could also be linked to the financial accelerator literature (Bernanke and Gertler 1989) or other theories predicting nonlinearities in the impact of monetary policy, e.g. the existence of a convex aggregate supply curve. More specifically, these theories predict stronger effects of restrictive monetary policy actions on economic activity and a stronger impact during recessions. The former has empirically been confirmed for the US by Cover (1992), while the latter has been shown by Peersman and Smets (2002, 2005) for the Euro area economy. In this paper, on the one hand, we also find support for a stronger impact of negative liquidity shocks, not only on economic activity but also on real asset prices. On the other hand, real GDP reacts also more to liquidity shocks during recessions and during periods of tight monetary policy. As a result, our findings can also be reconciled with the existence of a financial accelerator.

The rest of the paper is structured as follows. In the next section, we identify excess liquidity shocks in a benchmark structural VAR for the Euro area and describe their impact on different types of asset prices and some other relevant macroeconomic variables. We also make a distinction between the sources of increased liquidity. Section 3 extends the benchmark model to a time-varying framework. In particular, a VAR with a sample split around the beginning of the Great Moderation and a Bayesian VAR with time-varying parameters and stochastic volatility are estimated and discussed. To gain further insights into the sources of time variation and the state dependence, we perform some additional estimations using a single-equation approach in section 4. Finally, section 5 concludes.

2 The impact of liquidity shocks in the Euro area

2.1 Benchmark VAR

We first investigate the macroeconomic consequences of excess liquidity or exogenous shocks to liquidity.[3] Excess liquidity is typically defined as unusually high money growth with reference to price stability in the long run. Potential indicators are the real and nominal money gaps, monetary overhang or money/credit to GDP ratios. To avoid endogeneity of money and asset prices with respect to the business cycle, we prefer to use vector autoregressions. With this approach, it is possible to identify exogenous liquidity shocks which are not related to endogenous developments due to business or asset price cycles. As a result, these shocks or the accumulation thereof, can be interpreted as "excess liquidity". Vector autoregressions have been very popular to identify the impact of monetary policy shocks (e.g. Christiano, Eichenbaum and Evans 1999 for the US, Peersman and Smets 2003 and Peersman 2004 for the Euro area), but little evidence is available for liquidity disturbances, in particular for the Euro area. Our model has much in common with the panel specifications used by Adalid and Detken (2007) and Goodhart and Hofmann (2007). More specifically, the benchmark VAR has the following representation:

$$Y_t = C_t + B(L)Y_{t-1} + u_t \tag{1}$$

where Y_t is a vector of endogenous variables containing real GDP, HICP consumer prices, the short-term nominal interest rate, a real asset price index and the broad monetary aggregate M3. The VAR is estimated in first differences, except for the interest rate which remains in levels, for the sample period 1971Q1-2005Q4 with three lags.[4] We consider three different indices of asset prices, namely property prices, equity prices and an index which is a weighted average of different types of asset prices constructed by the BIS (labeled as aggregate asset prices). Original data are from Borio, Kennedy and Prowse (1994) and are widely used in other papers. A detailed explanation of the construction of these indices for the Euro area can be found in the data appendix. C_t is a matrix with exogenous variables. For the benchmark specification, this matrix contains two separate constants for respectively 1971-1984 and 1985-2005. This is the only way to capture the

[3] For a detailed description of the different transmission channels of liquidity to output and inflation, and in particular the role of asset prices, we refer to Mishkin (1996).

[4] The lag length is determined with the usual battery of selection criteria. The dataset itself starts in 1970Q1. A full description of the data is provided in Appendix A. The first-difference specification is selected to be consistent with the time-varying parameters specification of section 3.2, for which stationarity of all variables is required. Qualitatively consistent results are found for a log-level specification which allows for cointegration relationships among the variables.

shift in growth rates for some of the variables, e.g. inflation, money growth and asset price inflation, observed in the "Great Inflation" and "Great Moderation" periods which would otherwise affect the identified shocks.[5] Another problem we encountered during the analysis, especially for the specification with equity prices and M3-M1 in section 2.2, regards the influence of portfolio shifts due to e.g. macroeconomic uncertainty. These shifts and their unwinding are typically very asymmetric and/or nonlinear (Fischer et al. 2008). Consider, for instance, increased uncertainty because of a financial crisis. As a consequence, investors quickly substitute their risky assets with safer, capital-certain assets included in M3. Once financial conditions are back to normal however, portfolios are reversed but much more slowly. Since we will allow equity prices (and aggregate asset prices) to have an immediate effect on money in the VAR, this should in principle be captured by the estimated coefficient for this (average) contemporaneous impact. However, given the asymmetric and nonlinear nature of such events compared to normal (average) times, such portfolio shifts are often wrongly identified as exogenous liquidity shocks. As a result, a puzzling, significantly negative impact of shocks to liquidity on asset prices is found, in particular for equity prices and shocks to the M3-M1 component of broad money.[6] To capture these portfolio shifts, we add a world financial market volatility index to the exogenous block of the VAR which is constructed with data from Gerlach, Ramaswamy and Scatigna (2006).[7] In addition, to capture the nonlinearity, we allow this measure to have a different coefficient depending on a regime of high (above average) or low (below average) volatility. Estimations were also done by adding a commodity price index and US variables to the exogenous block but this did not influence the results. We therefore decided to drop these variables to gain degrees of freedom.

To identify a liquidity shock, we follow Adalid and Detken (2007) and Goodhart and Hofmann (2007) by using a standard Choleski decomposition with the broad monetary aggregate ordered last.[8] More specifically, we assume an immediate impact of all the other variables in the VAR system on the money aggregate and only a lagged effect of an exogenous liquidity shock on the other variables. Although this approach could somewhat underestimate actual shocks to liquidity, it guarantees that all endogenous movements

[5] Results are not sensitive to alternative split points backward or forward in time.

[6] Portfolio shifts are a phenomenon typically related to equity prices. The estimated impact on property prices seems to be hardly affected by it. It is also less of a problem for M1, because the destination of the switches is typically the interest-bearing component M3-M1. However, the estimated impact for aggregate asset prices and M3 are obviously also biased.

[7] See Appendix A for the exact construction of this index.

[8] Adalid and Detken (2007) order money second to last, before the real effective exchange rate, for a set of countries. We have excluded the latter variable in our estimations because it does not affect the results for a relatively closed economy like the Euro area.

with respect to the macroeconomy are filtered out which is the best way to measure the economic consequences. As such, the identified shock can be labeled as an "excess" liquidity shock. We do not take a stance on the underlying source of the liquidity shock. This could be monetary policy, but note that the shock is identified as being orthogonal to central bank interest rate decisions. In particular, we consider more or less liquidity in circulation relative to an equilibrium value determined by the interest rate and other macroeconomic variables.[9] Since we use a broad money aggregate, the source could also relate to shifts in the money multiplier, other developments in the financial sector such as financial deregulation, or portfolio shifts between different categories of assets by economic agents.

The benchmark results are shown in Figure 1. This graph displays the effects of a one-standard-deviation shock in liquidity together with 16^{th} and 84^{th} percentiles error bands. Responses for the conventional variables are shown for the specification with aggregate asset prices. Separate estimations were carried out for a specification where the aggregate asset price index is replaced by respectively the residential property and equity price indices. For the latter two, we only report their own responses. Responses for nominal asset prices are derived from the responses of real asset prices and consumer prices. While the contemporaneous impact of a typical liquidity shock on M3 is only 0.37 percent, the long-run change of this broad monetary aggregate is around 1 percent and only realized after approximately 3-4 years. Accordingly, it takes time before portfolios are fully adjusted. Consistent with expectations, this shock has a temporary positive effect on economic activity with a peak of 0.3 percent after 6 quarters. Inflationary consequences last for about 3 years resulting in a total increase in the price level by somewhat less than 0.6 percent. The latter implies that the final impact is less than proportional, which leads to a permanent increase in the real money stock by 0.5 percent. To stabilize the economy, monetary policy increases the nominal interest rate by more than the rise in inflation. A positive shock to liquidity boosts both nominal and real asset prices and their individual components. The impact on real asset prices is temporary and reaches a maximum of respectively 0.5, 2.0 and 1.0 percent for property, equity and aggregate asset prices.

Figure 2 shows the time series of the liquidity shocks and their historical contributions to a number of economic variables for the benchmark VAR. It turns out that liquidity shocks occurred mostly in clusters, perhaps as a result of periods of financial innovation or deregulation. We observe a series of positive liquidity shocks in the early 1970s having, by the mid-1970s, an accumulated impact on M3 of more than 6 percent. Also the period 1986-1994 is characterized by rising excess liquidity accumulating to 7 percent in total.

[9] This measure is thus comparable to a monetary overhang indicator.

Other shorter periods of increasing liquidity were 1980-1982 and the more recent period starting in 2004. The latter turning point is actually exactly the moment when the ECB started to worry about money growth (Fischer et al. 2008). Inbetween these periods, liquidity shocks were mainly negative and made a negative contribution to M3. Striking is the period 1994-2004, when there was a negative contribution to the total money stock of 10 percent, an average reduction of 1 percent per year. The rises and falls of liquidity obviously had significant consequences for inflation, economic activity and asset prices during these periods. For instance, average inflation was much higher in the first part of the 1970s, reaching values of 0.4 percent on a quarter-to-quarter basis. On the other hand, negative shocks to liquidity had a significant downward effect on inflation during most of the 1990s, but also on output and asset price growth in the first part of the 1990s. In sum, liquidity shocks were economically very important over the past 35 years.

2.2 Distinction between shocks to M1, M3-M1 and credit

In its monetary analysis, the ECB pays a lot of attention to the components and counterparts of M3. On the one hand, shifts in the more liquid components are considered as increases in the transaction demand for money and often judged to be indicative of growing risks to price stability. On the other hand, interest-bearing components of M3, e.g. money market funds, can be regarded as alternative assets in a portfolio of investors which are not necessarily used for increased spending. On the counterpart of the balance sheet, M3 growth driven by credit expansion also signals increased spending, while a shift in net external assets could reflect portfolio shifts at times of increased global uncertainty.

To analyze this into more detail, we also estimated the VARs by replacing broad money with its respective components M1 and M3-M1 and with total credit.[10] Results are shown in Figure 3. To make a comparison possible, we have normalized the impulse responses as a 1 percent liquidity increase in the long run. We notice some striking differences. A 1 percent long-run rise in M1 is almost fully reflected in additional inflation, i.e. there is no statistically significant long-run effect on real money holdings. In contrast, a shock to M3-M1 has a persistent impact on the real money stock whereas the price level rises by hardly 0.3 percent. This confirms our supposition that a shock in M3-M1 is more likely to be the result of a preference shift with respect to asset holdings and does not necessarily lead to increased spending. In fact, we observe only a small increase in economic activity which

[10] For total credit, data is only available from 1980 onwards. The results reported in the figures are based on a backward extrapolation using M3 for the 1970s. Very similar results, however, are found if we conduct the estimations for credit only for the sample period 1980-2005.

is just about one third of the output increase following a similar shock to M1. Portfolio adjustments are also much slower for M3-M1. While the maximum impact on M1 occurs almost instantaneously, the immediate impact on M3-M1 is only one third of its long-run effect. The reaction of asset prices is less clear. On the one hand, we observe a very similar impact of both components on real property prices. On the other hand, the impact on real equity prices, and as a consequence also aggregate asset prices, of a shock originating in M1 is much stronger. The reaction of real equity prices to a shock in M3-M1 is not even significant. One potential explanation could be that portfolio shifts, as described in section 2.1, are still not fully captured by our volatility index which could underestimate the actual impact.

With regard to the impact of shocks to credit, we observe very little differences compared to shocks in M3. The effect of a 1 percent long-run increase in credit on inflation is the same. We only observe a stronger impact on economic activity reaching a maximum of 0.6 percent, compared to 0.3 percent for M3. The reaction of real asset prices is somewhat stronger which is mainly driven by a stronger impact on real equity prices.

3 Time-varying effects of liquidity shocks in the Euro area

3.1 A simple sample split

As a first check for time variation, we re-estimate the benchmark VAR for two sub-samples, i.e. 1971Q1-1984Q4 and 1985Q1-2005Q4. As a breakpoint for the sample split, we select the mid-1980s. This is also the period where Gerlach (2004) detects a break in the forecasting performance of money for inflation. In addition, this period is also often characterized as the end of the "Great Inflation" period and the beginning of the "Great Moderation". One popular explanation for this change in regime is improved and more credible monetary policy. It is therefore likely that more credible monetary policy could affect the impact of shocks to liquidity.[11]

Impulse response functions normalized for a long-run increase in the nominal money stock of 1 percent are shown in Figure 4. Responses for the first sub-sample are dotted red lines whereas those for the second sub-sample are full black lines. We find some interesting differences across both periods. Consider the responses of nominal and real money. We observe a much faster reaction to an excess liquidity shock in the first part of the sample, while portfolios adjust more slowly in the second part of the sample. However,

[11] The results of this section are not sensitive to changes in the exact breakpoint for the sample split. VARs for both sub-samples are estimated with two lags instead of three for the whole sample period.

in contrast to the pre-1985 period, the shift of real money in the latter period is permanent. As a consequence, the impact on inflation and the price level was much stronger before 1985. During that period, any rise in liquidity was proportionally reflected in increased prices. Since the start of the Great Moderation, increased liquidity has a pass-through to prices which is only one fourth of the rise in money. This finding is consistent with the break found by Gerlach (2004). Output effects are also substantially different across both periods. There is a strong effect before 1985 which becomes insignificant thereafter. For real property prices, we find little differences across both periods. For real equity prices and aggregate asset prices, however, we do find a much stronger impact during the second part of the sample. Real aggregate asset prices did not even react significantly before 1985, which is driven by a negative effect on real equity prices. This negative reaction is puzzling and unexpected.

