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# 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 today's monetary transmission mechanism. We investigate empirically 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. Results also point to the presence of a positive feedback loop between asset valuations and credit availability. Finally, the response of equity and house prices to the easing of funding conditions is stronger following shocks to liquidity than after conventional interest-rate shocks. These novel results highlight potentially destabilizing properties of recent liquidity cycles and unconventional monetary policies.

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 benign macroeconomic environment dubbed as the "Great Moderation" between 1984 and 2006. It is now common to look at those very same conditions as to the origins of the widespread 2007-2009 downturn, the worst in decades. The worldwide financial crisis was triggered by the collapse of the US asset-backed securities market, in particular the segment linked to property prices, which catalyzed various macro and micro imbalances, leading to a severe and prolonged recession. One recurrent research question regards the claim that "easy

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access" to credit is to blame for potential departures of asset prices from their "fundamental" valuations. This question has clear implications also for the evaluation of recent monetary policies based on liquidity or "quantitative" easing.

This paper examines the role of funding conditions in the complex interplay between asset prices and the level of economic activity. We perform an empirical investigation of the effects of changes in the availability of credit on asset valuations and the business cycle, using US aggregate data. With an eye to the troublesome events that led to the 2007-2009 crisis, but over a longer 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: a) Is credit availability a leading indicator for future output developments? b) Do shocks to funding liquidity cause or reinforce asset price booms rather than just reflect an endogenous development of the business cycle? To this end, we introduce in the standard representation of the monetary transmission several new elements aimed at accounting more properly for the interaction between credit developments, the business cycle and asset markets. 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 credit availability: the ratio of credit to GDP, the size (relative again to GDP) of the balance sheet of market-based banking institutions (securities brokers-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 brokers-dealers assets because of the increased importance of such intermediaries as marginal providers of credit. In addition, the second and third measures might more explicitly reflect the role of risk-taking and leverage effects in credit developments.

Asset markets play a key role in the monetary transmission mechanism. Widely held accounts of this transmission mechanism attribute a special role to market revisions of the expected monetary policy stance: news about policy interest rates and banks' reserve holdings alter the risk-return profile of investment opportunities and their pricing. In turn, this shapes current and future developments 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 Gertler and Kiyotaki, 2010, for a summary). For instance, a permanent increase in wealth caused by significant growth of asset values might lead to increased spending and borrowing, as households attempt to smooth consumption out over their life cycles. In addition, as assets are commonly used as collateral, 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, there might be 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 destabilizing, loop. This complex interdependence has likely become stronger with the rise in importance of some relatively new channels of liquidity creation. In addition to conventional tools like changes in minimum reserve requirements and central bank-commercial banks operations, today's funding liquidity increasingly depends on the conditions prevailing in market segments such as that for collateralized loans. These markets are dominated by several types of financial intermediaries like brokers-dealers, money funds, hedge funds and other institutions. Fluctuations in the value of the assets of these institutions may therefore reflect changes in current and prospective funding conditions. Our study takes these recent developments into account and attempts to measure their macroeconomic implications.

We first 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 either macroeconomic variables and asset valuations, and that the changes in equity valuations predict future developments in funding conditions.

Next, we evaluate the dynamic responses of this set of variables to orthogonalized shocks, in the context of estimated Vector Autoregressions (VAR). The main result of our investigation 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. Our findings also point to 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. Besides revealing some potentially destabilizing properties in the transmission of shocks to funding conditions, this evidence may call into question the long-term effects of recent unconventional monetary policies.

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**

### **2.1 Literature**

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). However, results are far from conclusive, likely because they tend to depend on a mechanistic identification of boom/bust cycles and other identifying restrictions. In a pioneering study, Borio and Lowe (2004) assess the information content of credit and financial imbalances for future inflation and output, finding that the larger the imbalances during the boom, the greater the likelihood of subsequent output weakness and disinflation. In addition, credit developments emerge as more helpful than money in signaling the build-up of macroeconomic risks: the authors report that almost 80 percent of crises can be predicted on the basis of a credit boom at a one-year horizon. 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 tend to 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 measures of financial imbalances contain little information useful for forecasting future economic conditions.

