Funding Conditions, Asset Prices, and Macroeconomic Dynamics: Some U.S. Evidence

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Abstract

Funding liquidity, i.e., the ease with which firms, investors and consumers can obtain funding, is a key property of the monetary transmission mechanism. This paper is an empirical assessment of the role played by various measures of credit availability in shaping the dynamics of asset prices and the fluctuations of real activity in the US. We find that changes in funding conditions are more tightly associated with future asset valuations than with developments in key macroeconomic aggregates. This highlights some potentially destabilising properties in recent liquidity cycles.

Keywords: Business cycle, asset prices, funding conditions, monetary policy.

JEL Codes: E44, E51, G1.

1 Introduction

Financial liberalization and innovation, the establishment of credible anti-inflationary policies, and global market integration are often credited with the emergence of a benign macroeconomic environment between 1984 and 2006 (the "Great Moderation"). At the same time, it is now tempting to look into those very same conditions as to the origins of the widespread 2007-2009 downturn, the worst in decades. The financial crisis was triggered in the US by a collapse of the asset-backed securities market, in particular of the segment linked to property prices. This acted as a catalyst for various macro and micro imbalances, leading to a severe and prolonged recession. One paramount question pertains the relationship between credit and asset markets. Was the "irrational exuberance" in property prices the detonating imbalance, or should one blame excessively easy access to credit for a marked departure of various asset prices from their "fundamental" valuations?

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This paper examines the role of funding conditions in the interplay between asset prices and the level of economic activity, using US data. We perform an empirical investigation of the effects of changes in the availability of credit on asset valuations and the business cycle. With an eye to the troublesome events that led to the 2007-2009 financial and economic crisis, but over a longer time-series perspective, our analysis is motivated by the need to explore the interaction between funding conditions, asset prices and the level of economic activity. In brief, we search for answers to two questions: Is credit availability a leading indicator for future output developments? To what extent do shocks to funding liquidity cause or reinforce asset price booms rather than just reflect an endogenous reaction of the business cycle? To this end, we study the descriptive ability of various measures of funding conditions for the dynamics of house prices and equity market valuations and fluctuations in real activity. We explore the correlation and causation structure of a few measures of funding conditions with aggregate asset prices and the level of economic activity in 1975-2008 US data. We select three indicators of the availability of credit in the economy: the ratio of credit to GDP, the size (relative again to GDP) of the balance sheet of market-based banking institutions (broker-dealers' total assets), and the yield spread between Moody's seasoned Baa and Aaa corporate bonds. Whilst the first and third measures directly reflect the liquidity conditions prevailing in the economy, we employ the size of broker-dealer assets as a result of the increased importance of such intermediaries as marginal providers of credit. We perform multivariate Granger-causality tests to gauge the leading indicator properties of funding conditions for a broad set of macroeconomic and asset price variables. In particular, we look at the aggregate behaviour of house and equity prices, and at developments in personal consumption expenditure, residential and non-residential investment, and inflation. We find that funding liquidity does hold helpful information for future growth in both macroeconomic variables and asset valuations, and that the change in equity valuations predict future developments in funding conditions. Next, we evaluate the dynamic responses of this set of variables to orthogonalised shocks in the context of estimated Vector Autoregressions (VAR). The main finding of our exercises is that the expansionary effects of credit growth are significant and much more sizeable for asset prices than for consumption and investment. Also, on average, changes in funding conditions tend to be more tightly associated with future asset valuations than with developments in key macroeconomic aggregates. Results also confirm the existence of a positive feedback loop from asset valuations to credit availability, on to asset prices again. Finally, the response of equity and house prices to expansionary monetary conditions is stronger following shocks in credit availability than after conventional interest-rate shocks. Overall, this evidence reveals some potentially destabilising properties in the transmission of recent expansions in funding liquidity.

The outline of this paper is as follows. Section 2 discusses the literature background of our investigation and motivates the methodology we use. In Section 3 we assess the leading indicator properties of our measures of funding conditions by means of Granger causality tests,

while Section 4 presents VAR estimation results. Section 5 concludes.

2 Literature Background and Methodology

Asset markets play a key role in the monetary transmission mechanism. Besides matching demand for and supply of funds for investment and consumption, they facilitate the diversification of risk and process information on expected future cash flows and monetary policy. Widely held accounts of this transmission mechanism attribute a special role to market revisions of the expected policy stance: news about policy interest rates and banks' reserve holdings alter the risk-return trade-offs of investment opportunities and their pricing. In turn, this shapes current and future developments in the level of real economic activity along several dimensions.

When a permanent change in asset prices occurs, one is likely to observe adjustments in both credit demand and supply, through wealth and collateral effects (see Bernanke, 2007, and ECB, 2008, for a summary). For instance, a permanent increase in wealth following substantial growth in asset values might lead to an increase in spending and borrowing, as households attempt to smooth consumption out over their life cycles. In addition, assets are commonly used as collateral, which means that higher asset prices might induce firms and households to spend more, not least because of their enhanced borrowing capacity. Firms' investment decisions could follow a similar pattern, as might also traders' funding. Therefore, one might find not only an intuitive causal relationship from economic activity to credit and on to asset price changes and valuations, but also a positive feedback response of asset prices on to credit availability and so forth, along a mutually reinforcing, and potentially destabilising, loop.

Recent empirical research has focused on the dynamics followed by asset price valuations and economic growth when they are preceded by large changes in the availability of credit (Borio and Lowe, 2004; Adalid and Detken, 2007; Mendoza and Terrones, 2008; Adrian, Moench and Shin, 2010). Most studies rely on a mechanistic identification of boom/bust episodes, and investigate the macroeconomic environment leading to and following such episodes. However, results appear to be far from conclusive.

In a pioneering study of this literature, Borio and Lowe (2004) assessed the information content of credit and financial imbalances for future inflation and output. The authors uncovered evidence that the larger the imbalances in the boom phases, the greater the likelihood of subsequent output weakness and disinflation. In addition, credit developments emerged as more helpful than money in signalling the build-up of macroeconomic risks. Kannan et al. (2009) find that inflation, output and the stance of monetary policy do not typically display unusual behavior ahead of asset price busts. By contrast, credit, shares of investment in GDP, current account deficits, and some asset valuations typically rise, proving to be useful, if not perfect, leading indicators of broad asset price busts.

On the other hand, Adalid and Detken (2007) find that while shocks to money and private

credit growth are a driving factor of real estate prices during boom episodes, in normal times both variables turn out to be poor indicators for developments in asset prices, inflation and output. In turn, Assenmacher-Wesche and Gerlach (2010) study quarterly data spanning 1986–2008 for a panel of 18 countries and argue that their measures of financial imbalances contain little information useful for forecasting future economic conditions.

Our methodology departs from the event-study approach, common to most of the extant literature, as we do not focus just on boom/bust episodes. While we acknowledge that the response of asset prices and the macroeconomy to funding conditions might depend on whether asset markets experience positive or negative trends, we think there are at least three good reasons to adopt a more structural time-series approach. First, historically the financial imbalances at the origin of boom/bust episodes have tended to build up slowly, and trigger macroeconomic consequences along diverse paths (think of the dotcom bubble at the end of the 1990s or the boom of house prices in the 2000s). If buoyant credit conditions caused asset price increases that were not followed by significant expansions in real activity, this configuration would reveal an important bias in the transmission of monetary shocks. An approach that uncovers key dynamic relationships between the variables rather than static correlations in correspondence of mechanistically-determined episodes seems more appropriate. Second, endogeneity and the direction of causality between the variables are crucial aspects of the problem. Therefore, a VAR approach emerges as more appropriate than single-equation or more unrestricted analyses. Finally, we focus just on the US because of the depth of its asset markets and its incidence on worldwide monetary and macroeconomic trends. This means that both event-study and panel perspectives would likely blur the main insights we are looking for.

On aggregate and in the long run, the dynamics of equity and house prices should be tied to real variables such as productivity, profitability and demographic factors, with no or little correlation with changes in nominal aggregates like money supply and credit. Positive shocks to funding conditions should only drive the transitory components of asset prices. However, over recent financial cycles, the financial sector's balance sheet appeared to be particularly vulnerable to fluctuations in asset markets, which in turn likely affected business-cycle developments. This anecdotal evidence points to the size and composition of the balance sheet of financial intermediaries as playing an important role in regulating aggregate demand, via their impact on credit availability for investment and consumption.

Funding liquidity, i.e., the ease with which firms, investors and consumers can obtain funding (Brunnermeier and Pedersen, 2009), is tied to economic fluctuations through several channels. For instance, firms' borrowing capacity depends on their collateralized net worth. Well-known theoretical literature on the credit (balance sheet) channel shows that fluctuations in firms' net worth amplify macroeconomic shocks and can give rise to a financial accelerator effect (Bernanke et al. (1996)). Since changes in the level of economic activity are conditional on the general funding conditions in the economy, it is important to measure the impact that

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credit expansions have on asset prices, besides what is implied by the current level of interest rates, inflation and output. Some promising research has focused on the risk-taking attitude of banks, which might depend on the monetary-policy stance as well as on the market value of collateral assets, as priced in other financial markets like interbank, equity and bond segments (see Borio and Zhu, 2008, and Dell'Ariccia et al., 2010). Marked variations in these values affect real activity because they change the profitability of financial intermediaries, thus driving the supply of credit to the economy. This might induce destabilising pro-cyclicality in lending standards. In addition, monetary policy operations that provide liquidity might directly affect asset prices, thereby driving a wedge between actual and expected returns, which in turn may induce a "search for yield" across a wider array of assets[1].