While our sample split does provide more information about the impact of liquidity shocks under two different regimes, such a split is based on the assumption that the break occurs simultaneously in all the relationships captured by the model which is rather unlikely. In the next section, we therefore model time variation more properly by estimating a Bayesian VAR with time-varying parameters and stochastic volatility.

3.2 A Bayesian VAR with time-varying parameters

Structural changes in the economy, like the process of building up credibility by the monetary authority and ongoing financial innovations and deregulations which supposedly have contributed to a change in the way the economy experiences excess liquidity shocks, are more gradual in nature. Consequently, a sample split is not the most appropriate tool to represent such an evolutionary process. Moreover, such a split does also not capture state-dependent liquidity effects which could vary within subsamples. Thus, to allow for the possibility of smooth transitions, we extend our benchmark VAR to a VAR(p) model with time-varying parameters and stochastic volatility in the spirit of Cogley and Sargent (2002, 2005), Primiceri (2005) and Benati and Mumtaz (2007):

$$Y_t = C_t + B_{1,t}y_{t-1} + ... + B_{p,t}y_{t-p} + u_t \qquad (2)$$

where Y_t is an 5×1 vector of observed endogenous variables as in our benchmark specification, C_t is an 5×3 matrix of time-varying parameters that multiplies deterministic terms,[12]

[12] These terms correspond to the block of exogenous variables in the benchmark VAR. We include a constant and the volatility indicators as deterministic variables. Since we estimate the model with time-varying parameters, two constants and a volatility measure which depends on the volatility level are not needed.

$B_{p,t}$ are 5×5 matrices of time-varying coefficients on the lags of the endogenous variables where the number of lags is set to $p = 2$, and u_t are heteroscedastic reduced-form innovations with a time-varying variance covariance matrix Ω_t. The drifting coefficients are meant to capture possible nonlinearities or time variation in the lag structure of the model. The multivariate time-varying variance covariance matrix allows for heteroskedasticity of the shocks and time variation in the simultaneous relationships between the variables in the system. Even though there is no presumption for changes in the volatility of excess liquidity shocks, ignoring heteroskedasticity of the disturbance terms could lead to fictitious dynamics in the VAR coefficients, i.e. movements originating from the heteroskedastic covariance structure would be picked up by the VAR coefficients leading to an upward bias (Cogley and Sargent 2005). Thus, allowing for time variation in both the coefficients and the variance covariance matrix, leaves it up to the data to determine whether the time variation of the linear structure derives from changes in the size of the shock and its contemporaneous impact (impulse) or from changes in the propagation mechanism (response). We estimate this model using Bayesian methods. Technical details regarding the model setup, the prior specifications, the estimation strategy (Markov Chain Monte Carlo algorithm) and the computation of impulse responses are provided in Appendix B.

Figure 5 displays the median impulse responses of nominal and real M3 to a typical one-standard-deviation excess liquidity shock for horizons up to 28 quarters at each point in time spanning the period 1978Q4 to 2005Q4.[13] The estimated responses have been accumulated and are shown in levels. There is striking evidence of time variation in the dynamic responses of both monetary aggregates but their evolutionary patterns differ considerably. While the contemporaneous impact of an excess liquidity shock on nominal M3 is surprisingly constant over time, the long-run effect exhibits substantial time variation with an increasing trend over time. In contrast to the gradually stronger long-run responses of the nominal money stock, the pattern of responses of real M3 to an excess liquidity shock is characterized by alternating periods of stronger and weaker reactions over the whole sample period. The magnitude of the real money responses provides the degree of pass-through of additional liquidity into consumer prices with permanent increases in real money holdings corresponding to periods of low pass-through to inflation. As emerges from the graph, the pass-through to consumer prices has been most incomplete during the periods 1990-1995 and 1999-2001.

[13] The 3D graphs of the time-varying impulse responses are to be read in the following way: along the x-axis the starting quarters are aligned from 1978Q4 to 2005Q4, on the y-axis the quarters after the shock are displayed, and on the z-axis the value of the response is shown in percent. The estimation results only start in 1978Q3 because we need the first 8 years as a training sample to initiate the priors.

In order to evaluate the changes over time as a result of a 1% increase in liquidity in the long term, we have also normalized the responses of all endogenous variables on the long-run effect on nominal M3. These normalized time-varying median impulse responses for the macroeconomic variables and the different asset price indices are shown in Figure 6. To make comparisons with the sample split, note that impulse responses in these graphs only start in late 1978 since we need the first 8 years as a training sample to calibrate the priors. The first responses can therefore be considered as being close to the average of the period 1970-1978. While output effects have been decreasing gradually from the early 1980s until the end of the century, since the 2000s this trend is reverting back to stronger responses of economic activity. A similar picture emerges for the responses of prices. At the beginning of the sample, which is still heavily influenced by developments during the 1970s, excess liquidity is almost fully reflected in additional inflation with a negligible long-run effect on the real money stock. Over time the pass-through has become more and more incomplete reaching its lowest level during the early 1990s. However, the inflationary effects of shocks to liquidity recently follow again an upward trend i.e. additional liquidity increasingly translates into inflation in more recent times. The mirror image of this evolution is depicted in the responses of real M3 which attained a peak in the early 1990s and declined continuously ever since. The monetary authority appears to react preemptively by raising the short-term interest rate in response to increased liquidity anticipating possible inflationary pressures since the responses closely track those of consumer prices. Apart from greater real money holdings, more pronounced responses are also observed in real aggregate asset and property prices at around the same time implying that additional liquidity is directed towards financial and physical assets. Since nominal aggregate asset and property prices are the result of the responses of consumer prices and real asset and property prices, not much change is observed over time due to the fact that the movements in these components tend to compensate each other. Median time-varying impulse responses for equity prices show a puzzling pattern, with even a negative long-run impact on nominal equity prices. However, in contrast to aggregate asset and property prices, these responses are statistically insignificant since the 16^{th} and 84^{th} percentiles are extremely wide. It seems that a white noise variable like equity price growth cannot be captured by a TVP-BVAR. As a robustness check and an alternative way to allow for a gradual evolution of the reactions to excess liquidity shocks, we also recursively estimated the benchmark VARs and qualitatively similar results were found.[14]

The time-varying responses to excess liquidity shocks provide a much more detailed picture in comparison to the sample split but we are not yet able to tell in how far the

[14] These results are available upon request.

stronger and milder responses over time are dependent upon the business cycle, asset price boom-bust episodes, the stance of monetary policy and the process of financial liberalization, all of which might be conducive to altering the dynamics of excess liquidity shocks on the Euro area economy and asset prices. The next section analyses this in more detail.

4 Liquidity shocks and the state of the economy

4.1 A single-equation approach

We now perform a more formal analysis to investigate whether the impact of liquidity shocks depends on the underlying state of the economy. We consider five regimes which could play a role for the strength of the impact. To determine these regimes, some conventional measures obtained from the literature are used, which will be discussed in the next subsection.[15] Ideally, a full VAR which allows for different parameters in each state is estimated. This is done, for instance, by Balke (2000), Atanasova (2003), and Calza and Sousa (2005). However, these studies only consider two regimes which are respectively low and high credit growth. Since we want to investigate the impact for five regimes simultaneously, this approach is not appropriate due to overparameterization of the model. We therefore use a much simpler framework which allows us to combine several regimes at the same time and still leaves us with enough degrees of freedom to estimate the model. More specifically, we consider the following single equations:

$$\Delta y_t = \alpha C_t + \sum_{i=1}^{n} \lambda_i \Delta y_{t-i} + \sum_{i=1}^{n} \beta_i \varepsilon_{t-i}^{liq} + u_t \tag{3}$$

$$\Delta y_t = \alpha C_t + \sum_{i=1}^{n} \lambda_i \Delta y_{t-i} + \sum_{i=1}^{n} \beta_i \varepsilon_{t-i}^{liq} + \sum_{j=1}^{k} \sum_{i=1}^{n} \gamma_{j,i} state_{t-i}^{j} \varepsilon_{t-i}^{liq} + u_t \tag{4}$$

$$\Delta y_t = \alpha C_t + \sum_{i=1}^{n} \lambda_i \Delta y_{t-i} + \sum_{i=1}^{n} \beta_i \varepsilon_{t-i}^{liq} + \sum_{j=1}^{k} \sum_{i=1}^{n} \gamma_{j,i} state_{\mathbf{t-1}}^{j} \varepsilon_{t-i}^{liq} + u_t \tag{5}$$

Equation (3) estimates the *average* impact of a liquidity shock in the sample across all states, which could be used as a benchmark. More specifically, the dependent variable Δy_t

[15] Some graphs containing the underlying time series that we use to determine the states and additional information about the construction of the proxies can be found in Figure 1A and Appendix A. We find qualitatively similar results if we use proxies obtained with alternative filters, indicators or threshold values. These results are available upon request.

is respectively output growth, inflation, nominal and real aggregate asset price growth, nominal and real property price growth and, nominal and real equity price growth. C_t is a matrix containing the exogenous variables which were also included in the benchmark VAR. In addition, this matrix also includes four lags of the other structural shocks obtained by the recursive identification in the VAR system and, ε_{t-i}^{liq} is the estimated liquidity shock from the VAR at time $t-i$. For all estimations reported in this section, we have used four lags of the dependent variables and the liquidity shocks. The results for the average impact on respectively output growth, inflation and the nominal and real growth rates for property, equity and aggregate asset prices are reported in the first row of Table 1. The figures in the table are the sums of the coefficients for lags 1 to 4, together with standard errors between parentheses. Consistent with the VAR estimations, we find a significant positive impact on all variables under consideration. The magnitudes of the impact can be used to make comparisons in all further estimations.

The role of the state of the economy is captured by equations (4) and (5), where the liquidity shocks are interacted with the underlying regimes. Specifically, five states are considered simultaneously, where $state_{t-i}^{j}$ is a dummy reflecting state j at time $t-i$. This means that $\sum_{i=1}^{n}\gamma_{j,i}$ represents the additional effect (positive or negative) of a liquidity shock in state j compared to the impact of *not* being in this state. We introduce all five states jointly in the estimations because many states are overlapping. For instance, an economic boom is very likely to occur at the same time as an inflation boom and can even result in an asset price boom. The data then determine the exact driving factors. Since liquidity shocks are identified with a recursive ordering in the VAR, these shocks also have only a lagged impact on respectively output, prices and all asset prices in the single equations. This fact helps avoid an endogeneity problem for the accompanying underlying state variable. In particular, the state of the economy is only interacted with the liquidity shocks for the periods $t-1$ until $t-4$ in equation (4). This representation implicitly assumes that the impact of a liquidity shock on the macroeconomic variables depends on the regime at the moment of the shock. For example, the impact of a shock at $t-3$ on output growth at t depends on the state of the economy at $t-3$. As an alternative, represented by equation (5), we also estimate the impact of (lagged) liquidity shocks, but the impact now depends on the "current" state of the economy. Specifically, the impact is estimated for a liquidity shock at $t-i$ on e.g. output growth between $t-1$ and t depending on the state of the economy at $t-1$. Taking $t-1$ still guarantees that there is no endogeneity problem. There is no a priori theoretical reason to prefer specification (4) or (5).

4.2 Results

Estimation results for both specifications are reported in respectively the second and third block of Table 1. In the next subsections, we examine one by one all individual states which could affect the impact of liquidity shocks and the measures we have used to proxy these states in more detail.

Asset price booms and busts. There is a growing literature demonstrating that the effects of liquidity shocks, in particular for asset prices, are greater during asset price booms and busts compared to normal times. For instance, Herring and Wachter (2003) describe several features of the banking sector responsible for a credit expansion process taking place during asset price booms. First of all, increases in asset prices during booms augment the value of banks' capital, to the extent that they own assets themselves, thus making banks more willing to hold loans (the so-called bank capital channel). Secondly, in boom times, the market value of collateral on outstanding loans will rise, thereby reducing the risk for banks of suffering losses on their existing asset portfolio and accordingly raising the possibility to lend more without an increased probability of bankruptcy. Finally, two behavioral characteristics, which are present in the banking sector, explain why banks underestimate the risks of large concentrations of lending: (a) disaster myopia leads banks to underestimate the probability of low-frequency economic shocks, causing them to misjudge the true probability of a bust in asset prices; (b) perverse provisions, such as the availability of an official safety net to protect the economic system against the contagious collapse of a bank or the existence of deposit insurance, weaken creditors' and depositors' incentives to discipline banks' risk-taking behavior so that banks will take on more risky lending than they would in the absence of a safety net. The leverage targeting theory by Adrian and Shin (2008) contains an alternative explanation that could justify a tighter link between liquidity measures and asset prices during booms or busts. In a boom, rising asset prices strengthen banks' balance sheets, as a result of which banks' leverage falls. When banks target a certain leverage ratio, they want to increase their liabilities by borrowing more to buy new assets with these proceeds, thereby inducing further asset price rises, which will reignite the whole process. The exact same mechanisms will work in a comparable manner during busts.