That said, this paper departs from the event-study approach common to most of the extant literature. We do not focus just on boom/bust episodes and unstructured relationships between variables because the response of asset prices and the macroeconomy to funding conditions might depend on whether asset markets experience a sustained trending behaviour. There are at least three more reasons to prefer 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 to evolve along diverse macroeconomic paths<sup>1</sup>. If buoyant credit conditions caused asset price to increase in the absence of significant expansion in real activity, such an evidence would certainly alter the current view of the transmission of monetary shocks. An approach that uncovers key dynamic relationships between the variables, rather than raw correlations in correspondence of mechanistically determined episodes, seems more appropriate. Second, endogeneity and the direction of causality between the variables are crucial but undetermined aspects of the problem. Therefore, a VAR approach emerges as preferable to single-equation or more unrestricted analyses. Finally, we focus just on the US because of the depth of its asset markets and their influence on worldwide macroeconomic developments. Either event-study or panel perspectives would likely cloud the evidence.

At the aggregate level 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. Therefore, positive shocks to funding conditions should only drive the transitory components of asset prices. However, over recent cycles the financial sector's balance sheet has appeared to be particularly vulnerable to fluctuations in asset markets, which in turn likely affect 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

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<sup>1</sup>Think of the dotcom bubble at the end of the 1990s or the boom of house prices in the 2000s.

and consumption. In detail, funding liquidity, i.e., the ease with which consumers, firms and investors obtain funding, is tied to economic fluctuations through several channels (Brunnermeier and Pedersen, 2009). 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)). Although changes in the level of economic activity are conditional on funding conditions prevailing in the economy, relatively few studies have investigated the impact that 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. These connections might induce destabilizing pro-cyclicality in lending standards. In addition, there is evidence (Lown and Morgan, 2006; Madsen and Carrington, 2012) that fluctuating credit standards are useful in predicting several indicators of business activity, as well as future lending itself. Last, monetary policy operations that provide liquidity might directly affect asset prices, thereby driving a wedge between actual and expected returns, and inducing a "search for yield" across a wider array of assets<sup>2</sup>.

Adding to these factors, in recent years commercial banking and financial intermediation in the US and other advanced countries have witnessed a substantial increase in the importance of market-making activity, security underwriting, and market-based intermediation. These shifts, related to a widespread financial liberalization, 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, 2010b) have argued that there are important reasons why the balance sheet of securities brokers-dealers (BD) intermediaries offers in principle a better gauge than traditional money-supply and credit measures for funding conditions, asset mar-

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<sup>2</sup>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.

kets and even aggregate output developments<sup>3</sup>. Adrian and Shin (2009) show that asset growth of BD balance sheet is strongly correlated with the marginal availability of credit, much more directly than commercial banks' balance sheet. The latter is more affected by relationship-based, as opposed to short-term, lending. BD are marginal suppliers of credit. Therefore, the evolution of their asset position closely reflects 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.

Overall, credit supply and funding conditions should now be viewed as 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 (2010a) also document that BD asset growth is positively associated with leverage growth. This and further evidence (see also Geanakoplos, 2010; Kollmann and Zeugner, 2011) suggest 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. Of course, the effects of monetary policies critically depend on all these features, which further motivates our use of data on from brokers-dealers balance sheets.

## 2.2 Methodology

The direction of causality is the key and unsettled issue in the interplay between financial distress and economic activity. Most authors have looked at past banking crises in order to identify a set of stylized facts during episodes of financial distress. To measure financial imbalances, they compute asset-price and credit 'gaps' mostly defined as deviations of prices and credit from one-sided trends. This kind of event analyses 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 clear evidence on causality<sup>4</sup>. Borio and Lowe

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<sup>3</sup>This idea is not new. White (1990) reports on the linkage between brokers' loans and the exuberance of the stock market in the 1920s.

<sup>4</sup>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 characterizing real and financial developments around identified episodes of asset price or credit booms. Recent contributions



(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. All this lends clear support to an econometric strategy that exploits endogeneity and simultaneity in order to uncover correlations and dynamic causation relationships.

In this paper we extend the standard representation of the monetary transmission that emerges from the literature (see, for instance, Bernanke et al., 1996; Detken and Smets, 2004). We model the role played by credit developments and asset market values by assuming that the following variables are all endogenously determined:

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

$\Delta$  denotes 4-quarter logarithmic difference, *PCE* is real personal consumption expenditure, *INV* is real investment, *CPI* is the consumer price index, *INT* is the Federal funds rate<sup>5</sup>, *FUND* is an indicator of funding conditions and *ASP* is a measure of asset market valuation. 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 to the private sector (*CR*) or broker-dealer total assets (*BD*), both measured as fractions of GDP, and the yield spread between Moody's seasoned Baa and Aaa corporate bonds (*SPR*)<sup>6</sup>. The three indicators are only weakly correlated: the highest correlation is the one between *CR* and *BD*, at 0.40. *ASP* represents, alternatively, 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<sup>7</sup> (*PE*), or the analogous log change in the Real House Price Index (*HPI*). The sample spans 1975Q1 to 2008Q1 (see the Data Appendix for details about the measurement and construction of variables, as well as for descriptive statistics and graphs)<sup>8</sup>.