In recent years, commercial banking and financial intermediation in the US and other advanced countries have witnessed a marked increase in the importance of market-making activity, security underwriting, and market-based intermediation. These shifts have fostered innovative credit transfer activity and blurred the traditional distinction between the functioning of banks and capital markets. Recent studies in this area (see for instance Adrian and Shin, 2009, 2010, 2011) have argued that there are important reasons why the balance sheet of broker-dealer (BD) intermediaries offers in principle a better gauge than traditional money-supply measures for funding conditions in the economy. For instance, Adrian and Shin (2009) show that asset growth in BD balance sheet is strongly correlated with the marginal availability of credit, much more directly than it is with commercial banks' balance sheet. The latter is more affected by relationship-based, as opposed to short-term, market lending. BD are marginal suppliers of credit, therefore their balance sheets closely reflect the financing constraints faced by firms and individuals. Moreover, credit is generally recorded at book value, whereas BD asset growth is marked to market. Finally, capital and margin requirements of traders depend on overall market liquidity. Brunnermeier and Pedersen (2009) show that under certain conditions, market and traders' liquidity become pro-cyclical and destabilizing.

According to all these features, credit supply or funding conditions have become conditional on key institutional features like securitization, which enables credit expansion through higher leverage of the financial system as a whole. Indeed, Adrian and Shin (2010) also document that BD asset growth is positively associated with leverage growth, which suggests the existence of a two-way feedback from asset prices growth to leverage, leading to boom-bust cycles, persistence in asset valuations and in their rate of growth, and the potential disconnect of their dynamics from economic fundamentals (see also Geanakoplos, 2010).

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[1]It has also been argued that if financial intermediaries and market participants expect some kind of "insurance" from the central bank against downside risks to asset prices, this may lead to moral hazard issues in the form of excessive risk-taking on average over the business cycle and particularly during expansions.

2.1 Methodology

The debate concerning the direction of causality between financial stress and economic down-turns is far from settled. The contrast among existing studies reveals that the search for clear-cut results is inherently problematic. Most contributions have looked at past banking crisis to iden-tify a set of stylized facts across countries experiencing financial distress. To measure financial imbalances, several authors compute asset-price and credit 'gaps' that are often defined as de-viations of prices and credit from one-sided trends. This kind of event analysis has not only obvious pitfalls as far as precision, robustness and the ability of drawing general conclusions are concerned, but it also fails to provide unambiguous evidence on causality [2].

Borio and Lowe (2002) assess the potential role that developments in asset prices and credit could play as indicators of financial vulnerability. They also show that, in contrast with the use of individual indicators of credit expansion or asset prices booms, it is their joined realization that raises the likelihood of a financial crisis. This lends clear support to an econometric strategy that builds on endogeneity and simultaneity to uncover correlations and dynamic causation relationships.

In this paper we assume that the following variables are endogenously determined at the quarterly frequency:

$$X_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, FUND, \Delta ASP)^{'}$$

Δ denotes the 4-quarter logarithmic difference, PCE is real personal consumption expendi-ture, INV is real investment, CPI is the consumer price index, INT is the Eurodollar interest rate, $FUND$ is an indicator of funding conditions and ASP is a measure of asset market val-uation. Real aggregate expenditure on investment is either residential (RI), or non-residential investment (NRI). The indicators of funding conditions are the log change in either credit (CR) or broker-dealer total financial assets (BD), both measured as fractions of GDP, and the yield spread between Moody's seasoned Baa and Aaa corporate bonds (SPR). ASP represents, alter-natively, the (4-quarter log difference) in the ratio of the value-weighted S&P Composite stock market index to the 10-year-trailing average of earnings, or cyclically-adjusted price/earnings ratio[3] (PE), or the analogous log change in the Real House Price Index (HPI). The sample spans 1975Q1 to 2008Q1 (see the Data Appendix for full details about the measurement and construction of the variables).

Our investigation of the dynamic interactions between liquidity, asset prices, and key macro-economic variables involves two exercises. First, we study the leading indicator properties of

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[2] A recent example is provided by Reinhart and Rogoff (2008, 2009). Since, in most cases, asset price and credit booms are associated with periods of economic turbulence, a growing literature has also focused on characterising real and financial developments around identified episodes of asset price or credit booms. Recent contributions include Detken and Smets (2004), Adalid and Detken (2007), Mendoza and Terrones (2008), Kannan and Rabanal (2009), Gerdesmeier, Reimers and Roffia (2010).

[3] The series is calculated by R. Shiller, http://www.econ.yale.edu/~shiller/data.htm

funding conditions for a broad set of macroeconomic and asset prices variables. This task is accomplished by means of multivariate Granger non-causality tests. Next, we analyse the dynamic responses of the set of endogenous variables to orthogonalised shocks. This second task requires the study of Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD) of the estimated VAR.

While performing Granger causality tests only requires an unrestricted VAR model, in order to recover the orthogonalised shocks and the variance decomposition we need an appropriate identification scheme. On the one hand, we could use all the explicit and implicit restrictions provided by a structural model to identify orthogonalised shocks that could then be interpreted as structural shocks. The drawback is that this requires a complex and questionable identification scheme based on a combination of long- and short-run information or sign restrictions. The lack of a reference theoretical framework would force us to estimate a much smaller model. Alternatively, we could use a semi-automatic identification scheme to orthogonalise the impulses, the most popular being a Cholesky decomposition of the estimated VAR disturbance vector. Here, the drawback is that the Cholesky factor is unique only for a given order of the variables.

Pesaran and Shin (1998) suggested the use of Generalized Impulse Responses (GIRFs), which we adopt. The generalized impulse responses from an innovation to the j-th variable are derived by applying a variable-specific Cholesky factor computed with the j-th variable at the top of the Cholesky ordering. Robustness checks reveal that using a traditional Cholesky decomposition with different variables ordering does not substantially affect the results. Unlike for GIRFs, the variance decomposition of forecast errors will still depend on the variables' ordering. We work out the FEVD of the system based on a Cholesky decomposition with the ordering as given above. While the ordering of consumption, investment and inflation is standard in monetary VARs, the one chosen for interest rates, liquidity and asset prices block is based on the evidence that asset prices respond quickly to macroeconomic and financial conditions. This choice dampens the impact of asset price shocks on the system; the interpretation of our findings will account for this potential bias[4].

Given some data constraint at the quarterly frequency, the estimation sample cannot start before 1975Q1. Relative to a cross-country perspective, estimating the VAR for the US drastically reduces the number of variables that we can include in the system. Therefore, we include only six variables but we estimate alternative VAR specifications using different indicators of liquidity and asset prices, and alternative investment series. Goodhart and Hofmann (2008) estimate a fixed-effects panel VAR, with a vector of endogenous variables similar to ours, for 17

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[4]Most of the literature estimates these type of VARs in level rather than in differences. Marcet (2005) argues that a VAR in differences might be a more robust alternative to testing for unit roots and eventually estimating Vector Error Correction Models. However, as suggested by Jarocinski and Smets (2008), a VAR in growth rates discards important sample information contained in the level variables. This may be the main reason for larger error bands around impulse responses usually found in differences-VAR. Following this consideration, we also estimate a more traditional specification of the VAR in level. We find qualitatively similar results. Results from the level VAR are available upon request.

industrialized countries including the US. However, as the authors acknowledge, the problem with the panel approach is that it imposes pooling restrictions across countries, discarding key cross-country differences in the estimated dynamic relationships. Indeed, they find that the pooling restrictions implied by the panel model are rejected, indicating that these idiosyncratic effects are important.

Finally, at least two caveats of the VAR methodology we use are worth noting. First, it is difficult to evaluate if our attempt to address the endogeneity issue using a semi-automatic identification technology has been successful in isolating funding conditions shocks. Second, since the VAR methodology is a linear one, it is not suitable to address asymmetric, non-linear, and time-varying behaviour potentially associated with asset price dynamics.

3 Do Funding Conditions Granger-Cause Real Activity and Asset Prices?

We study the leading-indicator properties of funding conditions for macroeconomic variables at the quarterly frequency by means of Granger non-causality tests. In general, a variable x is said to Granger-cause variable y if the former helps in predicting future realizations of y. In a multivariate VAR setting, Granger-causation implies that the hypothesis that the coefficients of the lags of variable x in the VAR equation of variable y are all equal to zero is rejected by a Wald test. Obviously, the statement "x Granger-causes y" does not imply that y is the effect or the result of x.

Table 1 lists the sets of variables alternatively employed to test for Granger non-causality of funding conditions for the level of economic activity and asset prices, as well as our baseline results. Taking into account that two-way, or endogenous causation, is obviously quite likely, we also show results from Granger non-causality tests of the macroeconomic variables on CR, BD and SPR.

Since Granger non-causality would be characterized by zero restrictions on a VAR representation in levels, conventional Wald tests may have non-standard asymptotic properties if variables are instead integrated or cointegrated (Toda and Phillips, 1993). However, Yamada and Toda (1998) suggest that accurate determination of the number of unit roots and cointegration rank in small samples may lead to pre-test biases in Granger causality tests conditioned on the estimation of these parameters. Toda and Yamamoto (1995) identify a sequential procedure to deal with this trade-off. First, using standard lag-length selection criteria, we determine the VARs optimal lag length (k^*). Next, we estimate a ($k^* + Dmax$)th-order VAR, where $Dmax$ is the maximal order of integration suspected to occur among the variables in the system. Finally, disregarding the last $Dmax$ lagged terms, general restrictions on the first k^* coefficient matrices are tested for by using standard (asymptotic) inference[5].