The financial accelerator mechanism (Bernanke and Gertler 1989) reinforces these effects. As agents can profit from higher collateral values, which reduce asymmetric information and moral hazard problems, banks and other financial intermediaries will grant even more and cheaper access to credit. This process can result in mutually reinforcing cycles in asset prices and credit which exert an influence on consumption, investment, output and inflation via conventional transmission channels. The effect on economic activity even further aggravates the total impact by affecting the net worth of firms which also influences their access to credit. This leads us to expect a stronger link between liquidity and asset prices during asset price booms or busts compared to normal periods. As a result, output and inflation consequences should also be stronger.

A greater impact of liquidity shocks during asset price booms (not busts) has been confirmed in the recent empirical literature by Adalid and Detken (2007) and Goodhart and Hofmann (2007) using panel estimations for respectively 18 and 17 OECD countries. In contrast to these studies, we conduct a pure time-series approach for the Euro area and we also consider the effect on equity and aggregate asset prices. Following Adalid and Detken (2007), we define an *asset price boom* as a period in which the real aggregate asset price index exceeds its trend by more than 10 percent for at least 3 consecutive quarters. The trend is estimated using a very smooth recursive HP-filter ($\lambda = 100000$) taking into account only data available at the time. For the Euro area, this results in two periods of asset price booms of 25 quarters in total, i.e. 1987Q3-1991Q2 and 1999Q1-2001Q1.

The results in Table 1 (first line of second and third block for our two baseline specifications) indicate that the impact of liquidity shocks is considerably stronger during asset price booms. We find a statistically significant, greater effect on economic activity, inflation and real aggregate asset prices. A stronger impact, however, is statistically not confirmed for the property price component, and for equity prices only for the specification where the impact depends on the current state of the economy. The larger effects are also economically very relevant, as can be deduced from the size of the estimated coefficients. To illustrate this even better, Figure 7 shows simulations for the impact of a typical liquidity shock using the specification where the impact depends on the state of the economy at the time of the shock. The black lines represent the average impact of a liquidity shock in the sample period, when no differences across states are allowed for, i.e. equation (3). The red lines are the estimated effects during an asset price boom. We notice that the impact on the price level and output is almost double in an asset price boom compared to the average effect.[16] For real asset prices, we even find an impact which is three times as large as the average impact. From an economic and policy point of view, these differences are enormous. This does not mean that excess liquidity necessarily causes asset price booms, but any positive shock to liquidity during such a period seriously aggravates the boom. Moreover, such a shock results in significantly increased economic activity and inflation.

[16] Note that the *average* impact also contains periods of asset price booms. Accordingly, the differences relative to a state of *not* being in an asset price boom is even much larger.

The latter is somewhat in contrast to Adalid and Detken (2007), who find that inflation reacts less to liquidity shocks during asset price booms.

As an alternative indicator for aggregate asset price booms, we also consider the own cycles of property and equity prices as the underlying regime. To do so, we estimate exactly the same specifications, but now we replace the dummy for aggregate asset price booms with a dummy for the own cycle of respectively property and equity prices. Since this hardly affects the estimated coefficients for the other states in the regressions, we only report the coefficients of the newly added regimes. In principle, what should matter for increasing collateral values, is the cycle of aggregate asset prices. We nevertheless perform this check to see whether there are differences. As illustrated in the data appendix, booms in aggregate asset prices, especially their turning points, do not always fully correspond to booms in the individual components. For property prices, this makes no difference, we still find insignificant coefficients. For equity prices, we find improved significance (but a smaller coefficient) for the specification with the state at the time of the shock, but the opposite for the current state specification which makes it hard to draw any additional conclusions in relation to the own cycles of the asset price components.

As a second alternative, we substitute the asset price boom regime with an asset price bust regime. The latter is defined as a period where the real asset price index is more than 5 percent below its trend for at least three quarters.[17] Remarkably, we also find an increased responsiveness of economic activity and asset prices to liquidity shocks. We now even observe a considerable additional impact on (real) property prices. This implies that the mechanism is present in both directions, especially in extreme conditions.[18]

The business cycle. The financial accelerator mechanism is a popular explanation for a stronger impact of several types of fundamental shocks (including liquidity shocks) on output, asset and consumer prices in recessions compared to expansions. During economic downturns, the stronger dependence of firms and households on external financing and the already low collateral and cash-flow values, will worsen the impact due to increased informational and moral hazard problems and additional credit rationing. In economic booms on the other hand, the balance sheets of economic agents are solid, creditworthiness is high and firms and households can largely provide their own financing, which significantly

[17] While we define 10% above trend as an asset prices boom, we take only 5% below trend as a threshold for a bust because there were only 5 quarters during which asset prices were more than 10% below trend in our sample. For the 5% criterion, we find a long-lasting bust between 1993Q1-1996Q4 and another shorter one for the period 2002Q3-2003Q2.

[18] Not surprisingly, the size of the coefficients (and statistical significance) become even larger when both asset price booms and busts are included in the same estimation, results which are not presented.

reduces the effect of liquidity shocks on asset and consumer prices as well as economic activity (Bernanke and Gertler 1989). Models that are based on the existence of a convex short-run aggregate supply curve also predict a weaker impact on economic activity, whereas the inflationary effects should be stronger.[19] Convexity implies that the slope of the supply curve is steeper at higher levels of output and inflation than at lower levels. As a result, shifts in aggregate demand driven by changes in liquidity will have a smaller impact on output and a larger effect on inflation in an expansion, while the reverse occurs in a recession. Since it is costly and difficult to adjust housing supply, especially upwards due to adjustment costs and other constraints that retard an increase in the housing stock, a similar reasoning can be made for property prices. A convex short-run supply curve of properties predicts stronger effects of liquidity shocks on real asset prices when housing demand outpaces the supply of additional housing, which is typically the case in an economic boom. For equity prices, however, supply is probably much less constrained which makes an asymmetric impact less likely.

For the Euro area, Peersman and Smets (2002) present evidence which shows that the output effects of monetary policy shocks are significantly stronger at times of low economic growth compared to periods of high growth. Furthermore, at least part of this asymmetry can be explained by the existence of a financial accelerator (Peersman and Smets 2005). In our estimations, the economy is considered as being in an *economic boom* whenever actual real GDP growth is above its trend for at least 3 quarters. The trend is estimated using a standard HP-filter ($\lambda = 1600$).

Also the state of the business cycle matters for the impact of a liquidity shock. First, we find a significantly smaller effect on economic activity, but not on inflation, during an economic boom. The latter could be the result of both channels cancelling each other out. Second, the impact on nominal and real property prices is substantially stronger at times of an economic boom. Accordingly, the effect of convex supply is probably dominating the financial accelerator channel in the housing market. The property price reaction during economic expansions is estimated to be twice the average one (see Figure 7). In contrast, such an upward constraint is less binding for the supply of equity since we do not find a significant difference between recessions and booms.

Financial deregulation and liberalization. Goodhart, Hofmann and Segoviano (2004) explain how the liberalization of the banking sector strengthens the financial accelerator

[19] Several classes of models give rise to a convex short-run aggregate supply curve, e.g. models based on capacity constraints, the presence of menu costs and theories based on downward rigidity of wages as in the so-called insider-outsider theory of employment. See Peersman and Smets (2002) for an overview.

channel. Improvements in banking-sector competition due to financial deregulation are often accompanied by the liberalization of capital and stock markets. As a result, the safest segment of borrowers shifts away from the banking sector towards the stock market when in need of new capital. The search for new customers leads banks to smaller and riskier borrowers, which increases the importance of collateral values as a monitoring tool. Calza, Monacelli and Stracca (2006) show that financial liberalization in mortgage markets can also reinforce the balance sheet channel. Consequently, financial deregulation amplifies the importance of collateral values for lending decisions and thus the financial accelerator mechanism, leading to a stronger effect of excess liquidity on asset prices. Allen and Gale (2000) describe another mechanism that creates a link between liquidity and asset prices following periods of financial liberalization. Their model demonstrates that uncertainty about the extent of credit expansion can increase the magnitude of an asset price bubble, thus introducing a role for credit in the formation of asset price bubbles. Periods of financial liberalization are typically associated with high uncertainty about credit expansion, thereby establishing a link between liquidity and asset prices during episodes of financial deregulation.

Borio, Kennedy and Prowse (1994) find that real asset prices become more responsive in countries that underwent financial-sector liberalization. The existence of this channel is also confirmed by Goodhart, Hofmann and Segoviano (2004) who show that real property prices gain importance in explaining real bank lending growth in the aftermath of financial deregulation. Furthermore, Calza, Monacelli and Stracca (2006) find that the correlation between consumption and house prices is higher in countries with more liberalized mortgage markets. We consider a *credit boom* as a proxy for financial liberalization. We assume that periods of financial liberalization or deregulation will result in credit and money expansions relative to economic activity. More specifically, a credit boom is defined as a period of minimum 3 quarters in which the money/GDP ratio grows faster than its trend.[20] The latter is also determined by an HP-filter ($\lambda = 1600$).

When the economy is in a regime where money/credit to GDP grows faster than its trend, we observe a significantly increased responsiveness of output growth and all types of asset prices for both specifications. Somewhat surprisingly, we only find a stronger reaction for inflation in a credit boom when we model the impact to be dependent on the current state of the economy. The additional impact is also economically important, as illustrated in Figure 7. Relative to the average impact, all different types of asset prices react almost twice as much in a regime of credit expansion. For output, the additional

[20] A better proxy would be the credit/GDP ratio but credit data are only available from 1980 onwards. The correlation with money/GDP for the overlapping sample is, however, quite high.

impact is approximately one third of the average impact.

The fourth panel of Table 1 also shows the results for regimes of rising cumulative excess liquidity. For this estimation, we replace the credit boom regime indicator with a state in which the historical contribution of liquidity shocks to M3 (see section 2.1) is rising for at least three consecutive quarters, the underlying idea being that e.g. financial innovations will result in a series of positive liquidity shocks. In contrast to the money/credit to GDP ratio, any endogenous reaction of money to the interest rate and asset prices is filtered out. Also for this measure we find very similar results, i.e. an increased impact on the economy during periods of financial innovation and deregulation seems to be a robust finding.

Inflation regimes. Borio and Lowe (2002) and Borio (2006) argue that improved central bank credibility has anchored the public's inflation expectations, which could potentially dampen the effect of liquidity shocks on inflation, a reasoning which can be put into the much broader literature on the Great Inflation and Great Moderation. Part of this literature attributes the post-1985 stable and low inflation environment to improved and more credible monetary policy. In such an environment, however, excess liquidity could instead translate into higher asset prices. In addition, increased economic globalization has also supported central bank credibility and has put downward pressure on prices. The more intense international competition which also stimulates economic growth, could in turn have boosted asset prices. In a similar fashion, Borio and Lowe (2002) further argue that improvements deriving from the supply side have had comparable effects on inflation and asset prices. All of these arguments suggest that a low inflation environment is likely to be associated with a stronger link between liquidity and asset prices on the one hand and a weaker relationship between liquidity and inflation on the other hand.

We define an *inflation boom* as a period in which inflation is higher than its trend value for a minimum of 3 quarters. Again, the trend is calculated using an HP-filter ($\lambda = 1600$). Our evidence suggests that it is not possible to draw firm conclusions with respect to the inflation regime. We find a significantly stronger impact for real property prices and, to a lesser extent, for real equity and aggregate asset prices for the specification where the impact depends on the inflation regime at the time of the shock. However, when we consider the impact of a liquidity shock being dependent on the current inflation regime, the results are not robust anymore. No asymmetries are found for any type of asset prices, and for output growth we now even find a significantly weaker effect.

Monetary policy stance and positive versus negative liquidity shocks. Another nonlinear propagator of the financial accelerator is related to liquidity or credit constraints.

The intuition is that in a regime where economic agents are more liquidity constrained, any shock to the economy should have larger effects on investment and spending which is not the case in a regime of loose credit conditions. Liquidity constraints are typically related to the balance-sheet position of firms. When balance sheets are weak, the net worth of firms is low and their ability to borrow is limited. Conversely, when the net worth is high and balance sheets are strong, balance-sheet considerations tend to be less important when firms seek funding for investments. The above described asymmetry for the business cycle is a good example. In recessions, the net worth is low and economic agents are more liquidity constrained compared to an expansion, resulting in a stronger financial accelerator mechanism. However, there are other situations in which liquidity constraints become more binding. One popular example is the monetary policy stance. In periods of restrictive monetary policy, balance sheets will be weaker resulting in lower net worth and tighter liquidity constraints. As a consequence, the propagation of exogenous shocks to the economy will be stronger, including liquidity shocks. The opposite is true in situations of loose monetary policy.

In the estimations, *restrictive monetary policy stance* is a dummy equal to one for each quarter in which the actual interest rate is higher than the interest rate obtained from a Taylor rule. Output and inflation gaps are calculated as described above and the neutral real interest rate is computed with an HP-filter ($\lambda = 1600$). The coefficients for the reaction to output gap and inflation in the interest rate rule are both set to 0.5. We find little support for the proposition. Only in the first specification, we find a significantly stronger impact on economic activity and weak evidence for an increased reaction of nominal and real asset prices. This evidence however, is not confirmed for the specification where the impact depends on the current state of the economy, i.e. the additional reaction of output growth, nominal and real asset prices becomes insignificant. On the other hand, both specifications show a significantly weaker effect of liquidity shocks on inflation at times of tight monetary policy. Perhaps, this might be explained by increased credibility of monetary policy with respect to inflation during these periods. As shown in Figure 7, the economic relevance of the reduced pass-through is however rather small.