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include Detken and Smets (2004), Adalid and Detken (2007), Mendoza and Terrones (2008), Kannan and Rabanal (2009), Gerdesmeier, Reimers and Roffia (2010).

<sup>5</sup>Results from a VAR that instead included the Eurodollar rate are largely unchanged, and are available upon request.

<sup>6</sup>A further useful indicator of funding conditions would be based (as in Lown and Morgan, 2006, or Madsen and Carrington, 2012) on data from the Senior Loan Officer Opinion Survey. Such data however are not reported between 1984 and 1990.

<sup>7</sup>The series is calculated by R. Shiller, <http://www.econ.yale.edu/~shiller/data.htm>

<sup>8</sup>We employ data at the quarterly frequency because it is the only one with which long and reliable time series are available for all our variables. We also tried with 1-quarter differences, obtaining similar but less clear-cut

Prior to our reference VAR analysis, we implement cointegration tests in order to capture the existence of long-run relationships between the variables in levels. We carried out Johansen (1991, 1995) cointegration tests on two different VARs: the first one includes *PE* and *NRI*, while the second includes *HPI* and *RI*. The common variables are, as in the system below, personal consumption, the consumer price index, and a measure of funding conditions, either *CR* or *BD*. When the VAR includes *PE* and *NRI*, we find that the trace statistics (TR) and the maximum eigenvalue statistics (ME) do not reject the null of no cointegration only if the VAR excludes the CPI or the funding conditions measure. When the VAR includes all variables both TR and ME statistics do not reject one cointegration relationship. However, this result seems to be due to a spurious relationship: we are not able to reject, at the usual significance level, the null of no cointegration when performing the test on VARs that include only the CPI and one of the other variables in the system. Similarly, when the VAR includes *HPI* and *RI* we find that ME and TR statistics give different results. In particular, the ME statistic does not reject the null of no cointegration (and this result is robust to alternative definitions of funding conditions), while the TR statistic does not reject the null of one cointegration relationship. However, when we implement Johansen cointegration tests in the VAR system without *HPI*, both statistics do not reject the null of no cointegration. Overall, the evidence supports the hypothesis of no cointegration amongst the variables<sup>9</sup>.

We therefore investigate the interactions between liquidity, asset prices, and key macroeconomic variables through two exercises. First, we study the leading indicator properties of 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 analyze 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 orthogonalized shocks and the variance decomposition one needs to define an appropriate identification scheme. On the one hand, we could use all the explicit and implicit restrictions provided by a structural model to identify orthogonalized shocks

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results, likely because of irregular, low-frequency components in some of the series.

<sup>9</sup>Full results of the tests are available upon request.

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 go through semi-automatic identification by orthogonalizing 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 alongside the more conventional Cholesky decomposition. 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<sup>10</sup>. 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 order 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 may introduce a downward bias in the estimated impact of asset price shocks on the system; the interpretation of our findings will account for this effect<sup>11</sup>.

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 including measures of monetary and credit aggregates for 17 industrialized countries. However, as the authors

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<sup>10</sup>Full results from the Cholesky decomposition are available on request.

<sup>11</sup>Most of the literature estimates these type of VARs in levels rather than in differences. Marcat (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 argued 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 levels. We find qualitatively similar results. Results from the level VAR are available upon request.

acknowledge, the problem with the panel approach is that it imposes pooling restrictions across countries, blurring 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.

### 3 Does Liquidity Granger-Cause Real Activity and Asset Prices?

In general, a variable  $x$  is said to Granger-cause variable  $y$  if the former helps in predicting future realizations of  $y$ . In a VAR setting, Granger-causation implies rejection of the hypothesis that the coefficients of the lags of variable  $x$  in the VAR equation of variable  $y$  are all equal to zero. 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<sup>12</sup>.

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 optimal order as selected by conventional lag-length criteria. Endogenous

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<sup>12</sup>Trecroci and Vega (2002) apply the same procedure to the investigation of the leading indicator properties of monetary aggregates for inflation and output in the euro area.