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[5] Trecroci and Vega (2002) apply the same procedure to the investigation of the leading indicator properties

Taking into account Toda and Yamamoto's suggestions, we perform Granger non-causality tests in two different VAR models. In the first, we estimate a VAR(5), where five is the order selected by the majority of lag-length criteria. Endogenous variables are defined in annual growth rates and the model assumes that all variables are stationary (that is, $Dmax$ is zero). In the second specification, which takes into account the possibility of mis-specification of the lag order, we estimate a VAR(4) and allow for the chance that at least one variable might be non stationary (that is, $Dmax$ is one). Following Toda and Yamamoto's procedure, this implies estimating a VAR(5) and testing restrictions only on the first four coefficient matrices. Table 1 reports estimates from our Granger non-causality tests. P-values for the first model are in parentheses, while those for the second model are shown in normal text.

The choice of the variable with which we measure funding conditions makes a difference: when BD is used (middle column in Table 1), liquidity turns out to have very significant predictive content for future consumption and investment (both residential and non residential). Non-causality of SPR for non-residential investment is borderline; however, this result is robust to VAR specification only when the system includes house price valuations. On the other hand, current funding conditions do have some forecasting power for PE (in the case of CR) and HPI (when BD is used). In particular, the statistics reject non-causality of CR for PE at very low significance level, which means that credit growth has a significant effect on future earnings-adjusted stock market valuations. Changes in broker-dealer assets help predict future house prices developments; this happens when the VAR includes non-residential investment. With CR or SPR in place of BD the relationship between aggregate spending components and asset valuations emerges only marginally. Quite surprisingly, there is no evidence that credit growth, regardless of its definition, is helpful in predicting future inflation, whereas current inflation seems to have consistent predictive content for future funding conditions (both as CR and SPR). In addition, growth in asset valuations does not seem to forecast future macroeconomic developments, with the notable exception of SPR. This is robust to the inclusion of residential or non-residential investment in the VAR system, as well as to the specification of the VAR model.

As to the relationship between aggregate macro variables and developments in funding conditions, the test statistics reject non-causality of growth in consumption and residential investment for SPR, and of non-residential investment growth for BD. In general, the use of the default spread in the VAR yields valuable insights on the transmission mechanism described by the VAR; therefore, we will include it in further analysis.

Overall, some findings stand out at this preliminary stage. First, funding conditions (especially when measured by CR and BD) contain some information for future growth of consumption and investment. However, such content seems to be very limited for asset valuations in general. On the contrary, current investment and consumption growth are helpful in forecasting

of monetary aggregates for inflation and output in the euro area.

future developments of the default spread, which also moves with lagged PE.

Although Granger-causality tests allow evaluating the significance of the direct lead-lag relationships between endogenous variables, they fail to account fully for the feedback effects of the other variables in the system. Moreover, the analysis is only focused on VAR coefficients, therefore on the correlations between variables' expected changes rather than their shocks. Therefore, we now complement the investigation with the structural analysis of the estimated VARs.

4 VAR Estimation Results

4.1 The role of broad credit

The aim of this exercise is to shed some light on the dynamic interaction between shocks to funding conditions, as measured by the availability of credit, the size of broker-dealer balance sheet and the default spread, and asset prices. In turn, we also examine the feedback of those indicators on to developments in the business cycle. A plausible estimation strategy would have implied studying a composite asset price indicator pointing to relative over- or under-valuation of asset markets. However, such a choice might have significantly blurred estimation results and inference. Alternatively, for each of our three measures of funding conditions we estimate two different VARs, each using a different indicator of asset market valuation: the first model includes PE, while the second replaces it with HPI. In turn, for each specification we further estimate two versions, depending on the alternative definition of the aggregate investment series: either residential investment (RI), or non-residential investment (NRI). We comment on impulse responses, obtained using the Generalized Impulse Response Functions (GIRFs), and on forecast error variance decomposition (FEVD).

We begin with a baseline specification in which the change in credit/GDP is the measure of funding conditions. Figures 1-4 plot the impulse responses we obtained by estimating the specifications based on residential (Figures 1 and 3), or non-residential investment (Figures 2 and 4), and PE (Figures 1 and 3) or HPI (Figures 2 and 4) as indicators of asset market valuation.

A number of interesting insights emerge. Personal consumption and residential investment exhibit a textbook-type and long-lasting (at least 3-4 quarters) reaction to a unit shock both in interest rates and CR. However, non-residential investment accelerates on impact and for 4-5 quarters following a positive shock to interest rates (but not to CR). Therefore, contractionary interest-rate policies appear to have recessionary effects on consumption, but not on the non-residential components of aggregate investment. Most interesting, a CR shock triggers a significant and sizeable acceleration of PE, which lasts for more than one year. Credit growth has therefore a clear expansionary effect on earnings-adjusted stock market valuations, beyond what appears to be mechanistically due to growth in the GDP components, whose shocks do

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not significantly affect PE. Such effect is not significant after an interest-rate shock. Moreover, credit in turn rises significantly after a positive shock to PE, which has also an expansionary effect on consumption (wealth effect) and on both residential and non-residential investments (Tobin's q effect). The use of residential versus non-residential investment does not seem to matter: in both cases, PE grows significantly only after a credit shock. Overall, the expansionary effects of credit growth are much more sizeable and significant for PE than for consumption and investment. This finding emerged already in the results of Granger non-causality test. Besides this broad finding, there are key differences across specifications. The responses to a CR shock (fifth column) are swifter for residential than for non-residential investment, although they are only marginally significant. The reaction of personal consumption after a CR shock is much smaller but quicker than following an interest-rate shock. The response of inflation to interest rates instead displays the usual price puzzle, whereas the responses to an inflation shock appear to be consistent with the effects of a supply shock: consumption and residential investment fall significantly and for a long interval (6-8 quarters), whereas non-residential investment grows slightly but not significantly.

To gauge the relative importance of these effects, we evaluate the forecast error variance decomposition. Figures 1A and 2A in the Appendix show the FEVD for the VAR with PE, using residential and non-residential investment, respectively. At a two-year horizon, the exogenous variation in consumption growth is mainly accounted for by inflation and interest rate shocks (each shock contributes almost 20%). The credit shock explains around 2% of the variation in consumption growth while the wealth effect of shocks to PE contributes no more than 8%. It is worth noting the different impact of shocks on residential and non-residential investment. An interest-rate shock explains around 50% of variance in residential investment, while it contributes only around 15% to the variance of non-residential investment. This confirms the claim that residential investment is more sensitive to interest rates than its non-residential counterpart. Also, the shock to PE accounts for just 3-4% of total variation in investment growth. Importantly, at any horizon, roughly 50% of PE variance is explained by a credit shock, while shocks to interest rates and non-residential investment contribute no more than 6-7%. This complements the marked expansionary reaction of PE to credit that we find in impulse response analysis.

We now examine the evidence obtained using a different specification in which we insert the log change of the House Price Index (HPI) in place of PE in the VAR system. Figures 2 and 4 present the GIRFs of VARs estimated over the sample 1977q2 to 2008q1, using residential and non-residential investment, respectively.

The overall descriptive ability of the VAR is robust to the substitution of PE with house price changes. Therefore, we focus on the interactions between macro variables and house prices. Several patterns are immediately apparent. House prices do respond positively to a credit shock, but unlike for PE, their reaction is not statistically significant. Instead, HPI

slows down significantly following inflation and interest-rate shocks. This effect is significant and long-lasting. Higher interest rates and inflation reduce the present value of current and future expected payoffs from investment, which in turn depresses house prices. In turn, house prices accelerate significantly following a shock to residential investment but decelerate after one to NRI. This is intuitive and consistent with the idea that some components of residential and non-residential investment spending are perceived as substitutes. On the other hand, a shock to HPI is followed by a significant increase in consumption growth (likely via a wealth effect) and in residential investment. Unlike a PE shock, HPI shocks do not trigger any significant response by non-residential investment and credit. The collateral effect of house price appreciation does not show up in our estimates. There is also a significant fall of inflation, which is the opposite we found in response to a PE shock.

Results on the variance decomposition (Figures 3A and 4A in the Appendix) somehow qualify the above results. They confirm that, at a two-year horizon, the variation in consumption growth is mainly accounted for by inflation and interest-rate shocks, while the wealth effect of house prices drives about 10% of the variation in consumption. Variation in residential investment is mainly explained by interest rates shocks, while Tobin's q effect of house prices does not seem to be relevant. Around 30% of the variability in HPI growth is explained by inflation, around 20% by residential investments and 10% by interest rates, while the contribution of credit is negligible. The variability of credit explained by a house price shock is nearly zero. This confirms results obtained for PE and permits to add that while broad credit appears to be a key driver of changes in equity market valuations, this does not apply to housing valuations. Also, the collateral effect of asset prices is not helpful in explaining broad credit expansions.

4.2 The role of broker-dealer assets

As discussed above, over the past two decades several innovations in the regulatory and operating framework of credit markets have likely made brokers-dealers balance sheets a useful indicator of funding conditions (as claimed also by Adrian and Shin, 2009, and Geanakoplos, 2010). We now evaluate empirically the interdependence of such measure with asset prices. We present results from a VAR that includes the log change of broker-dealer total financial assets on GDP (BD) instead of credit. Again, we alternatively insert the log change of PE and HPI as indicators of asset markets pressures, and each time estimate two specifications, one with RI and the other with NRI. Figures 5-8 show the GIRFs of VARs estimated over the sample 1977q2 till 2008q2. Most findings seem to be robust with respect to the use of BD as an indicator of credit availability, though some clear differences emerge.