The same mechanism predicts greater effects of negative shocks to liquidity compared to positive liquidity shocks. Negative shocks will make the credit constraints more binding and reduce the net worth of firms resulting in a stronger financial accelerator, whereas positive shocks relax the constraint leading to a weaker balance sheet channel. On the other hand, a convex short-run aggregate supply curve also predicts stronger output effects of negative liquidity shocks relative to positive ones, but smaller effects on inflation. Cover (1992) does not find an effect of positive money supply shocks on US output, while negative shocks significantly reduce economic activity. Oliner and Rudebusch (1995) show that a financial accelerator is stronger after restrictive monetary policy shocks. The final row of Table 1 makes a distinction between negative and positive liquidity shocks.[21] There is a significant additional output effect of a liquidity shock in case the shock is negative confirming the existing evidence. In addition, we also find a considerably larger effect on all types of asset prices, something which has not been documented before. For inflation, no asymmetry is found, which is probably due to both channels cancelling each other out.

5 Conclusions

In this paper, we have investigated how the dynamic effects of liquidity shocks on economic activity, asset prices and inflation differ over time. We find strong evidence that the impact depends on the source of increased liquidity and the underlying state of the economy. More specifically, when the source of increased liquidity is a rise in M1, the impact on economic activity is very strong and the ultimate pass-through to inflation is proportional. In contrast, when the rise in liquidity originates in M3-M1, there is only a small reaction of economic activity and the pass-through to inflation is only one third of the rise in money. Such a shock rather results in a permanent rise of real money holdings. When we compare shocks to M3 with shocks to its counterpart, credit, we notice very similar reactions of the main macroeconomic variables. The only difference is a stronger rise in economic activity following a credit expansion.

We also find substantial time variation in the impact of liquidity shocks. When we consider the Great Inflation and the Great Moderation as two different regimes, we find a complete pass-through to inflation and a strong output reaction before 1985, whereas in the post-1985 period the impact on inflation is rather subdued and the output effects are insignificant. However, when we extend the analysis to a more sophisticated Bayesian VAR with time-varying parameters and stochastic volatility, we observe increases in the impact of liquidity shocks during some periods and decreases during other periods.

Using a single-equation approach where we allow the impact of liquidity shocks to depend on the state of the economy, we are able to shed more light on the observed time variation. In particular, we find support for the fact that the impact of a liquidity shock on economic activity becomes stronger when the underlying economy is characterized by an extreme state of asset prices, i.e. during asset price booms or busts, but also during a

[21] Here the monetary policy stance regime is replaced with a dummy which is equal to one in case of a negative liquidity shock.

credit boom, when the business cycle is in a recession or when the monetary policy stance is restrictive. On the other hand, inflationary effects are larger during an asset price boom as well as a credit boom. Also the impact of shocks to liquidity on asset prices strongly depends on the state of the economy. The effects are much stronger in booms and busts of the asset price cycle, when the business cycle is in an expansion, during a credit boom and slightly stronger at times of tight monetary policy. In addition, we also find evidence that negative shocks to liquidity have a stronger impact on economic activity and asset prices than positive liquidity shocks. All these types of asymmetries are also economically very relevant.

For the European Central Bank, this paper should help to monitor the signals offered by the monetary analysis. A broadly based assessment of the sources of increased liquidity is a first requirement to determine the exact consequences for economic activity and inflation. However, the accompanying state of the economy is also very important to predict the effects of shifts in money. This requires an analysis which goes beyond pure monetary and financial variables. More specifically, the interaction with the outcome of its other pillar, the economic analysis, turns out to be very relevant to make accurate predictions.

A Data appendix

A.1 Sources and construction of variables

Asset Prices. Asset price data have been kindly provided by Steve Arthur and Claudio Borio of the BIS. The construction of the BIS asset price indices is extensively described in Borio, Kennedy and Prowse (1994). The aggregate asset price index consists of residential property prices, commercial property prices and equity prices, where each component is weighted according to its importance in the economy. The weight on each sub-index is infrequently updated over time. The three sub-indices and the aggregate index are available on a quarterly basis from 1970Q1 to 2006Q4 for 18 OECD countries, among which are the following Euro area countries: Belgium, Germany, Spain, France, Ireland, Italy, the Netherlands and Finland. We have constructed a Euro area aggregate for the equity price, residential property price and aggregate asset price index by applying the 1995 PPP-weights for the EU12, which are also used to compile the updated Area Wide Model data (ECB 2005). Since the BIS asset price data are not available for all Euro area member countries, we have rescaled the original EU12-weights. The total sum of the 1995 PPP-weights of the Euro area member countries for which the asset price data are available, amounts to 91,8%. For the first year of the sample, data on Spanish residential property prices are missing and aggregate asset price data are lacking for the following countries and periods: Spain, 1970Q1-1970Q4; Italy and Belgium, 2005Q1-2006Q4. Whenever asset price data are incomplete, we have rescaled the original EU12-weights and computed the asset price index using these new weights. In order to keep the asset price series consistent, we have applied the growth rates of this newly weighted asset price index to extrapolate the originally weighted asset price index whenever observations were missing.

Real GDP, HICP and the short-term nominal interest rate. Real GDP, HICP and short-term interest rate data for the Euro area have been collected from the updated Area Wide Model (AWM) dataset for the period 1970Q1-2005Q4. The short-term nominal interest rate in the AWM dataset is the three-month Interbank Offered interest rate.

Monetary Aggregates. Non-seasonally adjusted data for the monetary aggregates M3 and M1 have been retrieved from the ECB website (series code for M3: BSI.M.U2.N.V.M30.

X.I.U2.2300.Z01.E; for M1: BSI.M.U2.N.V.M10.X.I.U2.2300.Z01.E). These series are available on a monthly basis and represent indices of notional stocks. Seasonal adjustment has been carried out by means of the Census X-12 method in EViews 6. Quarterly data on M3 and M1 have been compiled by taking averages of the monthly observations. M3 minus M1 data have been constructed using series for M3 and M1, which are expressed as outstanding amounts at the end of each period (stocks), in millions of euro. The monthly data series for M3 and M1, seasonally and working day adjusted, have been downloaded from the ECB website (series code for M3: BSI.M.U2.Y.V.M30.X.1.U2.2300.Z01.E; for M1: BSI.M.U2.Y.V.M10.X.1.U2.2300.Z01.E). The monthly observations for both series have been averaged over the quarter and then the quarterly M1 series has been subtracted from the M3 series, resulting in a new data series for M3 minus M1. Outliers in this constructed series (more specifically, in 1990Q3 (German reunification), 1999Q1 (start of stage three of EMU), 2001Q1 (entry of Greece to the Euro area), 2005Q2 and 2005Q3) have been corrected for by applying the growth rate of the index of notional stocks of M3 (see above) to the series for M3 minus M1 in these specific quarters.

Volatility of Stocks and Bonds. Monthly data on the volatility of stocks and bonds have been kindly provided by Stefan Gerlach, Srichander Ramaswamy and Michela Scatigna. For a detailed description of how these volatility series have been compiled, we refer the reader to Gerlach, Ramaswamy and Scatigna (2006). In order to obtain a proxy for world financial market volatility for both types of markets, we have aggregated the stock and bond market volatility data for Canada, France, Germany, Italy, Japan, the US and the UK by applying the 1995 PPP-weights for each country. The resulting world financial market volatility index has been converted to quarterly frequency by taking monthly averages to span the period 1970Q1-2005Q4.

A.2 Construction of the indicators

Asset price booms. Following Adalid and Detken (2007), we extract the trend component of real aggregate asset prices, residential property prices and equity prices by recursively estimating a one-sided HP-filter with a smoothing parameter of $\lambda = 100000$. After an initial (non-recursive) estimate over 20 quarters, the recursive trends were derived by adding one observation period by period so as to take only information into account which was available at each point in time. Deviations from trend that exceed a threshold of 10 percent for at least three consecutive quarters are characterized as an asset price boom. For an equity price boom, the threshold is set to 20 percent, while the 10 percent threshold is kept to identify housing booms. Three consecutive periods in which real asset prices are more than 5 percent below trend are identified as asset price busts. The original time series and the accompanying states are shown in Figure 1A.

Economic boom. To derive the output gap we apply an ex-post HP-filter over the whole sample period with $\lambda = 1600$ to extract trend growth of real GDP. An economic boom is defined as a period of above trend growth for a minimum of three quarters.

Credit boom. A standard HP-filter with $\lambda = 1600$ is applied to the ratio of nominal M3 over nominal GDP to determine its trend growth for the entire sample. A period of at least three consecutive quarters in which the money/GDP ratio grows faster than its trend is considered a credit boom.

Inflation boom. The inflation gap is computed as the deviation of inflation from its HP-trend ($\lambda = 1600$). Above average growth of inflation for at least three quarters is classified as an inflation boom.

Monetary policy stance. Following Detken and Smets (2004), we determine the monetary policy stance by computing the Taylor gap as deviations of the nominal interest rate i from the Taylor rule interest rate: $i_t - [r_t^* + \pi_t + 0.5\,(\pi_t - \pi_t^*) + 0.5\,(y_t - y_t^*)]$, where r^* is the trend value of the real interest rate obtained from applying a standard HP-filter ($\lambda = 1600$) to the difference between the nominal short-term interest rate and current inflation and the coefficients on the output and inflation gaps (calculated as described above) are fixed at 0.5.

B A Bayesian SVAR with time-varying parameters and stochastic volatility

Model setup. The observation equation of our state space model is

$$Y_t = X_t'\theta_t + u_t \tag{6}$$

where Y_t is a 5×1 vector of observations of the dependent variables, X_t is a matrix including lags of all the dependent variables, an intercept and data on two deterministic terms (the volatility measures), and θ_t is a $5(5p{+}3) \times 1$ vector of states which contains the lagged coefficients and the parameters of the deterministic variables. The u_t of the measurement equation are heteroskedastic disturbance terms with zero mean and a time-varying covariance matrix Ω_t which can be decomposed in the following way: $\Omega_t = A_t^{-1} H_t \left(A_t^{-1}\right)'$. A_t is a lower triangular matrix that models the contemporaneous interactions among the endogenous variables and H_t is a diagonal matrix which contains the stochastic volatilities:

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix} \qquad H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 & 0 \\ 0 & 0 & 0 & h_{4,t} & 0 \\ 0 & 0 & 0 & 0 & h_{5,t} \end{bmatrix} \tag{7}$$

Let α_t be the vector of non-zero and non-one elements of the matrix A_t (stacked by rows) and h_t be the vector containing the diagonal elements of H_t. Following Primiceri (2005), the three driving processes of the system are postulated to evolve as follows:

$$\theta_t = \theta_{t-1} + \nu_t \qquad \nu_t \sim N(0, Q) \tag{8}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \qquad \zeta_t \sim N(0, S) \tag{9}$$

$$\ln h_{i,t} = \ln h_{i,t-1} + \sigma_i \eta_{i,t} \qquad \eta_{i,t} \sim N(0, 1) \tag{10}$$

The time-varying parameters θ_t and α_t are modeled as driftless random walks.[22] The elements of the vector of volatilities $h_t = [h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t}, h_{5,t}]'$ are assumed to evolve as geometric random walks independent of each other.[23] The error terms of the three transition equations are independent of each other and of the innovations of the observation equation. In addition, we impose a block-diagonal structure for S of the following form:

$$S \equiv Var(\zeta_t) = \begin{bmatrix} S_1 & 0_{1x2} & 0_{1x3} & 0_{1x4} \\ 0_{2x1} & S_2 & 0_{2x3} & 0_{2x4} \\ 0_{3x1} & 0_{3x2} & S_3 & 0_{3x4} \\ 0_{4x1} & 0_{4x2} & 0_{4x3} & S_4 \end{bmatrix} \tag{11}$$

which implies independence also across the blocks of S with $S_1 \equiv Var(\zeta_{21,t})$, $S_2 \equiv Var\left([\zeta_{31,t}, \zeta_{32,t}]'\right)$, $S_3 \equiv Var\left([\zeta_{41,t}, \zeta_{42,t}, \zeta_{43,t}]'\right)$, and $S_4 \equiv Var\left([\zeta_{51,t}, \zeta_{52,t}, \zeta_{53,t}, \zeta_{54,t}]'\right)$ so that the covariance states can be estimated equation by equation.[24]

[22] As has been pointed out by Primiceri (2005), the random walk assumption has the desirable property of focusing on permanent parameter shifts and reducing the number of parameters to be estimated.

[23] Stochastic volatility models are typically used to infer values for unobservable conditional volatilities. The main advantage of modelling the heteroskedastic structure of the innovation variances by a stochastic volatility model as opposed to the more common GARCH specification lies in its parsimony and the independence of conditional variance and conditional mean. Put differently, changes in the dependent variable are driven by two different random variables since the conditional mean and the conditional variance evolve separately. Implicit in the random walk assumption is the view that the volatilities evolve smoothly.

[24] As has been shown by Primiceri (2005, Appendix D), this assumption can be easily relaxed.