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 misspecification 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. For both models, standard hypotheses on residuals are not rejected. Table 1 reports estimates from our Granger non-causality tests. P-values for the first model are in parentheses, while those from the second are shown in normal text.

The choice of the measure of funding conditions does make 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 the specification of the VAR 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 securities brokers-dealers assets help to 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 yields valuable insights on the transmission mechanism

described by the VAR; therefore, we will include it in further analysis.

Overall, some findings stand out. First, funding conditions (especially when measured by  $CR$  and  $BD$ ) do 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 future developments of the default spread, which also moves with lagged  $PE$ . Granger-causality tests allow evaluating the significance of the direct lead-lag relationships between endogenous variables. That said, those tests fail to account fully for the feedback effects of the other variables in the system. Moreover, the analysis only focuses on VAR coefficients, therefore on the correlations between the variables' expected changes rather than following their shocks. Therefore, we now extend the investigation to 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 interplay between asset prices and shocks to funding conditions, as measured by the availability of credit, the size of broker-dealer balance sheet and the default spread. In turn, we also examine the feedback of those indicators on to developments in the business cycle. Using a composite asset price indicator able to point to relative over- or under-valuation of asset markets would have been a plausible alternative. 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  $PE$ , the indicator of stock market valuation, while the second replaces it with  $HPI$ , the index of house prices. 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). Full VAR estimation output is available from the working paper version of this study, Vassalli and Trecroci (2011) (<http://ssrn.com/abstract=1733975>).

We begin with a baseline specification in which the change in credit/GDP measures funding conditions. Figures 1-4 plot impulse responses for a system 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  $CR$ . In contrast, non-residential investment accelerates on impact and for 4-5 quarters following a positive shock to interest rates (but not to  $CR$ ). Therefore, surprise rises in interest rates have recessionary effects on consumption and residential investment, but not on the non-residential components of aggregate investment. The latter are likely more sensitive to the prospects of asset market values rather than those of policy rates. Interestingly, 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 not significantly affect  $PE$ . Such effect is not significant after an interest-rate shock. Moreover, credit too rises 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<sup>13</sup>). Here the nature of investment, whether residential or non-residential, 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 configuration had emerged already in the results of Granger-causality tests and implies that the transmission of credit and liquidity shocks may give rise to potentially destabilizing outcomes. Further, it casts some doubts on the long-term benefits of recent, liquidity-based, unconventional monetary policies.

Besides this broad finding, there are key differences across specifications. The responses to a  $CR$  shock 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

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<sup>13</sup>In a Tobin's  $q$  model, investors find it attractive to invest in a new building when the price of existing property is higher than its replacement cost.

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<sup>14</sup>. 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 about 50% of variance in residential investment, while it contributes only to around 15% of the variance of non-residential investment. This confirms that residential investment is more sensitive to interest rates than its non-residential counterpart is. 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 evidence on the marked expansionary reaction of  $PE$  to credit that we find in impulse response analysis.

The overall descriptive ability of the VAR is robust to the substitution of  $PE$  with the log change of the House Price Index ( $HPI$ ). Figures 2 and 4 present the GIRFs of VARs estimated over the sample 1977q2 to 2008q1, using residential and non-residential investment, respectively. 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. Next, house prices accelerate significantly following a shock to residential investment, but decelerate after one to  $NRI$ . This is intuitive and consistent with the notion 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.

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<sup>14</sup>These are not shown here for brevity, but can be found in Trecroci and Vassalli (2011).



The collateral effect of house price appreciation does not show up in our estimates. There is also a significant fall of inflation, the opposite of what we found in response to a  $PE$  shock.

Results on the variance decomposition somehow qualify the above findings. 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 there does not seem to be a Tobin's  $q$  effect of house prices. 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 is in keeping with the results obtained for  $PE$  and permits to add that while broad credit is a key driver of equity market valuations, it does not exert the same effect on housing valuations. In addition, the collateral effect of asset prices is not helpful in explaining broad credit expansions.