First, a unit shock to broker-dealer balance sheets, unlike a credit shock, triggers a significant decrease in inflation and interest rates. This confirms one of Adrian and Shin's findings, i.e., the pro-cyclicality of interest rates relative to broker-dealer balance sheet. Also, the response of PE to a BD shock is positive and significant, suggesting that larger balance sheets feed greater

demand for assets, leading in turn to asset price increases. Moreover, the reaction of residential investment to BD shocks is positive and significant, while that of non-residential investment is negative but insignificant. This bears out that residential investment is more sensible to changes in the BD-based definition of liquidity than is its non-residential counterpart.

The impulse responses of broker-dealer assets to the other shocks are virtually indistinguishable from those of credit/GDP. In particular, a shock to interest rates and inflation is followed by a short-term fall in BD asset growth. Interestingly, a shock to PE leads to a significant increase in BD asset growth (although smaller than that undergone by CR), confirming the existence of a positive feedback loop from asset valuations to credit availability, on to asset prices again.

The variance decomposition for the VAR with PE and using BD assets (Figures 5A and 6A in the Appendix) confirms that a BD shock, like a credit shock, explains only a small fraction of forecast error variance in consumption growth and that the wealth effect of stock prices barely contributes to consumption variation. In particular, at the two-year horizon no more than 2% and 5% of variation in consumption growth is due to BD and PE shocks, respectively. However, residential investment is confirmed to be more sensitive to an interest-rate shock than NRI is, while now a PE shock explains more than 20% of variation in non-residential investment growth. In turn, at any horizon a BD asset shock explains about 15-20% of PE variance. This is roughly half the variation in PE attributable to a conventionally-defined credit shock, but it is still a substantial effect. Interest rate and investment shocks (both residential and non residential) explain a smaller fraction of PE variability compared to what one obtains in a system with broad credit. Finally, the fraction of variance of BD asset growth explained by a PE shock is around 2-3%.

As a further step, we examine the responses from a VAR that includes HPI instead of PE (Figures 7 and 8). While the thrust of our results is confirmed, some differences do emerge. First, a shock to BD assets, unlike a credit shock, triggers a significant fall of inflation and interest rates. As noted above, this confirms the positive correlation of interest rates with broker-dealer balance sheets, which are therefore pro-cyclical. Also, the response of residential investment to BD shock is positive and significant, corroborating what obtained from the VAR with PE, as the response of non-residential investment is negative but insignificant.

Second, the reaction of broker-dealer assets are often insignificant and virtually indistinguishable from credit's reaction to the same shocks. However, unlike a PE shock, a positive shock to house prices does not trigger any significant increase in BD asset growth. This result does not depend on the definition of credit we adopt: while a shock to PE leads to a significant increase in credit and BD assets, the one to house prices does not trigger significant changes in either indicators. As to the response of house prices to endogenous shocks, the results obtained for the VAR with credit growth are confirmed and reinforced by some more significant response using BD. In particular, the response of house prices to a BD shock is stronger and significant

compared to the corresponding response in the VAR with broad credit growth. As before, this could be explained by the fact that stronger balance sheets feed greater demands for assets, including houses, leading to house price increases.

The variance decomposition widely confirms the results obtained from the VAR with credit (see Figures 7A and 8A in the Appendix). At the two-year horizon, the wealth effect of house prices accounts for roughly 10% of variation in consumption growth. Variation in residential investment is mainly explained by the interest-rate shock, while Tobin's q effect of house prices seems not to be relevant. The ballpark of house prices variation (nearly 30%) is explained by the inflation shock. Shocks to residential investment and interest rates contribute slightly more than 10%, while the contribution of BD assets is negligible. Consequently, while a BD-based liquidity shock explains a relevant portion of variation in stock prices, its contribution to house prices variation is negligible. As for the variance of BD assets, between 12% and 14% of it is explained by an inflation shock, while house prices shock contribute by about 2%. Therefore, only between 2% and 3% of the increase in broker-dealers balance sheets is due to shocks in the growth of house prices.

4.3 Bond spreads as indicators of funding conditions

An increase in bond yields in general signals higher credit risk premia and tighter credit conditions, which is main the reason why we also present estimates (Figures 9 to 12) from a specification that includes the default spread (SPR) [6]. Focusing first on the endogenous responses of macro variables and spread shocks (column 5 and row 5), we find that, as expected, a positive spread shock (i.e., a contraction in funding liquidity) is followed by a significant decrease in inflation and non-residential investments. On the contrary, the responses of interest rates, consumption, residential investment and PE to SPR shocks, although barely or not significant, apparently clash with the textbook-like effects of a monetary restriction. In turn, the default spread exhibits a significant and long-lasting (6 quarters) negative response to a positive PE shock. This is consistent with the following intuition: as equity values increase, credit risk premia enjoy a marked contraction, which may not only reflect buoyant expectations about firms' profitability, but also a tendency for looser credit standards as the stock market rises. The same occurs for stronger growth in spending for residential investment, which displays a significant and long-lasting effect (5 quarters). All this may be picking up some interesting features of US credit markets in the 2000s, starting with the relatively benign credit conditions faced by property buyers in the 2000s. Our GIRFs document that positive shocks to inflation and interest rates are followed by a spread increase. On the other hand, the absence in the 2000s of significant inflation and a low-interest-rate environment have prevented credit risk premia from widening up. The endogenous, two-way responses following shocks to consumption and the spread are muted. Forecast-error variance decomposition (Figures 9A and 10A in the Appendix)

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[6]As above, SPR measures the yield spread between Moody's seasoned Baa and Aaa corporate bonds.

makes it clear that, even when the spread shock is significant, its contribution is quite modest: at a two-year horizon, the spread shock accounts for no more than 9% of variation in inflation and 6% of variation in non-residential investment, while its contribution to variation in interest rates is negligible. On the other hand, nearly 30% of variation in the spread is accounted for by the interest rate shock, while inflation, residential investment and PE shocks each contribute by about 15%.

Last, Figures 11 and 12 present the GIRFs (and Figures 11A-12A in the Appendix the forecast error variance decomposition) of VARs centred on HPI. The responses to a positive spread shock are all as expected. A surprise increase of the spread triggers not only a significant decrease in inflation, interest rates and non-residential investments (like in the VAR with PE), but also an impact decrease in consumption, residential investments and house prices. However, the fall of consumption and house prices growth are significant only in the VAR with non-residential investment. The spread exhibits a significant negative response to a HPI shock. As expected, this effect is weaker and shorter (3 quarters) than that following a PE shock. Inflation and interest rate shocks are followed by an increase in the spread, while the reduction in SPR after a positive residential investment shock is even more significant than that obtained from the VAR with PE. This corroborates the view that the low-inflation, low-interest rates environment may have encouraged the relatively loose credit standards observed in the 2000s according to some accounts.

Some FEVD results are worth noting. First of all, the spread's contribution to asset valuations and macroeconomic variables is not negligible. Results are stronger when the VAR includes non-residential investments. In particular, at the two/three-year-horizon, spread shocks explain 17% of variation in consumption growth and between 8 and 13% of variation in aggregate investment. At the same horizon, the spread accounts for 13% of variation in interest rates and 14% of variation in inflation. Moreover, while it is confirmed that the main source of variation in house prices (more than 30%) is the inflation shock, the spread shock comes second, accounting for 10% at the one-quarter horizon. Finally, at the two-year horizon, the wealth effect of house prices accounts for 12% of variation in consumption growth. This is the strongest wealth effect of house prices obtained from our empirical exercise.

5 Conclusions

Our investigation has shed light on key aspects of the transmission of shocks to funding conditions over the last decades in the US. Results are obtained within a vector autoregression estimated over 1975-2008 and they are therefore likely, if any, to underestimate the impact of securitisation, financial liberalisation and other recent institutional developments in credit markets.

First, aggregate asset prices appear to contain helpful information about future macroeco-

nomic developments. Second, both asset prices and the level of economic activity do accelerate significantly following expansionary shocks to funding liquidity. Funding liquidity have a clear expansionary effect on asset-market valuations, beyond what appears to be mechanistically due to growth in the GDP components. Moreover, the expansionary effects are clearer for asset valuations than for macroeconomic aggregates like consumption and investment. Results also confirm the existence of a positive feedback loop between asset valuations and credit availability. Finally, the response of equity and house prices to expansions in monetary conditions is stronger following shocks to liquidity than after conventional interest-rate shocks. The latter finding is particularly relevant for the debate over the financial-stability effects of conventional versus unconventional monetary policy operations.

6 Data Appendix

Data used are quarterly series, extracted from OECD Main Economic Indicators, Thomson Financial Datastream, Federal Reserve Bank of S.Louis Economic Data (FRED) and Federal Reserve Board's Flow of Funds.

The following is a short description of variables and their sources.

PCE: Real Personal Consumption Expenditure in billions of chained 2000 dollars (source: FRED, GDP and Components, Personal Income & Outlays, code PCECC96, seasonally adjusted).

RRI: Real Private Residential Fixed Investment in billions of chained 2000 dollars (source: FRED, GDP and Components, Saving & Investment, code PRFIC96, seasonally adjusted).

RNRI: Real Private Non residential Fixed Investment in billions of chained 2000 dollars (source: FRED, GDP and Components, Saving & Investment, code PNFIC96, seasonally adjusted).

CPI: Consumer Price Index for all Urban Consumer, Index 1982-84=100 (source: FRED, Consumer Price Indexes, code CPIAUCSL, monthly, seasonally adjusted). The quarterly series is obtained by taking the last observation in each quarter.

INT: Three Month Interest Rate on Eurodollar Deposits (source: OECD, Main Economic Indicators, code 426243d).

CR: Total Credit to the Private Sector in billions of dollars (source: IMF, Datastream code USQ52...A) on GDP at current prices (source: OECD, Main Economic Indicators, code 421021XSA, billions of dollars, seasonally adjusted).