Prior distributions and initial values. The priors for the initial states of the regression coefficients, the covariances and the log volatilities, $p(\theta_0)$, $p(\alpha_0)$ and $p(\ln h_0)$ respectively, are assumed to be normally distributed, independent of each other and independent of the hyperparameters. The priors are calibrated on the point estimates of a constant-coefficient VAR(2) estimated over the period 1970-1978.

We set $\theta_0 \sim N\left[\widehat{\theta}_{OLS}, \widehat{P}_{OLS}\right]$ where $\widehat{\theta}_{OLS}$ corresponds to the OLS point estimates of the training sample and $\widehat{P}_{OLS}$ to four times the covariance matrix $\widehat{V}\left(\widehat{\theta}_{OLS}\right)$. With regard to the prior specification of α_0 and h_0 we follow Primiceri (2005) and Benati and Mumtaz (2007). Let $P = AD^{1/2}$ be the Choleski factor of the time-invariant variance covariance matrix $\widehat{\Sigma}_{OLS}$ of the reduced-form innovations from the estimation of the fixed-coefficient VAR(2), where A is a lower triangular matrix with ones on the diagonal and $D^{1/2}$ denotes a diagonal matrix whose elements are the standard deviations of the residuals. Then the prior for the log volatilities is set to $\ln h_0 \sim N(\ln \mu_0, 10 \times I_5)$ where μ_0 is a vector that contains the diagonal elements of $D^{1/2}$ squared and the variance covariance matrix is arbitrarily set to ten times the identity matrix to make the prior only weakly informative. The prior for the contemporaneous interrelations is set to $\alpha_0 \sim N\left[\widetilde{\alpha}_0, \widetilde{V}(\widetilde{\alpha}_0)\right]$, where the prior mean for α_0 is obtained by taking the inverse of A and stacking the elements below the diagonal row by row in a vector in the following way: $\widetilde{\alpha}_0 = [\widetilde{\alpha}_{0,21}, \widetilde{\alpha}_{0,31}, \widetilde{\alpha}_{0,32}, \widetilde{\alpha}_{0,41}, \widetilde{\alpha}_{0,42}, \widetilde{\alpha}_{0,43}, \widetilde{\alpha}_{0,51}, \widetilde{\alpha}_{0,52}, \widetilde{\alpha}_{0,53}, \widetilde{\alpha}_{0,54}]'$. The covariance matrix, $\widetilde{V}(\widetilde{\alpha}_0)$, is assumed to be diagonal with each diagonal element arbitrarily set to ten times the absolute value of the corresponding element in $\widetilde{\alpha}_0$. While this scaling is obviously arbitrary, it accounts for the relative magnitude of the elements in $\widetilde{\alpha}_0$ as has been noted by Benati and Mumtaz (2007).

With regard to the hyperparameters, we make the following assumptions along the lines of Benati and Mumtaz (2007). We postulate that Q follows an inverted Wishart distribution: $Q \sim IW\left(\overline{Q}^{-1}, T_0\right)$, where T_0 are the prior degrees of freedom which are set equal to the minimum value allowed for the prior to be proper, $T_0 = \dim(\theta_t) + 1$. Following Cogley and Sargent (2002), we adopt a relatively conservative prior for the time variation in the parameters setting the scale matrix to $\overline{Q} = (0.01)^2 \cdot \widehat{V}\left(\widehat{\theta}_{OLS}\right)$ multiplied by the prior degrees of freedom. This is a weakly informative prior and the particular choice for its starting value is not expected to influence the results substantially since the prior is soon to be dominated by the sample information as time moves forward adding more time variation. The four blocks of S are postulated to follow inverted Wishart distributions, with the prior degrees of freedom set equal to the minimum value required for the prior to be proper: $S_1 \sim IW\left(\overline{S}_1^{-1}, 2\right)$, $S_2 \sim IW\left(\overline{S}_2^{-1}, 3\right)$, $S_3 \sim IW\left(\overline{S}_3^{-1}, 4\right)$ and

$S_4 \sim IW\left(\overline{S}_4^{-1}, 5\right)$. As for the scale matrices, they are calibrated on the absolute values of the respective elements in $\widetilde{\alpha}_0$ as in Benati and Mumtaz (2007). Given the univariate feature of the law of motion of the stochastic volatilities, the variances of the innovations to the univariate stochastic volatility equations are drawn from an inverse Gamma distribution as in Cogley and Sargent (2005): $\sigma_i^2 \sim IG\left(\frac{10^{-4}}{2}, \frac{1}{2}\right)$.

MCMC algorithm (Metropolis within Gibbs sampler): Simulating the Posterior Distribution. Since sampling from the joint posterior is complicated, we simulate the posterior distribution by sequentially drawing from the conditional posterior of the four blocks of parameters: the coefficients θ^T, the simultaneous relations A^T, the variances H^T, where the superscript T refers to the whole sample, and the hyperparameters collectively referred to as V. Posteriors for each block of the Gibbs sampler are conditional on the observed data Y^T and the rest of the parameters drawn at previous steps.

Step 1: Drawing coefficient states

Conditional on A^T, H^T, V and Y^T, the measurement equation is linear and has Gaussian innovations with known variance. Therefore, the conditional posterior is a product of Gaussian densities and θ^Tcan be drawn using a standard simulation smoother (see Carter and Kohn 1994; Cogley and Sargent 2002) which produces a trajectory of parameters:

$$p\left(\theta^T \mid Y^T, A^T, H^T\right) = p\left(\theta_T \mid Y^T, A^T, H^T\right) \prod_{t=1}^{T-1} p\left(\theta_t \mid \theta_{t+1}, Y^T, A^T, H^T\right)$$

From the terminal state of the forward Kalman filter, the backward recursions produce the required smoothed draws which take the information of the whole sample into account. More specifically, the last iteration of the filter provides the conditional mean $\theta_{T|T}$ and variance $P_{T|T}$ of the posterior distribution. A draw from this distribution provides the input for the backward recursion at $T-1$ and so on until the beginning of the sample according to:

$$\begin{aligned} \theta_{t|t+1} &= \theta_{t|t} + P_{t|t}P_{t+1|t}^{-1}\left(\theta_{t+1} - \theta_t\right) \\ P_{t|t+1} &= P_{t|t} - P_{t|t}P_{t+1|t}^{-1}P_{t|t} \end{aligned}$$

Following Primiceri (2005) we do not impose a stability constraint on the draws obtained from the unconstrained normal distributions for the coefficient vector, i.e. we are not ruling out explosive behavior for our VAR since little posterior probability is associated with such a behavior.

Step 2: Drawing covariance states

Similarly, the posterior of A^Tconditional on θ^T, H^T, and Y^T is a product of normal densities and can be calculated by applying the same algorithm as in step 1 thanks to the block diagonal structure of the variance covariance matrix S. More specifically, a system of unrelated regressions based on the following relation: $A_t u_t = \varepsilon_t$, where ε_t are orthogonalized innovations with known time-varying variance H_t and $u_t = y_t - X_t'\theta_t$ are observable residuals, can be estimated to recover A^T according to the following transformed equations where the residuals are independent standard normal:

$$
\begin{aligned}
u_{1,t} &= \varepsilon_{1,t} \\
\left(h_{2,t}^{-\frac{1}{2}} u_{2,t}\right) &= -\alpha_{2,1}\left(h_{2,t}^{-\frac{1}{2}} u_{1,t}\right) + \left(h_{2,t}^{-\frac{1}{2}} \varepsilon_{2,t}\right) \\
\left(h_{3,t}^{-\frac{1}{2}} u_{3,t}\right) &= -\alpha_{3,1}\left(h_{3,t}^{-\frac{1}{2}} u_{1,t}\right) - \alpha_{3,2}\left(h_{3,t}^{-\frac{1}{2}} u_{2,t}\right) + \left(h_{3,t}^{-\frac{1}{2}} \varepsilon_{3,t}\right) \\
\left(h_{4,t}^{-\frac{1}{2}} u_{4,t}\right) &= -\alpha_{4,1}\left(h_{4,t}^{-\frac{1}{2}} u_{1,t}\right) - \alpha_{4,2}\left(h_{4,t}^{-\frac{1}{2}} u_{2,t}\right) - \alpha_{4,3}\left(h_{4,t}^{-\frac{1}{2}} u_{3,t}\right) + \left(h_{4,t}^{-\frac{1}{2}} \varepsilon_{4,t}\right) \\
\left(h_{5,t}^{-\frac{1}{2}} u_{5,t}\right) &= -\alpha_{5,1}\left(h_{5,t}^{-\frac{1}{2}} u_{1,t}\right) - \alpha_{5,2}\left(h_{5,t}^{-\frac{1}{2}} u_{2,t}\right) - \alpha_{5,3}\left(h_{5,t}^{-\frac{1}{2}} u_{3,t}\right) - \alpha_{5,4}\left(h_{5,t}^{-\frac{1}{2}} u_{4,t}\right) + \left(h_{5,t}^{-\frac{1}{2}} \varepsilon_{5,t}\right)
\end{aligned}
$$

Step 3: Drawing volatility states

Conditional on θ^T, A^T, and Y^T, the orthogonalized innovations $\varepsilon_t \equiv A_t\left(y_t - X_t'\theta_t\right)$, with $Var\left(\varepsilon_t\right) = H_t$, are observable. However, drawing from the conditional posterior of H^T is more involved because the conditional state-space representation for $\ln h_{i,t}$ is not Gaussian. The log-normal prior on the volatility parameters is common in the stochastic volatility literature but such a prior is not conjugate. Following Cogley and Sargent (2005, Appendix B.2.5) and Benati and Mumtaz (2007) we apply the univariate algorithm by Jacquier, Polson, and Rossi (1994) that draws the volatility states $h_{i,t}$ one at a time.[25]

Step 4: Drawing hyperparameters

The hyperparameters of the model can be drawn directly from their respective posterior distributions since the disturbance terms of the transition equations are observable given θ^T, A^T, H^T and Y^T.

We perform 50,000 iterations of the Bayesian Gibbs sampler but keep only every 10^{th} draw in order to mitigate the autocorrelation among the draws. After a "burn-in" period of 50,000 iterations, the sequence of draws of the four blocks from their respective conditional posteriors converges to a sample from the joint posterior distribution

[25] As opposed to Primiceri (2005) who uses the method proposed by Kim, Shephard and Chib (1998) which consists of transforming the non-Gaussian state-space form into an approximately Gaussian one by using a discrete mixture of normals. This linear transformation then allows to apply a standard simulation smoother conditional on a member of the mixture.

$p\left(\theta^T, A^T, H^T, V \mid Y^T\right)$. We have performed the usual set of convergence test (see Primiceri 2005; Benati and Mumtaz 2007) to ensure that our chain has converged to the ergodic distribution. In total, we collect 5000 simulated values from the Gibbs chain on which we base our structural analysis.

Impulse responses. Here we describe the Monte Carlo integration procedure we use to compute the path of structural impulse response functions to an excess liquidity shock. In the spirit of Koop, Pesaran and Potter (1996) we compute the generalized impulse responses as the difference between two conditional expectations with and without the exogenous shock:

$$IRF_{t+k} = E\left[y_{t+k} \mid \varepsilon_t, \omega_t\right] - E\left[y_{t+k} \mid \omega_t\right]$$

where y_{t+k} contains the forecasts of the endogenous variables at horizon k, ω_t represents the current information set and ε_t is the current disturbance term. At each point in time the information set we condition upon contains the actual values of the lagged endogenous variables and a random draw of the model parameters and hyperparameters. More specifically, in order to calculate the conditional expectations we simulate the model in the following way: We randomly draw one possible state of the economy at time t from the Gibbs sampler output represented by the time-varying lagged coefficients and the elements of the variance covariance matrix. Starting from this random draw from the joint posterior including hyperparameters, we stochastically simulate the future paths of the coefficient vector as well as the (components of the) variance covariance matrix based on the transition laws for 28 quarters into the future.[26] By projecting the evolution of the system into the future in this way, we account for all the potential sources of uncertainty deriving from the additive innovations, variations in the lagged coefficients and changes in the contemporaneous relations among the variables in the system.

Since we are identifying the excess liquidity shock as the only shock that does not have a contemporaneous effect on the other variables in the system, we compute the time-varying structural impact matrix as $B_{0,t} = A_t^{-1} H_t^{\frac{1}{2}} = chol\left(\Omega_t\right)$. Given this contemporaneous impact matrix, we compute the reduced-form innovations based on the relationship $u_t = B_{0,t}\varepsilon_t$, where ε_t contains five structural shocks obtained by drawing from a standard

[26] Alternatively, one could compute impulse responses based on the set of coefficients drawn from the Gibbs sampler at time t, i.e. assuming the parameters of the model to be fixed for horizon k over which one wants to study the dynamics of the system (see Primiceri 2005). In other words, one investigates the propagation of the shock given the present structure of the economy. Since this approach is closest to the exercises performed in Section 2.1 and 3.1, we have calculated impulse responses also in this way but there was no discernible difference in the results.

normal distribution. Impulse responses are then computed by comparing the effects of a shock on the evolution of the endogenous variables to the benchmark case without shock, where in the former case the shock is set to $\varepsilon_{i,t} + 1$, while in the latter we only consider $\varepsilon_{i,t}$. The reason for this is to allow the system to be hit by other shocks during the propagation of the shock of interest. For each point in time, we randomly draw 500 current states of the economy which provide the distribution of impulse responses taking into account possible developments of the structure of the economy. The representative impulse response function for each variable at each date is the median of this distribution.