## 4.2 The role of brokers-dealers assets

Over the past two decades several innovations in the regulatory and operating framework of credit markets have made securities brokers-dealers balance sheets a potentially useful indicator of funding conditions. We now evaluate empirically the interdependence of such measure with macroeconomic variables and asset prices, using a VAR that includes the log change of brokers-dealers 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 until 2008q2. Most of the findings in the preceding subsection 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 brokers-dealers assets, unlike a credit shock, triggers a significant decrease of inflation and interest rates. This confirms one of Adrian and Shin's results, i.e., the pro-cyclicality of interest rates relative to brokers-dealers balance sheet. In addition, 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 prices 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 its non-residential counterpart. The impulse responses of brokers-dealers 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* (although smaller than the one experienced by *CR*), confirming the existence of a positive feedback loop from asset valuations to credit availability, on to asset prices again. Clearly, this finding is in line with the marked increase in market-making activity, security underwriting, and market-based intermediation who has accompanied the rise of importance of brokers-dealers institutions in the credit market.

The variance decomposition from the VAR with *PE* and using *BD* assets confirms that a *BD* shock, like a broad credit shock, explains only a small fraction of forecast error variance in consumption growth. Also, 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* that can be attributed to a 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 brokers-dealers balance sheets, whose size is therefore pro-cyclical. In addition, the response of residential investment to the *BD* shock is positive and signif-

icant, corroborating what obtained from the VAR with  $PE$ <sup>15</sup>. Second, the reaction of brokers-dealers assets is often insignificant and virtually indistinguishable from credit's reaction to the same shocks. However, unlike with  $PE$ , house prices shocks do 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 indicator. As to the response of house prices to endogenous shocks, the results obtained for the VAR with credit growth are confirmed and reinforced by more significant responses using  $BD$ . In particular, the response of house prices to a  $BD$  shock is significant and stronger than the one in the VAR with broad credit growth. As before, this could be explained by the fact that stronger balance sheets foster the demand for assets, including houses, thus leading to house price increases.

The variance decomposition widely confirms the results obtained from the VAR with credit. 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, whilst 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, 12% to 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

In general, an increase in bond yields signals higher credit risk premia and tighter credit conditions, which is the main reason why we also present estimates (Figures 9 to 12) from a specification that includes the default spread ( $SPR$ )<sup>16</sup>. We find that, as expected, a shock to the spread (i.e., a contraction in funding liquidity) is followed by a significant

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<sup>15</sup>The response of non-residential investment is negative but insignificant.

<sup>16</sup> $SPR$  measures the yield spread between Moody's seasoned Baa and Aaa corporate bonds.

decrease in inflation and non-residential investments. The responses to *SPR* shocks by interest rates, consumption, residential investment and *PE*, although barely or not significant, seem to clash with the textbook effects of a monetary contraction. In turn, the default spread exhibits a significant and long-lasting (6 quarters) negative response to a positive *PE* shock. Likely, as equity values increase, credit risk premia shrink; this may reflect not only buoyant expectations about firms' profitability, but also a tendency for looser credit standards. The same occurs for stronger growth in spending on 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 early 2000s, starting with the relatively benign credit conditions faced by property buyers. Our GIRFs document that positive shocks to inflation and interest rates are followed by a rise in the spread. On the other hand, in the 2000s the absence of significant inflation and the low interest rates environment may have prevented credit risk premia from widening up. The endogenous, two-way responses to consumption and spread shocks are muted. Forecast-error variance decomposition makes it clear that, even when the spread shock is significant, its contribution is quite modest: at a two-year horizon, it 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; inflation, residential investment and *PE* shocks each contribute by about 15%.

Last, Figures 11 and 12 present the GIRFs of VARs centered on *HPI*. The responses to a positive spread shock are all as expected. A surprise increase of the spread pushes down inflation, interest rates and non-residential investments (like in the VAR with *PE*), but it also triggers falls in consumption, residential investments and house prices. However, the fall of consumption and house prices growth is 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 the one 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 some observers claim to be paramount in the early 2000s. It will be in-

teresting in the future to assess whether similar conditions have emerged in the current, near-zero interest-rate environment.

Some FEVD results are worth noting. First, 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, and is broadly in line with findings in Case, Shiller and Quigley (2005).

## 5 Concluding Remarks

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 as such they are likely, if any, to underestimate the impact of securitization, financial liberalization and other recent institutional developments in credit markets.

Our empirical model moves beyond the standard representation of the monetary transmission by introducing a larger role for credit developments and asset values. Our results improve on the existing evidence along several dimensions. First, aggregate asset prices appear to contain helpful information about future macroeconomic developments. Second, both asset prices and the level of economic activity do accelerate significantly following expansionary shocks to funding liquidity. Funding liquidity has 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 recent, liquidity-based, unconventional monetary policies.

## 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).

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

NRI: 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: Federal funds rate (source: OECD, Main Economic Indicators, code 426217d).