BD: Security Broker-Dealer Total Assets (source: Federal Reserve Board's Flow of Funds, table L 129, million of dollars) on GDP at current prices (source: OECD, Main Economic Indicators, cod. 421021XSA, billions of dollars, seasonally adjusted).

SPR: Difference between Moody's seasoned Baa yield and Aaa yield on corporate bond (source: FRED, Interest Rates, Corporate Aaa & Baa, cod. AAA and BBB, monthly). The

quarterly series are obtained by taking last observation in each quarter.

PE: Cyclically-adjusted price/earnings ratio (http://www.econ.yale.edu/~shiller/data.htm)

HPI: Real House Price index. (source: Office of Federal Housing Enterprise Oversight, Datastream code 4q05hp_cbsa)

All variables are in 4-quarter log differences, with the exception of INT and SPR.

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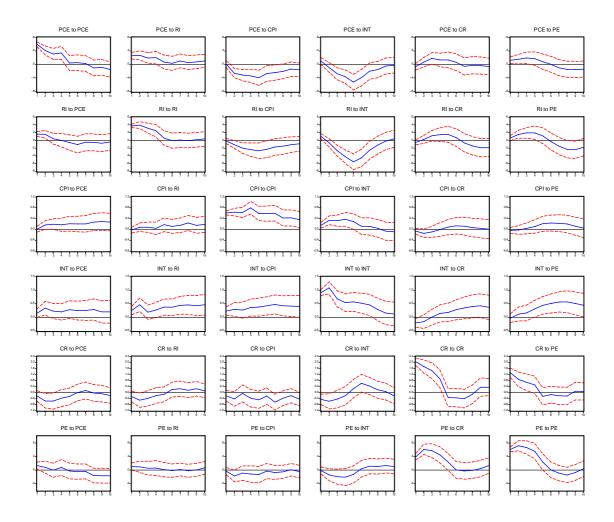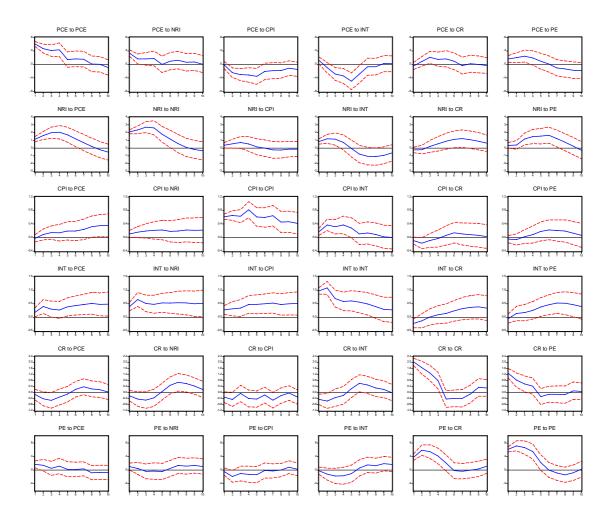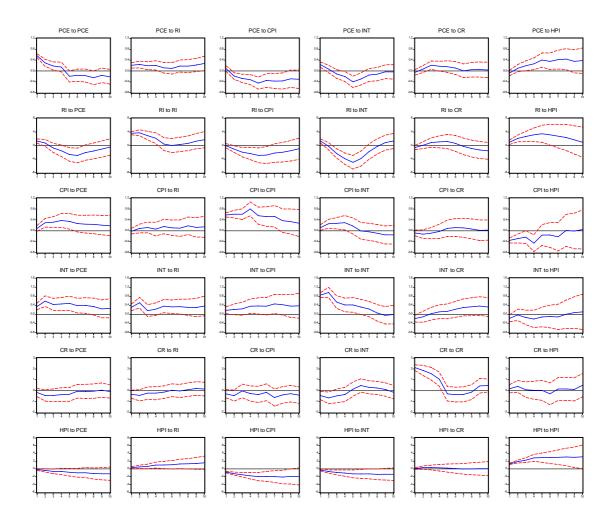
Figure 1 - Impulse responses from VAR with PE and RI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the price/earnings ratio (PE). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).
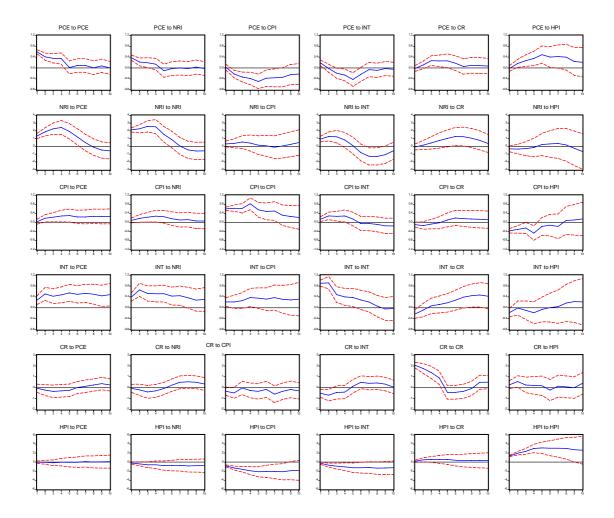
Figure 2 - Impulse responses from VAR with PE and NRI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$, where INV is non-residential investment (NRI) and ASP is the log change in the price/earnings ratio (PE). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).
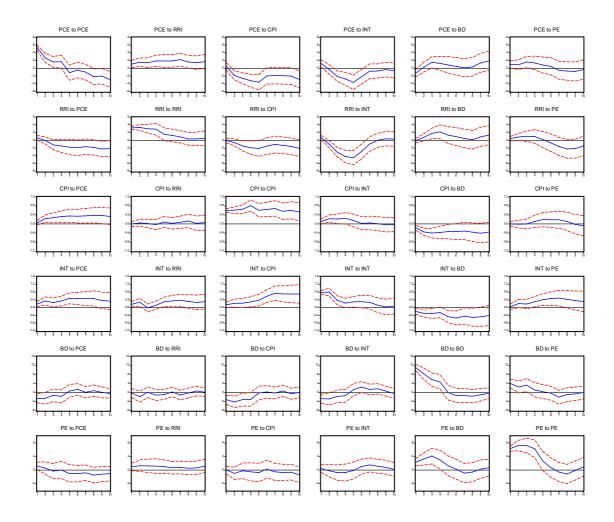
Figure 3 - Impulse responses from VAR with HPI and RI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the House Price Index (HPI). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).
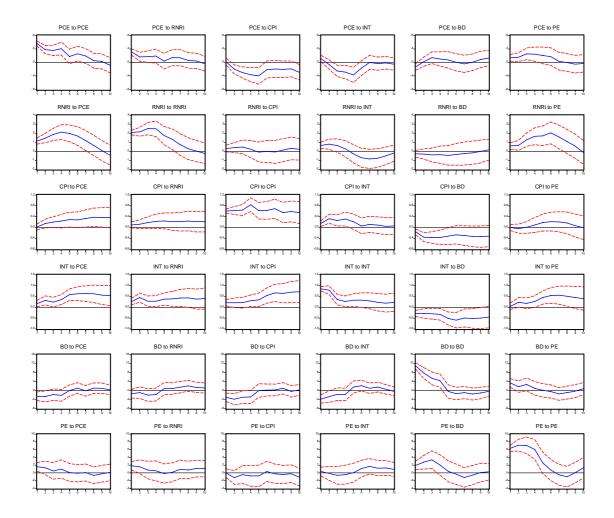
Figure 4 - Impulse responses from VAR with HPI and NRI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$, where INV is non-residential investment (NRI) and ASP is the log change in the House Price Index (HPI). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).
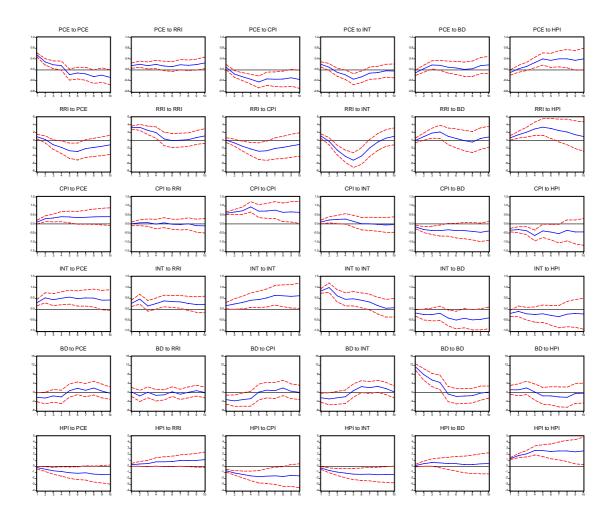
Figure 5 - Impulse responses from VAR with PE and RI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta BD, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the price-earnings ratio (PE). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).