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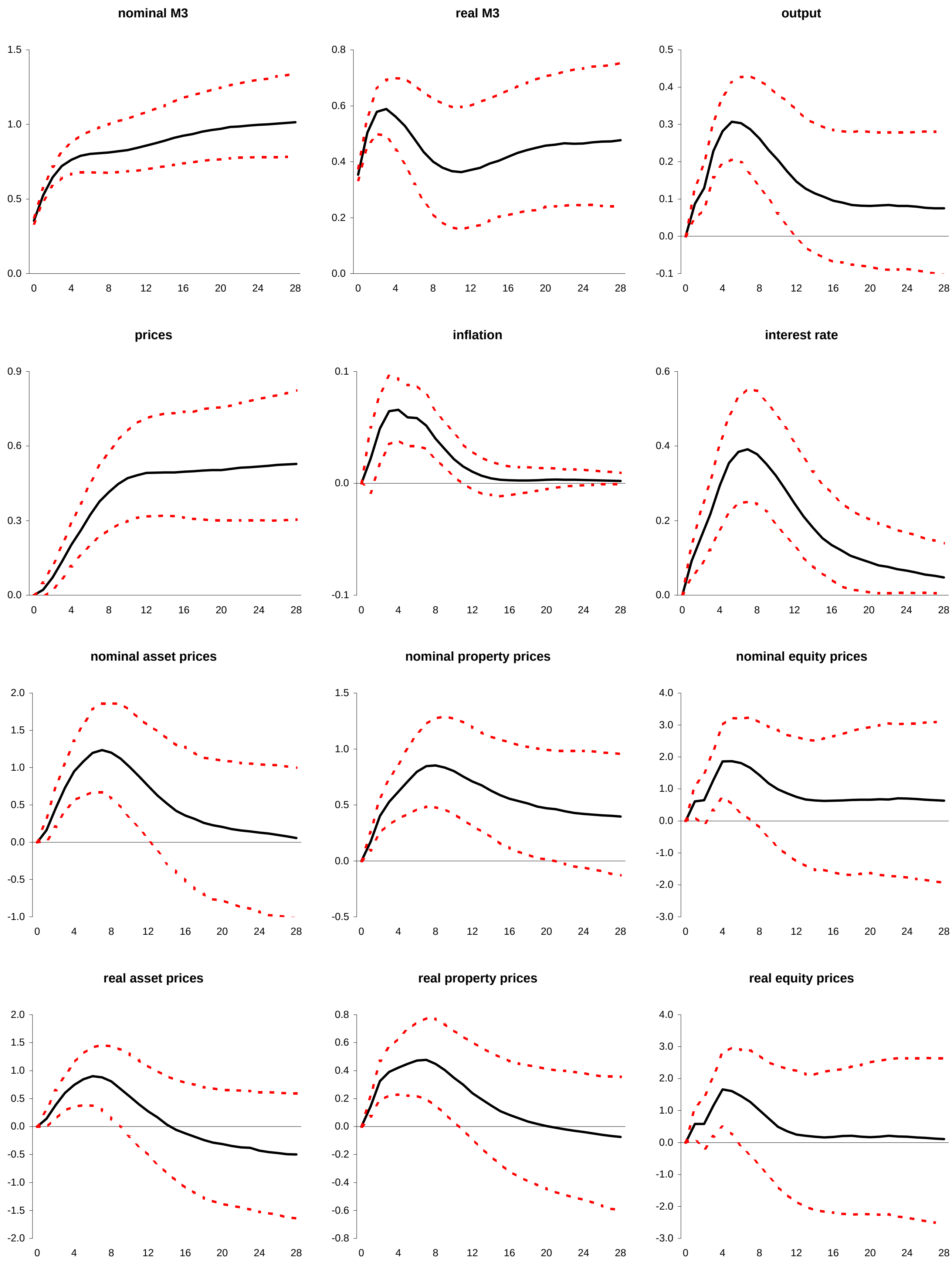
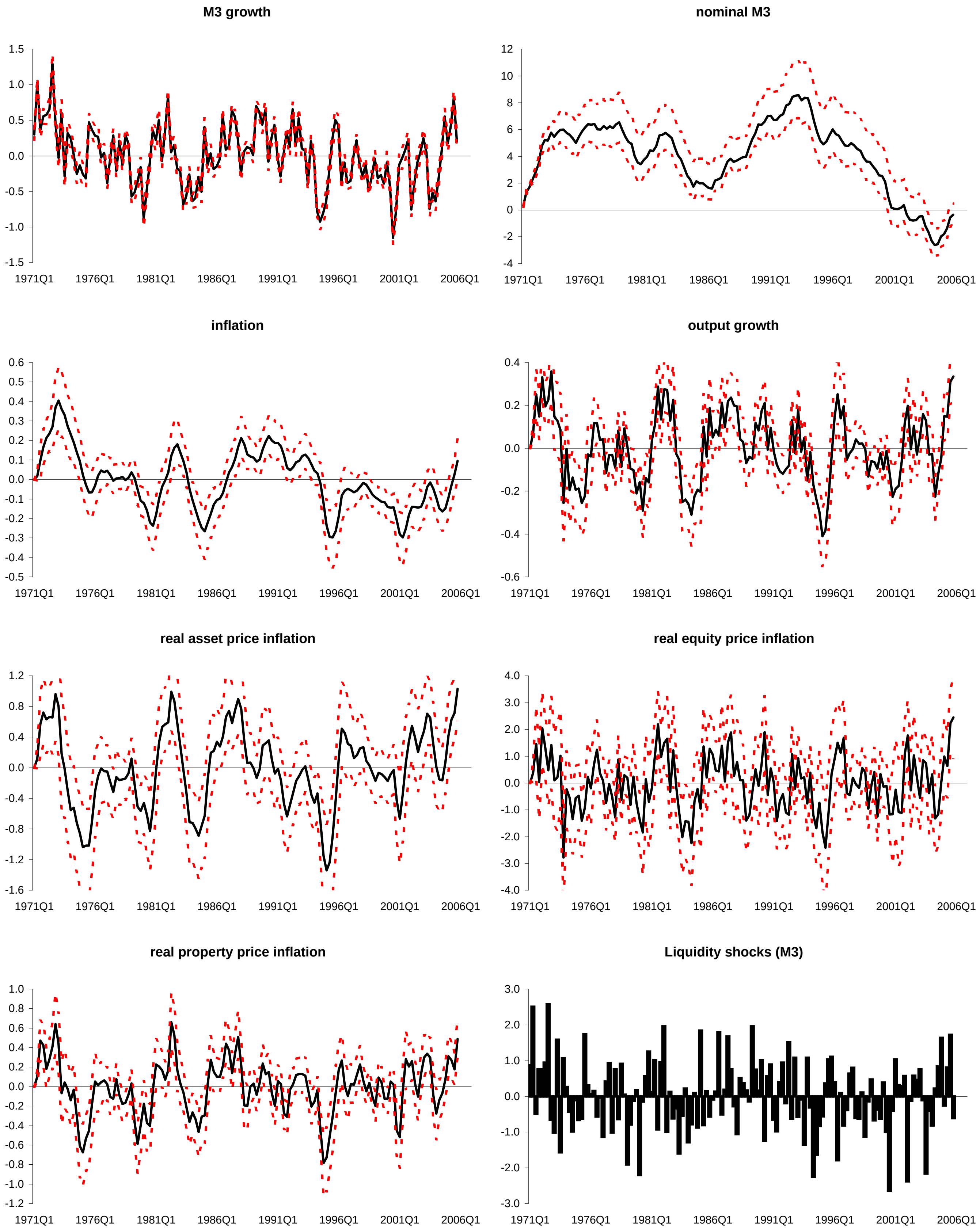
Figure 1: Benchmark model - Impulse responses to a liquidity shock (M3)



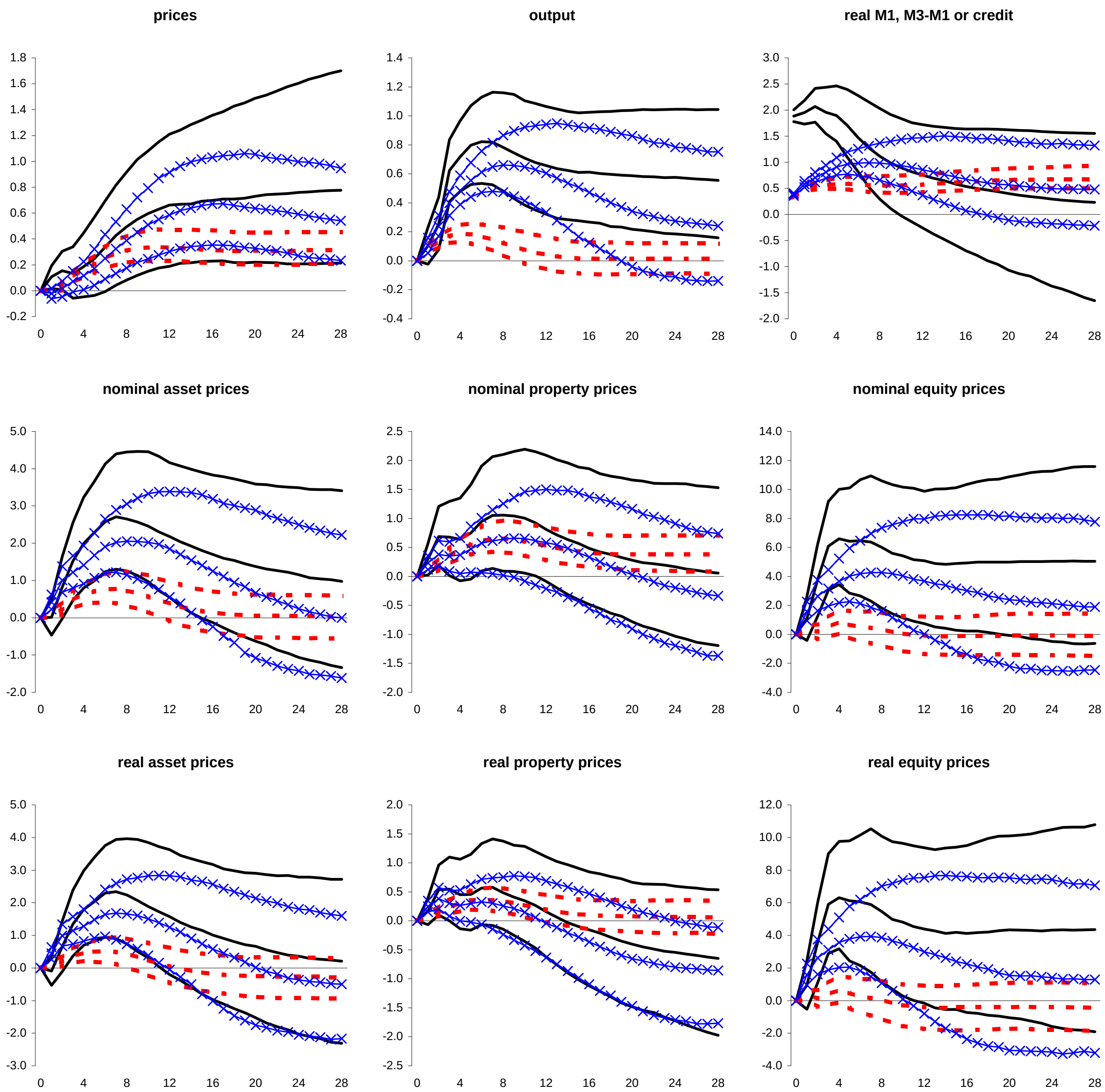
Note: sample period 1971Q1-2005Q4, separate estimations for asset, property and equity prices
median of the posterior together with 16th and 84th percentiles

Figure 2: Historical contributions of liquidity shocks (M3)



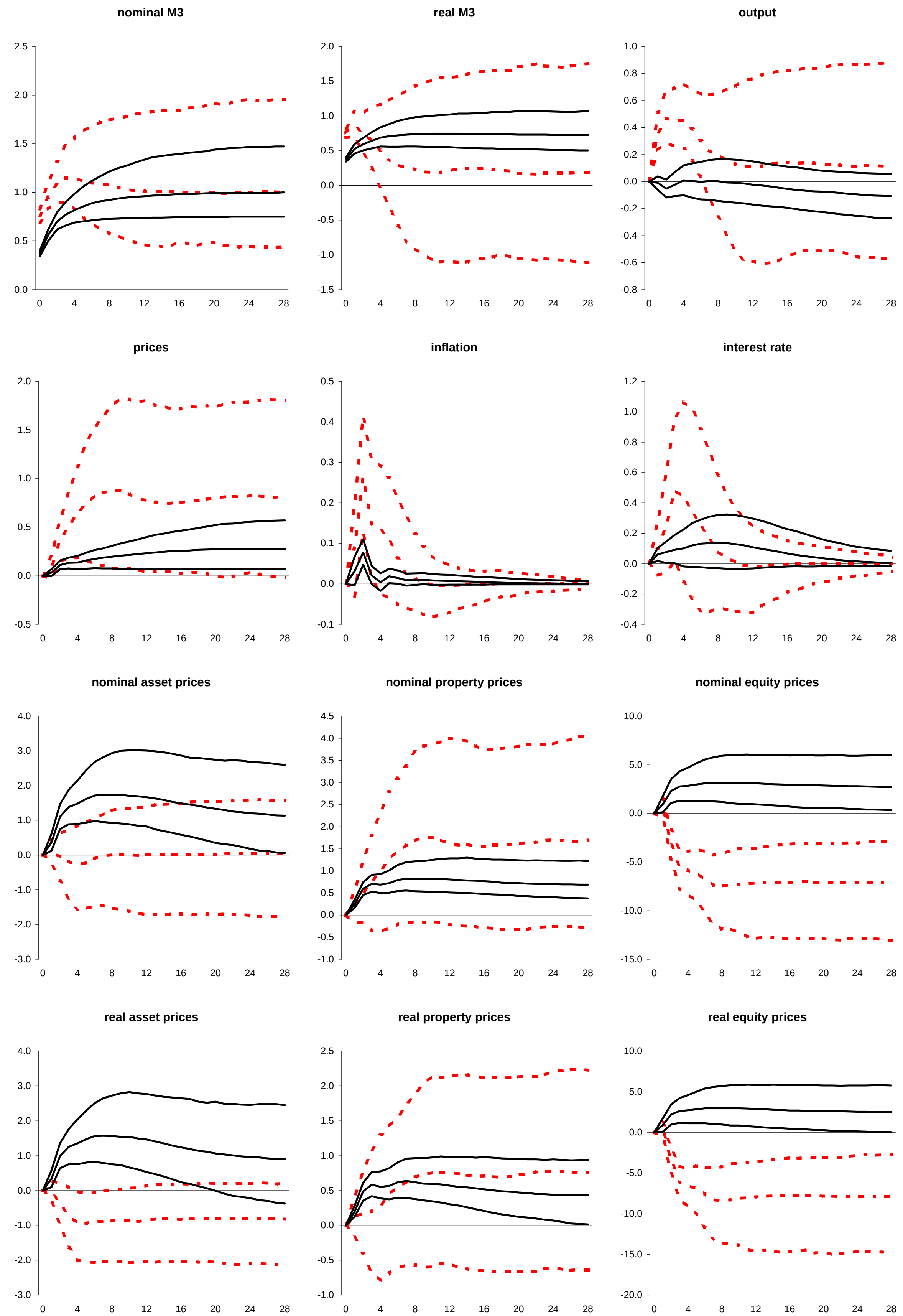
Note: benchmark model, separate estimations for asset, property and equity prices
median of the posterior together with 16th and 84th percentiles

Figure 3: Impulse responses for a 1% long-run increase in M1, M3-M1 and credit



Note: sample period 1971Q1-2005Q4, separate estimations for asset, property and equity prices
median of the posterior together with 16th and 84th percentiles
M1 responses: full (black) lines, M3-M1 responses: dotted (red) lines, credit: blue (crossed) lines

Figure 4: Sample split - Impulse responses for a 1% long-run increase in M3



Note: sample periods are respectively 1971Q1-1984Q4 (red dotted lines) and 1985Q1-2005Q4 (black full lines), separate estimations for asset, property and equity prices, median of the posterior together with 16th and 84th percentiles

Figure 5: Time-varying median impulse responses of nominal and real M3 after a one-standard-deviation excess liquidity shock

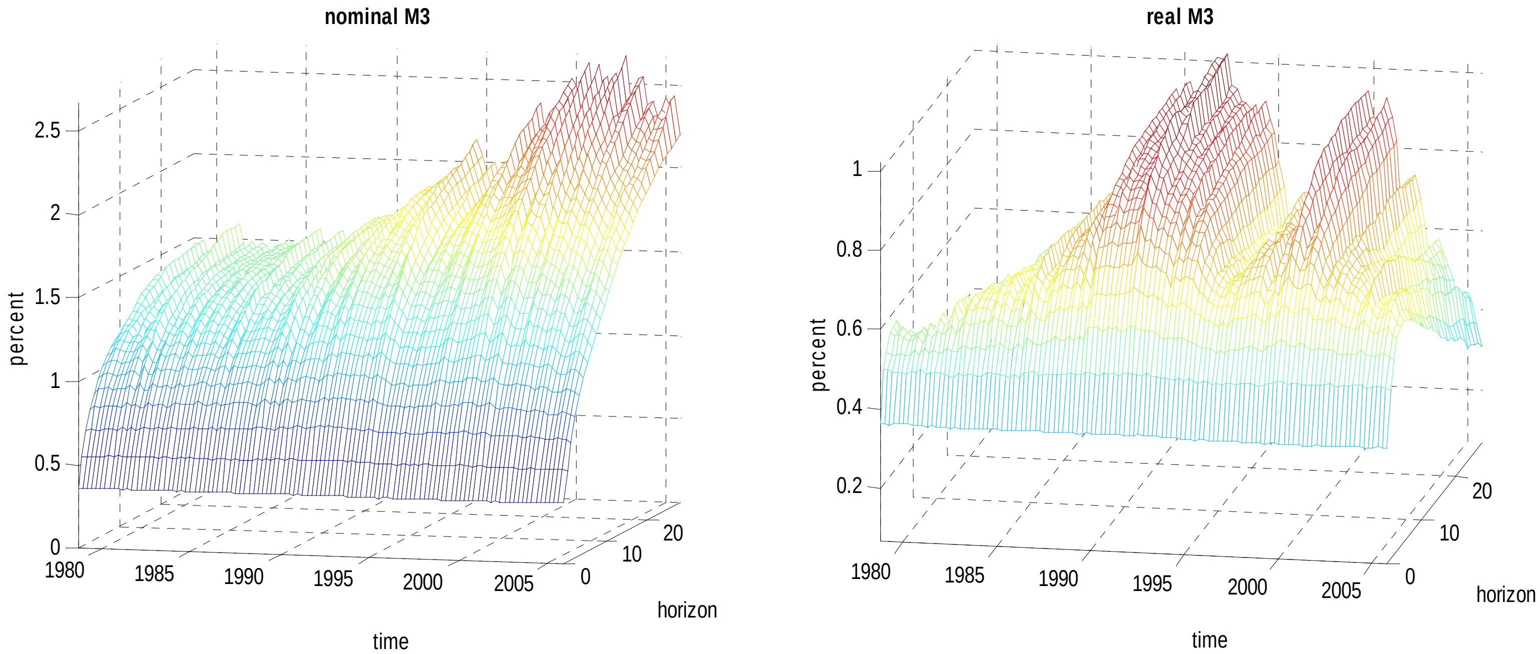


Figure 6: Time-varying median impulse responses for a 1% long-run increase in M3

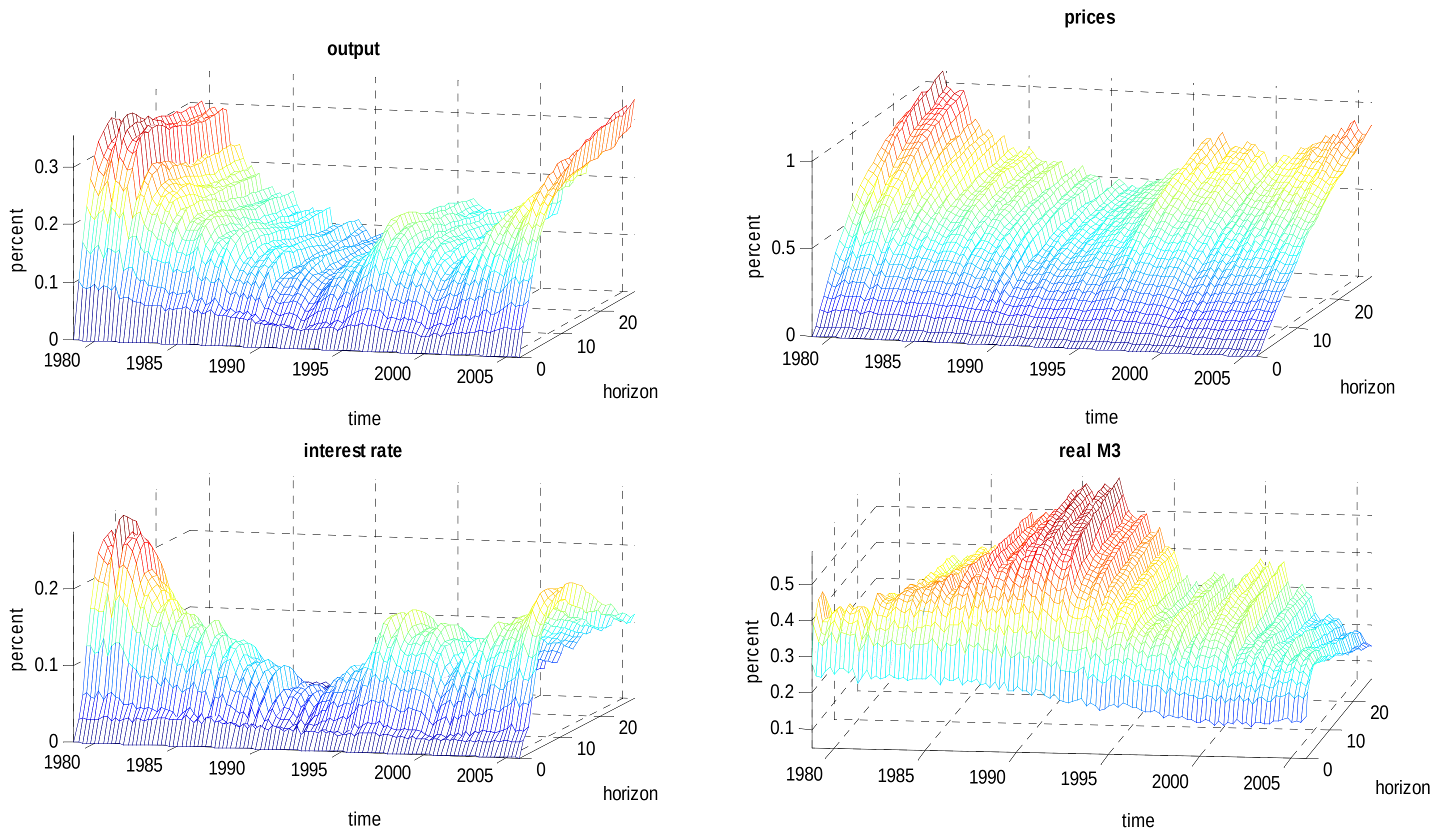


Figure 6 continued: Time-varying median impulse responses for a 1% long-run increase in M3