Figure 6 - Impulse responses from VAR with PE and NRI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta BD, \Delta ASP)$, where INV is non-residential investment (NRI) and ASP is the log change in the price-earnings ratio (PE). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).
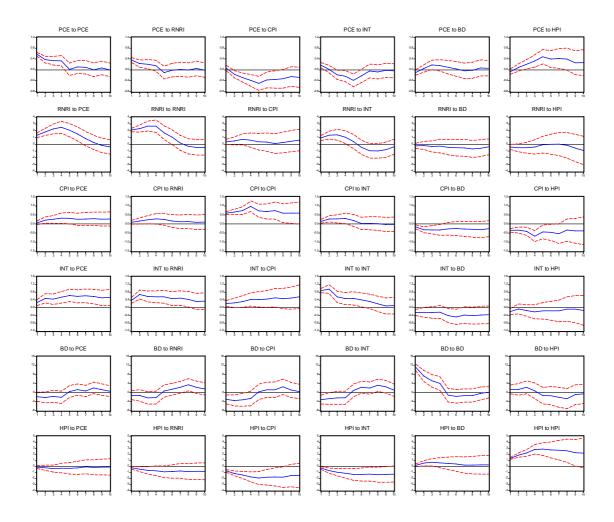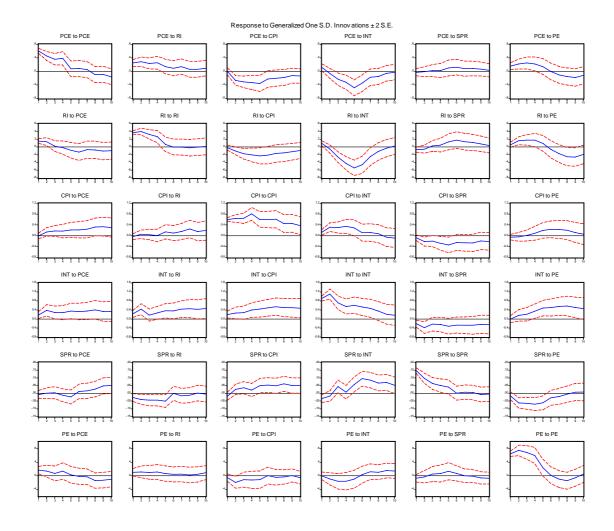
Figure 7 - Impulse responses from VAR with HPI and RI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta BD, \Delta ASP)$, where INV is residential investment and ASP is the log change in the House Price Index (HPI). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).

Figure 8 - Impulse responses from VAR with HPI and NRI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X'_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta BD, \Delta ASP)$, where INV is non-residential investment and ASP is the log change in the House Price Index (HPI). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).

Figure 9 - Impulse responses from VAR with PE and RI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X'_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, SPR, \Delta ASP)$, where INV is residential investment and ASP is the log change in the price/earnings ratio (PE). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).
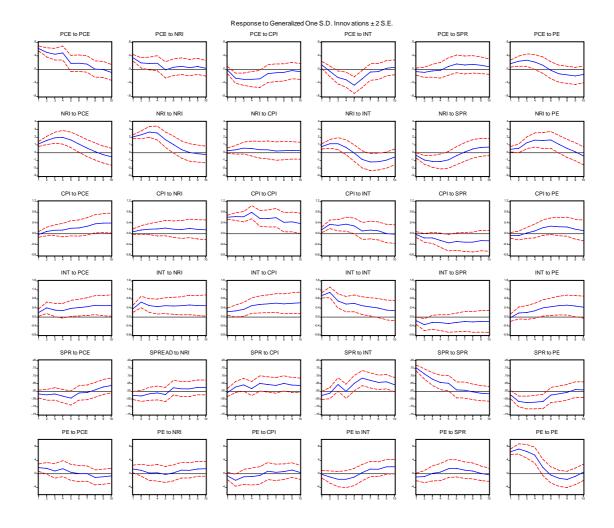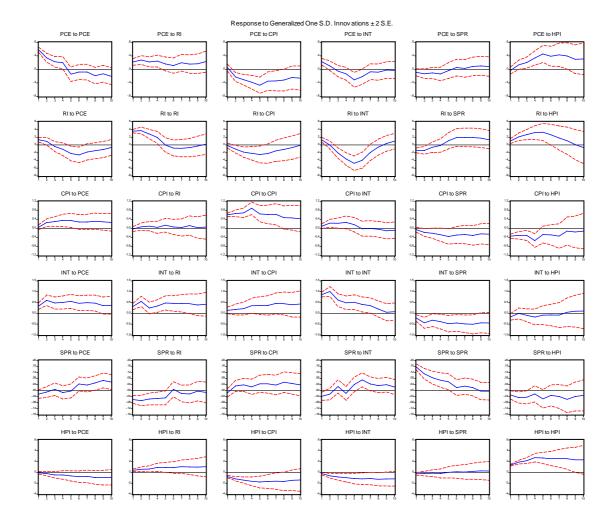
Figure 10 - Impulse responses from VAR with PE and RI

Generalized impulse responses to a one-standard deviation shock, ± two standard errors bands. The VAR lag length is 5, and it includes the variables $X'_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, SPR, \Delta ASP)$, where INV is non-residential investment (NRI) and ASP is the log change in the price/earnings ratio (PE). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).

Response to Generalized One S.D. Innovations ± 2 S.E.

Figure 11 - Impulse responses from VAR with HPI and RI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, SPR, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the House Price Index (HPI). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).
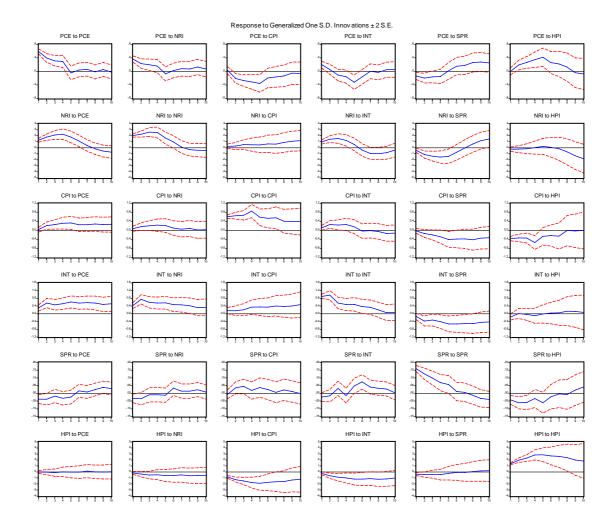

Response to Generalized One S.D. Innovations ± 2 S.E.

Figure 12 - Impulse responses from VAR with HPI and NRI

Generalized impulse responses to a one-standard deviation shock, $\pm$ two standard errors bands. The VAR lag length is 5, and it includes the variables $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, SPR, \Delta ASP)$, where INV is non-residential investment (NRI) and ASP is the log change in the House Price Index (HPI). Captions denote the response of the first variable to a shock in the second (see main text for details on variables' definition).

Response to Generalized One S.D. Innovations ± 2 S.E.

Table 1 - Tests for Granger non-causality of CR, BD and SPR

The table reports p-values for Granger non-causality tests (Wald tests) on VAR coefficients on system vector $X_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, FUND, ASP)'$, where $FUND = CR, BD$ or SPR, and ASP is PE or HPI. Results for model one ($k^* = 5$; $Dmax = 0$) are in parentheses. For model two, $k^* = 4$, $Dmax = 1$. k^* is the VAR's optimal lag length, while $Dmax$ is the maximal order of integration suspected to occur among the variables. Entries in bold denote significance at least at the 90% level. Data are quarterly and the estimation sample is from 1975Q1 to 2008Q1 (see main text for details on variables' definition).

$FUND{=}CR$	$FUND{=}BD$	$FUND{=}SPR$
$X_t = (\Delta PCE, \Delta RI, \Delta CPI, INT, FUND, \Delta PE)^{'}$		
$CR \to PCE : 0.36 \ (0.17)$	$\mathbf{BD \to PCE : 0.00 \ (0.00)}$	$SPR \to PCE : 0.60 \ (0.73)$
$CR \to RI : 0.65 \ (0.76)$	$\mathbf{BD \to RI : 0.00 \ (0.00)}$	$SPR \to RI : 0.63 \ (0.57)$
$CR \to CPI : 0.84 \ (0.89)$	$BD \to CPI : 0.12 \ (0.20)$	$SPR \to CPI : 0.19 \ (0.28)$
$\mathbf{CR \to PE : 0.00 \ (0.00)}$	$BD \to PE : 0.37 \ (0.51)$	$SPR \to PE : 0.90 \ (0.93)$
$PCE \to CR : 0.80 \ (0.88)$	$PCE \to BD : 0.73 \ (0.82)$	$\mathbf{PCE \to SPR : 0.08 \ (0.08)}$
$RI \to CR : 0.45 \ (0.29)$	$RI \to BD : 0.14 \ (0.22)$	$\mathbf{RRI \to SPR : 0.04 \ (0.04)}$
$\mathbf{CPI \to CR : 0.02 \ (0.02)}$	$CPI \to BD : 0.48 \ (0.62)$	$CPI \to SPR : 0.17 \ (0.23)$
$PE \to CR : 0.79 \ (0.51)$	$PE \to BD : 0.30 \ (0.28)$	$\mathbf{PE \to SPR : 0.00 \ (0.01)}$
$X_t = (\Delta PCE, \Delta NRI, \Delta CPI, INT, FUND, \Delta PE)^{'}$		
$CR \to PCE : 0.63 \ (0.18)$	$\mathbf{BD \to PCE : 0.00 \ (0.00)}$	$SPR \to PCE : 0.61 \ (0.62)$
$CR \to NRI : 0.44 \ (0.38)$	$\mathbf{BD \to NRI : 0.04 \ (0.07)}$	$SPR \to NRI : 0.11 \ (0.07)$
$CR \to CPI : 0.90 \ (0.95)$	$BD \to CPI : 0.20 \ (0.28)$	$SPR \to CPI : 0.18 \ (0.26)$
$\mathbf{CR \to PE : 0.01 \ (0.01)}$	$BD \to PE : 0.32 \ (0.43)$	$SPR \to PE : 0.84 \ (0.87)$
$PCE \to CR : 0.84 \ (0.90)$	$PCE \to BD : 0.66 \ (0.62)$	$PCE \to SPR : 0.20 \ (0.31)$
$RNRI \to CR : 0.49 \ (0.15)$	$\mathbf{RNRI \to BD : 0.08 \ (0.05)}$	$RNRI \to SPR : 0.44 \ (0.55)$
$\mathbf{CPI \to CR : 0.03 \ (0.02)}$	$CPI \to BD : 0.43 \ (0.47)$	$CPI \to SPR : 0.16 \ (0.19)$
$PE \to CR : 0.77 \ (0.37)$	$PE \to BD : 0.16 \ (0.12)$	$\mathbf{PE \to SPR : 0.00 \ (0.01)}$
$X_t = (\Delta PCE, \Delta RRI, \Delta CPI, INT, FUND, \Delta HPI)^{'}$		
$\mathbf{CR \to PCE : 0.06 \ (0.04)}$	$\mathbf{BD \to PCE : 0.00 \ (0.01)}$	$SPR \to PCE : 0.25 \ (0.30)$
$CR \to RI : 0.64 \ (0.69)$	$\mathbf{BD \to RI : 0.00 \ (0.00)}$	$SPR \to RI : 0.79 \ (0.50)$
$CR \to CPI : 0.42 \ (0.28)$	$BD \to CPI : 0.38 \ (0.39)$	$SPR \to CPI : 0.32 \ (0.44)$
$CR \to HPI : 0.70 \ (0.74)$	$BD \to HPI : 0.12 \ (0.20)$	$SPR \to HPI : 0.96 \ (0.97)$
$PCE \to CR : 0.89 \ (0.93)$	$PCE \to BD : 0.41 \ (0.50)$	$PCE \to SPR : 0.35 \ (0.11)$
$RI \to CR : 0.63 \ (0.59)$	$RI \to BD : 0.38 \ (0.51)$	$\mathbf{RI \to SPR : 0.07 \ (0.05)}$
$\mathbf{CPI \to CR : 0.04 \ (0.05)}$	$CPI \to BD : 0.50 \ (0.64)$	$\mathbf{CPI \to SPR : 0.06 \ (0.09)}$
$HPI \to CR : 0.55 \ (0.64)$	$HPI \to BD : 0.59 \ (0.72)$	$HPI \to SPR : 0.61 \ (0.73)$
$X_t = (\Delta PCE, \Delta NRI, \Delta CPI, INT, FUND, \Delta HPI)^{'}$		
$CR \to PCE : 0.18 \ (0.17)$	$\mathbf{BD \to PCE : 0.00 \ (0.00)}$	$SPR \to PCE : 0.18 \ (0.07)$
$CR \to NRI : 0.42 \ (0.36)$	$BD \to NRI : 0.23 \ (0.34)$	$\mathbf{SPR \to NRI : 0.04 \ (0.02)}$
$CR \to CPI : 0.47 \ (0.51)$	$BD \to CPI : 0.30 \ (0.32)$	$SPR \to CPI : 0.14 \ (0.18)$
$CR \to HPI : 0.53 \ (0.66)$	$\mathbf{BD \to HPI : 0.05 \ (0.1)}$	$SPR \to HPI : 0.84 \ (0.88)$
$PCE \to CR : 0.95 \ (0.94)$	$PCE \to BD : 0.37 \ (0.35)$	$PCE \to SPR : 0.40 \ (0.45)$
$NRI \to CR : 0.52 \ (0.16)$	$NRI \to BD : 0.45 \ (0.25)$	$NRI \to SPR : 0.28 \ (0.39)$
$\mathbf{CPI \to CR : 0.05 \ (0.06)}$	$CPI \to BD : 0.53 \ (0.62)$	$\mathbf{CPI \to SPR : 0.1 \ (0.15)}$
$HPI \to CR : 0.46 \ (0.59)$	$HPI \to BD : 0.45 \ (0.59)$	$HPI \to SPR : 0.66 \ (0.79)$

Appendix: Forecast Error Variance Decomposition

Figure 1A - Variance decomposition from VAR with PE and RI

The VAR lag length is 5, and it includes the variables
$X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$, where INV is residential investment and
ASP is the log change in the price/earnings ratio. Captions denote the fraction of forecast error
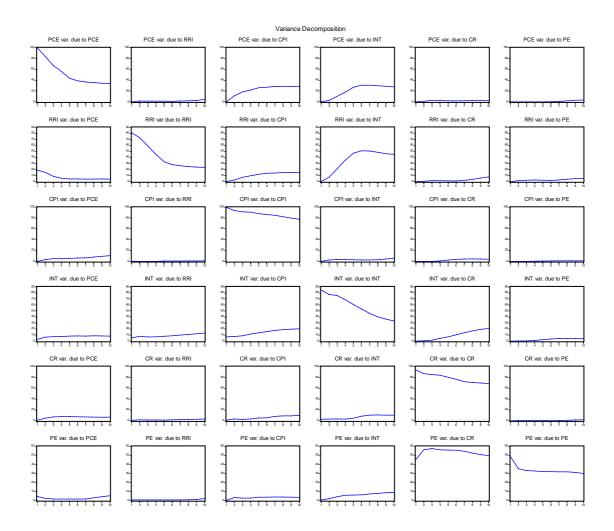variance of the first variable to a shock in the second (see main text for details on variables' definition).
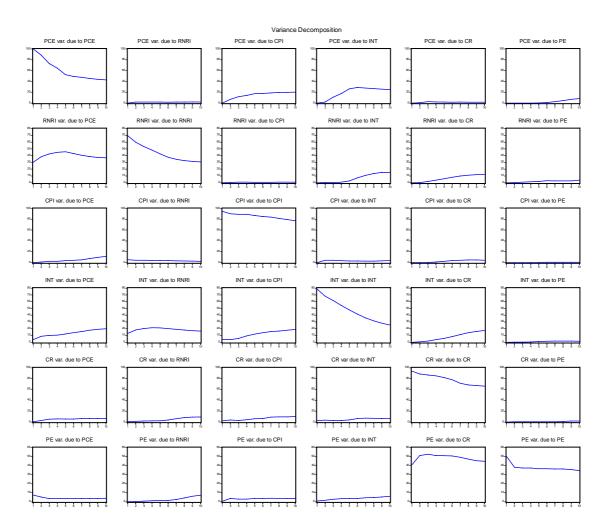

Variance Decomposition

Figure 2A - Variance decomposition from VAR with PE and NRI

The VAR lag length is 5, and it includes the variables
$X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$, where INV is non-residential investment and
ASP is the log change in the price/earnings ratio. Captions denote the fraction of forecast error
variance of the first variable to a shock in the second (see main text for details on variables' definition).
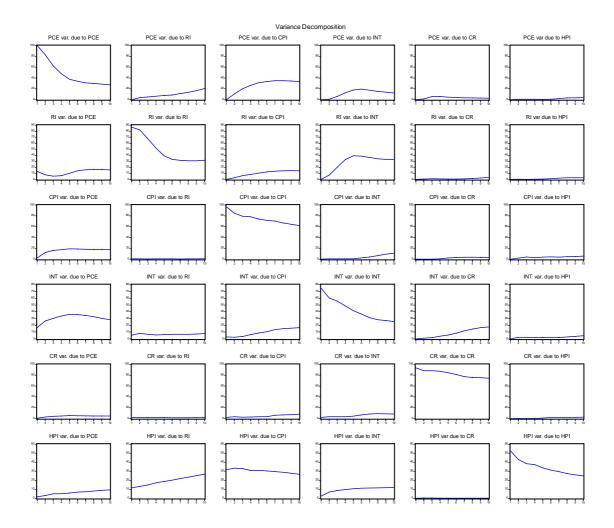

Variance Decomposition

Figure 3A - Variance decomposition from VAR with HPI and RI

The VAR lag length is 5, and it includes the variables
$X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the house price index (HPI). Captions denote the fraction of forecast error variance of the first variable to a shock in the second (see main text for details on variables' definition).

Variance Decomposition

Figure 4A - Variance decomposition from VAR with HPI and NRI

The VAR lag length is 5, and it includes the variables
$X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$, where INV is non-residential investment
(NRI) and ASP is the log change in the house price index (HPI). Captions denote the fraction of
forecast error variance of the first variable to a shock in the second (see main text for details on
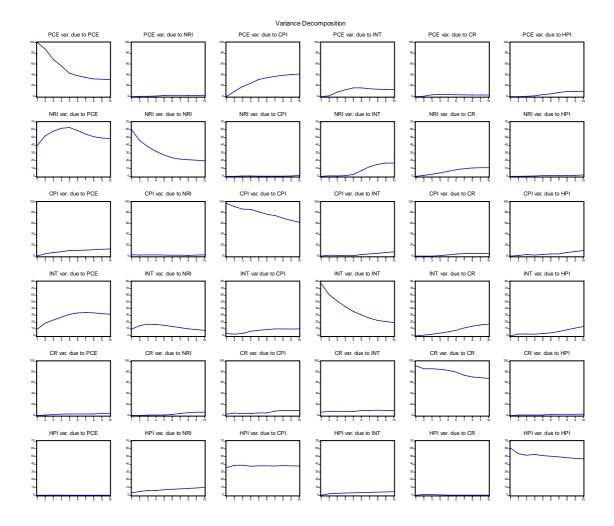variables' definition).