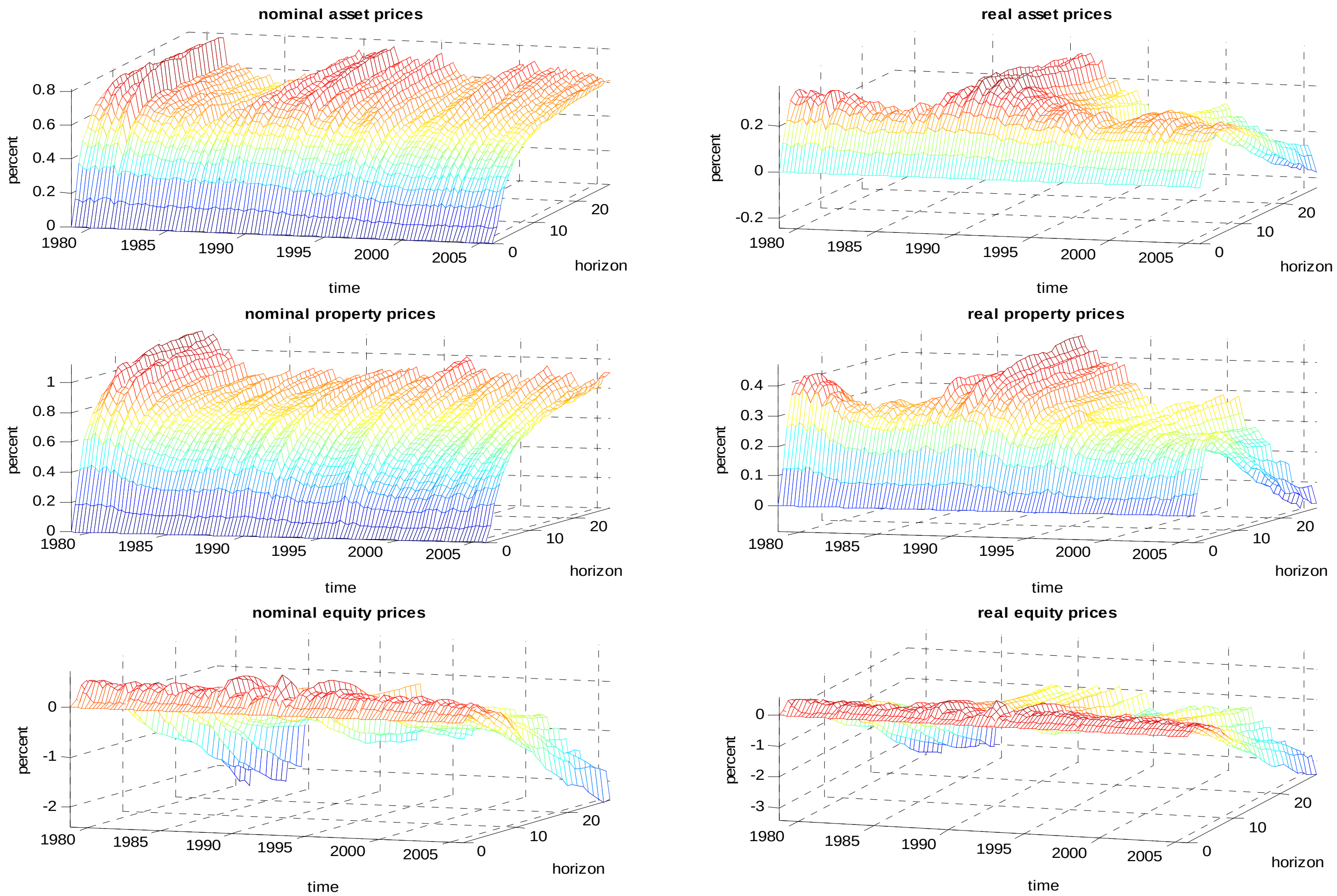
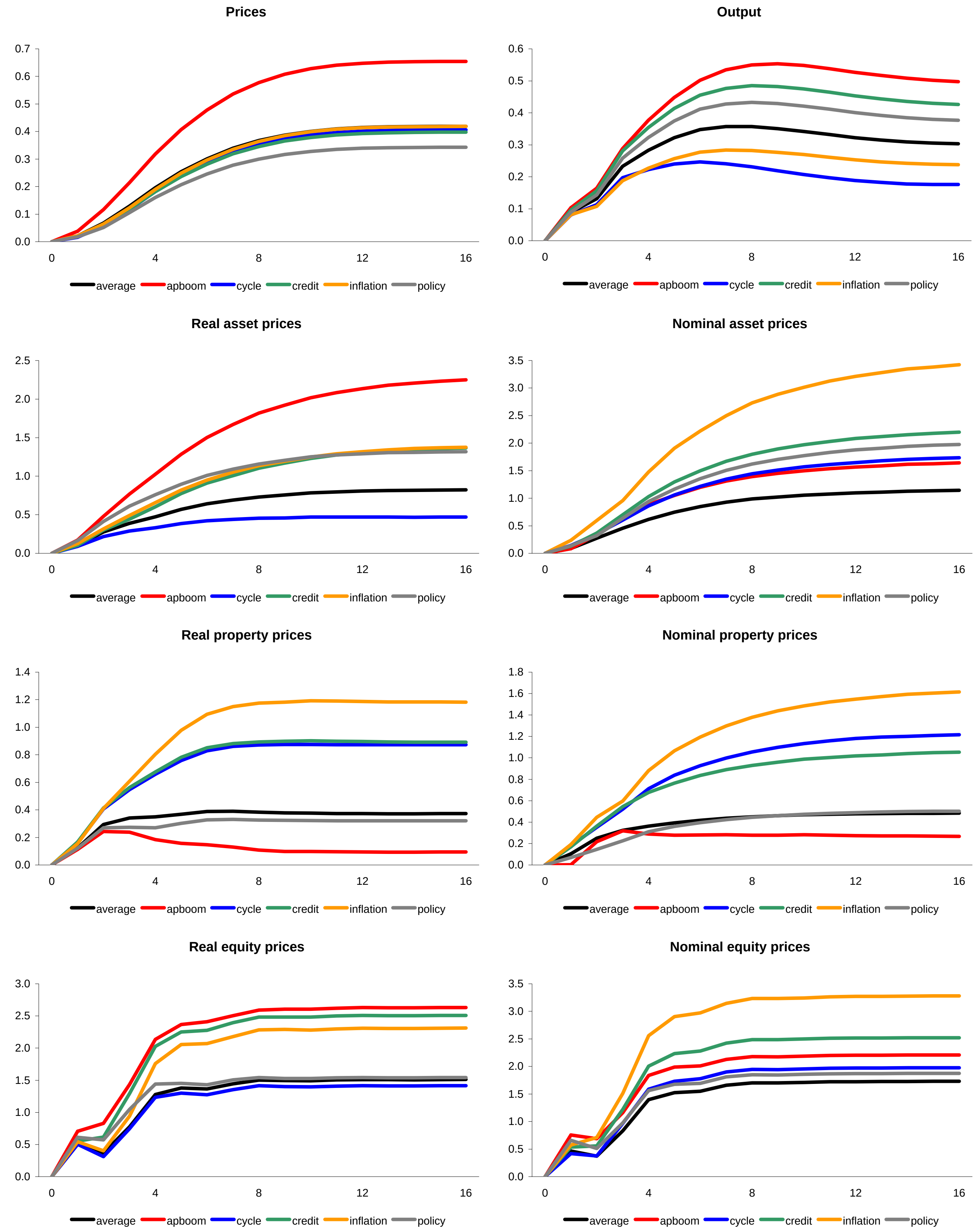


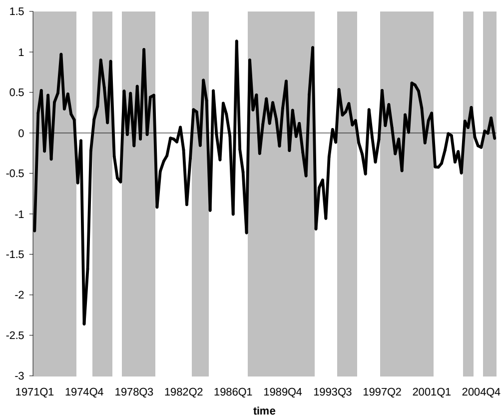
Figure 7: Single equations - Responses to a one standard deviation liquidity shock (baseline specification)



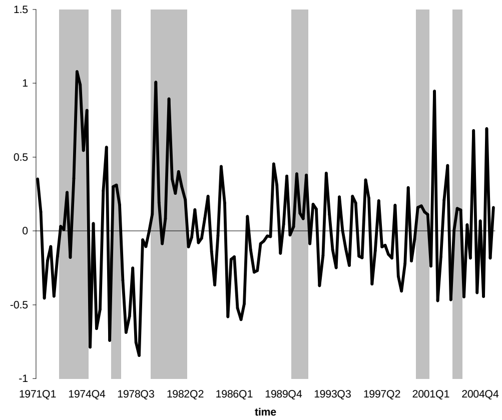
Note: "average" is the average impact for the whole sample period not allowing for differences across states, "apboom" is the impact in an asset prices boom, "cycle" in an economic boom, "credit" in a credit boom, "inflation" in an inflation boom and "policy" in periods of restrictive monetary policy

Figure 1A: Indicators

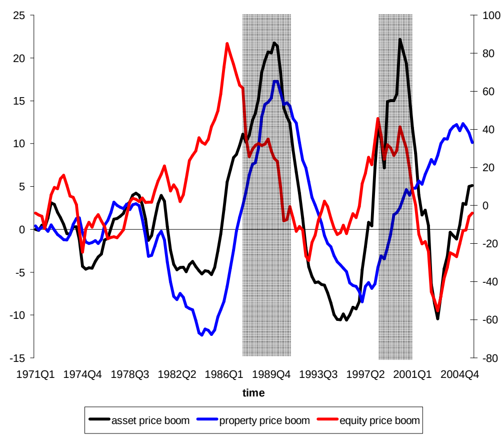
economic boom



inflation boom

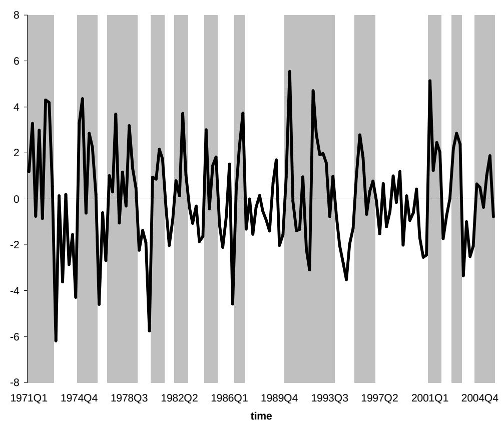


asset price boom

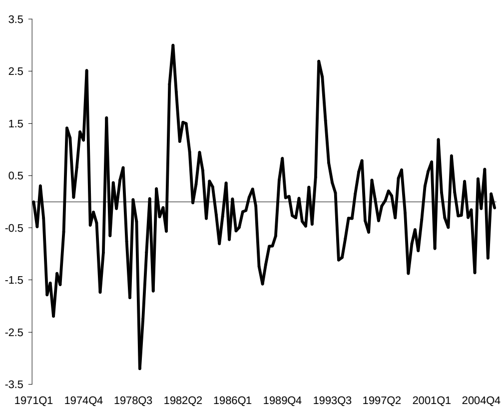


Source: Bank of International Settlements
Note: the left-hand scale refers to aggregate asset prices and property prices, the right-hand scale to equity prices

credit boom



monetary policy stance



Note: the grey bars indicate the boom periods of each indicator variable as defined in the text

Table 1: Single equation estimations

	Output growth	Inflation	Asset prices growth nominal	Asset prices growth real	Property prices growth nominal	Property prices growth real	Equity prices growth nominal	Equity prices growth real
Average impact across all states								
	0.071 (0.010)	0.082 (0.013)	0.274 (0.089)	0.117 (0.041)	0.179 (0.061)	0.095 (0.033)	0.927 (0.155)	0.680 (0.108)
Impact depending on state at time of shock								
asset prices boom	0.053 (0.021)	0.058 (0.021)	0.136 (0.190)	0.227 (0.103)	-0.069 (0.173)	-0.078 (0.074)	0.325 (0.313)	0.629 (0.621)
economic boom	-0.070 (0.026)	-0.006 (0.023)	0.306 (0.242)	-0.108 (0.116)	0.556 (0.168)	0.298 (0.080)	0.340 (0.514)	-0.089 (0.338)
credit boom	0.058 (0.023)	-0.009 (0.024)	0.462 (0.279)	0.154 (0.149)	0.363 (0.172)	0.257 (0.084)	0.922 (0.526)	0.975 (0.347)
inflation boom	-0.018 (0.025)	-0.001 (0.020)	0.631 (0.196)	0.095 (0.099)	0.461 (0.127)	0.258 (0.080)	1.168 (0.329)	0.473 (0.286)
restrictive monetary policy stance	0.031 (0.017)	-0.028 (0.017)	0.343 (0.186)	0.123 (0.106)	0.015 (0.128)	-0.021 (0.064)	0.150 (0.362)	0.028 (0.292)
Impact depending on current state								
asset prices boom	0.018 (0.023)	0.093 (0.023)	0.429 (0.241)	0.230 (0.112)	-0.011 (0.189)	-0.085 (0.083)	0.473 (0.413)	0.537 (0.289)
economic boom	-0.036 (0.026)	-0.004 (0.023)	0.100 (0.217)	0.072 (0.104)	0.350 (0.161)	0.329 (0.089)	-0.061 (0.487)	0.339 (0.360)
credit boom	0.046 (0.022)	0.035 (0.019)	0.403 (0.247)	0.292 (0.127)	0.303 (0.157)	0.249 (0.072)	0.897 (0.505)	1.130 (0.313)
inflation boom	-0.047 (0.020)	-0.006 (0.015)	0.051 (0.180)	0.022 (0.113)	-0.084 (0.171)	0.002 (0.088)	-0.430 (0.402)	-0.127 (0.294)
restrictive monetary policy stance	-0.009 (0.018)	-0.036 (0.015)	-0.080 (0.180)	0.034 (0.088)	-0.186 (0.138)	-0.060 (0.058)	0.277 (0.311)	-0.129 (0.214)
Alternative regimes								
boom in own cycle for PP and EP								
impact depending on state at time of shock	0.053 (0.021)	0.058 (0.021)	0.136 (0.190)	0.227 (0.103)	-0.023 (0.203)	-0.060 (0.073)	0.677 (0.252)	0.345 (0.212)
impact depending on current state	0.018 (0.023)	0.093 (0.023)	0.429 (0.241)	0.230 (0.112)	-0.036 (0.189)	-0.065 (0.072)	0.034 (0.275)	0.019 (0.236)
asset prices bust								
impact depending on state at time of shock	0.026 (0.016)	-0.016 (0.015)	0.580 (0.196)	0.250 (0.096)	0.250 (0.134)	0.296 (0.062)	1.118 (0.308)	0.805 (0.251)
impact depending on current state	0.013 (0.022)	-0.027 (0.016)	0.013 (0.213)	0.074 (0.104)	0.012 (0.173)	0.192 (0.075)	0.056 (0.409)	0.149 (0.364)
rising cumulative excess liquidity								
impact depending on state at time of shock	0.028 (0.024)	0.044 (0.023)	0.589 (0.302)	0.326 (0.149)	0.236 (0.159)	0.134 (0.071)	0.876 (0.532)	1.154 (0.366)
impact depending on current state	0.037 (0.021)	-0.010 (0.021)	0.367 (0.270)	0.346 (0.136)	0.197 (0.170)	0.127 (0.074)	0.349 (0.495)	0.830 (0.317)
Negative versus positive liquidity shocks								
	0.060 (0.039)	-0.061 (0.043)	1.229 (0.375)	0.339 (0.190)	0.963 (0.264)	0.346 (0.110)	2.629 (0.592)	1.233 (0.458)

Note: figures are sum of coefficients of additional impact being in the respective state compared to ***not*** being in this state, standard errors between parenthesis