Variance Decomposition

Figure 5A - Variance decomposition from VAR with PE and RI

The VAR lag length is 5, and it includes the variables
$X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta BD, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the price/earnings ratio (PE). Captions denote the fraction of forecast error variance of the first variable to a shock in the second (see main text for details on variables' definition).
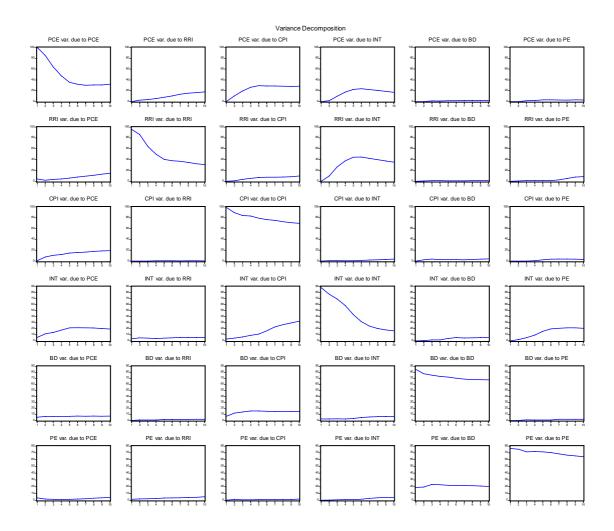

Variance Decomposition

Figure 6A - Variance decomposition from VAR with PE and NRI

The VAR lag length is 5, and it includes the variables
$X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta BD, \Delta ASP)$, where INV is non-residential investment (NRI) and ASP is the log change in the price/earnings ratio (PE). Captions denote the fraction of forecast error variance of the first variable to a shock in the second (see main text for details on variables' definition).
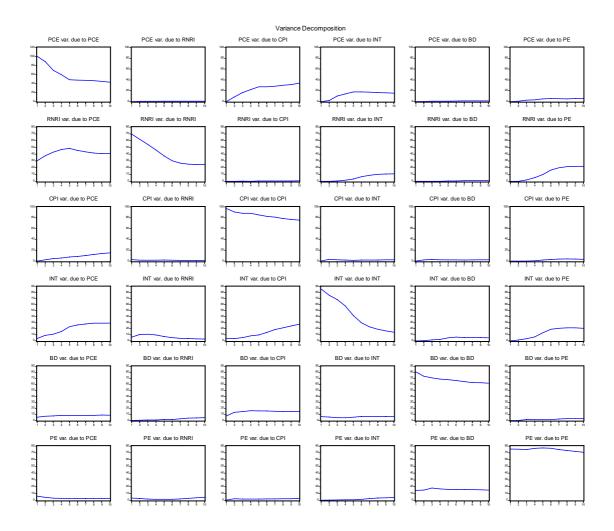

Variance Decomposition

Figure 7A - Variance decomposition from VAR with HPI and RI

The VAR lag length is 5, and it includes the variables
$X'_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta BD, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the House Price Index (HPI). Captions denote the fraction of forecast error variance of the first variable to a shock in the second (see main text for details on variables' definition).
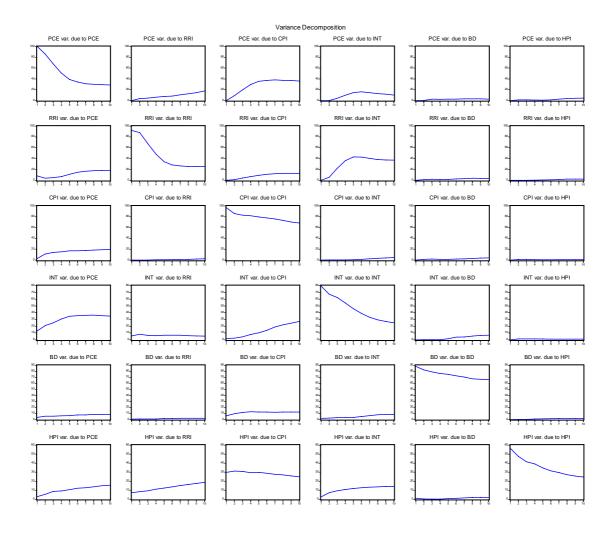
Figure 8A - Variance decomposition from VAR with HPI and NRI

The VAR lag length is 5, and it includes the variables
$X'_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta BD, \Delta ASP)$, where INV is non-residential investment
(NRI) and ASP is the log change in the House Price Index (HPI). Captions denote the fraction of
forecast error variance of the first variable to a shock in the second (see main text for details on
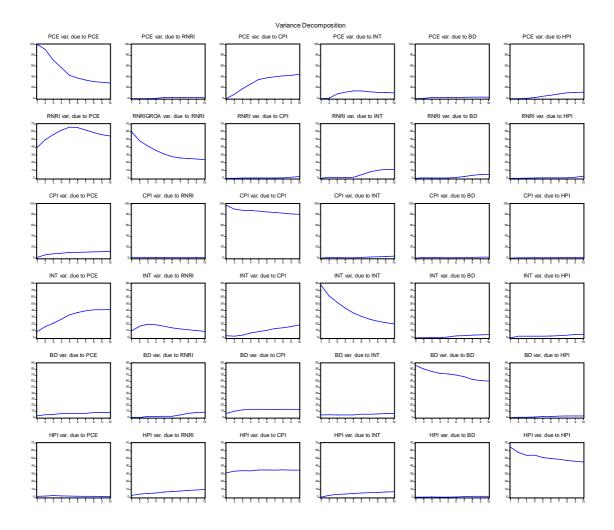variables' definition).

Figure 9A - Variance decomposition from VAR with PE and RI

The VAR lag length is 5, and it includes the variables
$X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, SPR, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the price/earnings ratio (PE). Captions denote the fraction of forecast error variance of the first variable to a shock in the second (see main text for details on variables' definition).
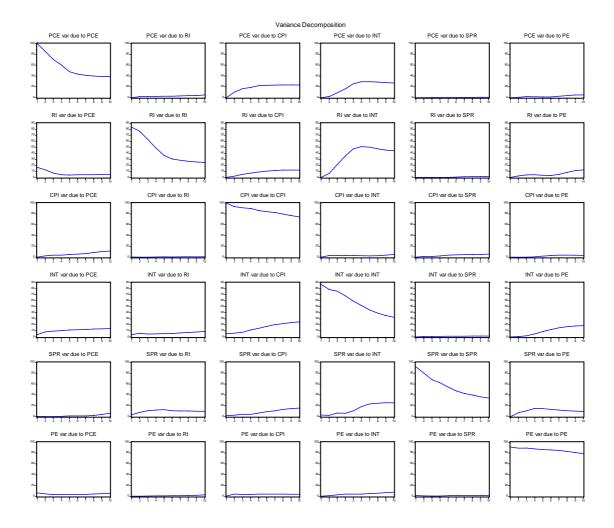

Variance Decomposition

Figure 10A - Variance decomposition from VAR with HPI and NRI

The VAR lag length is 5, and it includes the variables
$X'_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, SPR, \Delta ASP)$, where INV is non-residential investment
(NRI) and ASP is the log change in the House Price Index (PE). Captions denote the fraction of
forecast error variance of the first variable to a shock in the second (see main text for details on
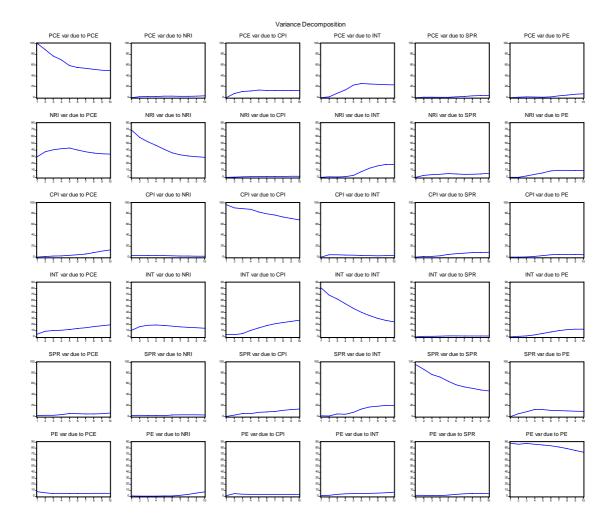variables' definition).

Variance Decomposition

Figure 11A - Variance decomposition from VAR with HPI and RI

The VAR lag length is 5, and it includes the variables
$X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, SPR, \Delta ASP)$, where INV is residential investment (RI) and ASP is the log change in the House Price Index (HPI). Captions denote the fraction of forecast error variance of the first variable to a shock in the second (see main text for details on variables' definition).
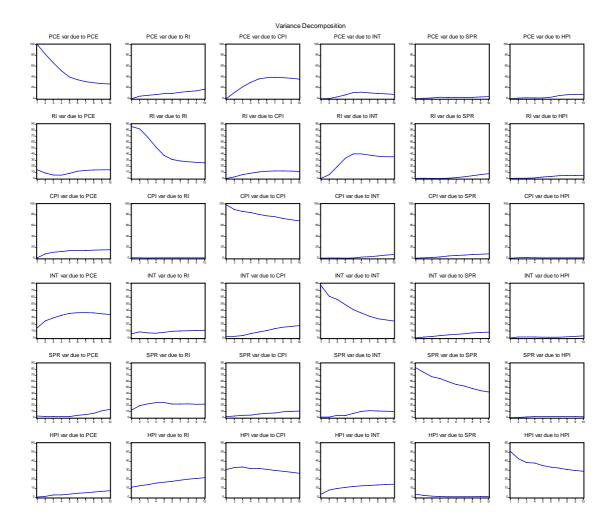

Variance Decomposition

Figure 12A - Variance decomposition from VAR with HPI and NRI

The VAR lag length is 5, and it includes the variables
$X'_t = (\Delta PCE, \Delta INV, \Delta CPI, INT, SPR, \Delta ASP)$, where INV is non-residential investment
(NRI) and ASP is the log change in the House Price Index (HPI). Captions denote the fraction of
forecast error variance of the first variable to a shock in the second (see main text for details on
variables' definition).

Variance Decomposition