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 bonds (source: FRED, Interest Rates, Corporate Aaa & Baa, 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)

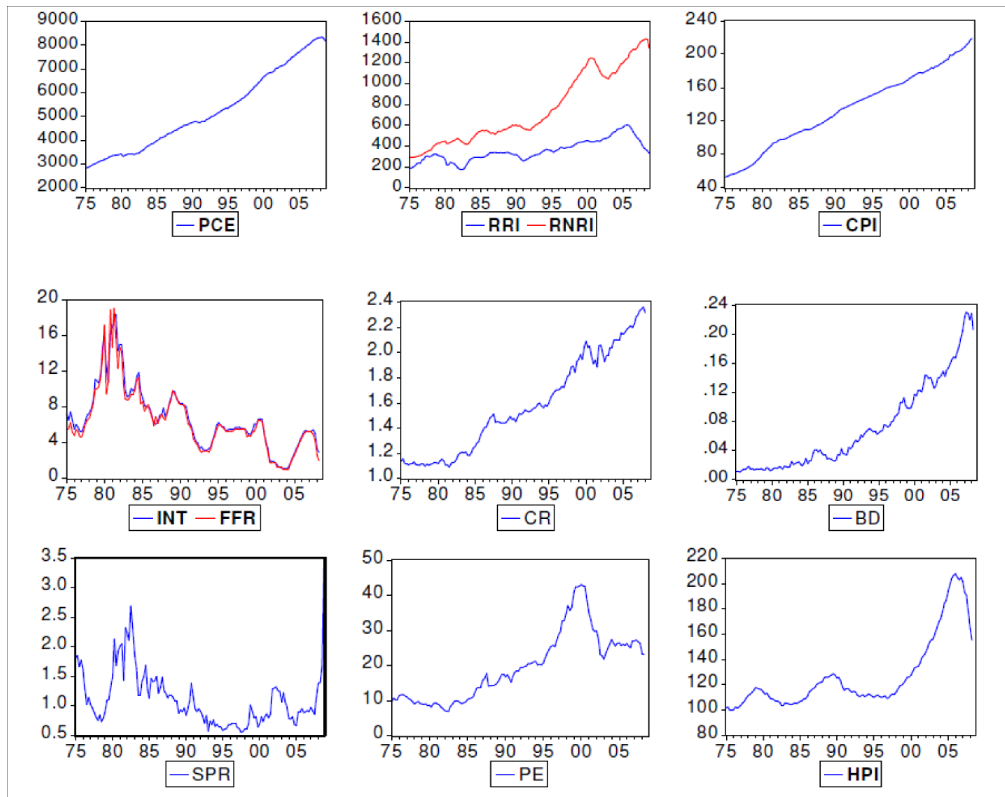
All variables are in 4-quarter log differences, with the exception of INT and SPR.

**UNIT ROOT TESTS**

VARIABLE	ADF test statistic (P-value)	PP test statistic (P-value)
PCE	-1.89 (0.654)	-1.61 (0.785)
ΔPCE	-9.14*** (0.000)	-9.81*** (0.000)
D4PCE	-3.16** (0.024)	-3.15** (0.025)
RI	-1.88 (0.660)	-1.67 (0.761)
ΔRI	-6.31*** (0.000)	-6.40*** (0.000)
D4RI	-4.84*** (0.000)	-3.55*** (0.001)
NRI	-2.271 (0.447)	-2.058 (0.564)
ΔNRI	-3.889*** (0.000)	-5.757*** (0.000)
D4NRI	-2.715*** (0.007)	-2.582** (0.010)
CPI	-2.141 (0.518)	-1.739 (0.729)
ΔCPI	-3.233** (0.020)	-11.352*** (0.000)
INFL	-2.684* (0.079)	-2.010** (0.043)
INT	-1.246 (0.195)	-2.622 (0.271)
ΔINT	-9.350*** (0.000)	-9.693*** (0.000)
CR	-2.931 (0.156)	-2.781 (0.207)
ΔCR	-10.957*** (0.000)	-11.336*** (0.000)
D4CR	-2.334** (0.019)	-4.202*** (0.000)
BD	-1.275 (0.890)	-1.275 (0.890)
ΔBD	-13.246*** (0.000)	-13.196*** (0.000)
D4BD	-4.429*** (0.000)	-4.179*** (0.000)
SPR	0.040 (0.694)	0.004 (0.682)
ΔSPR	-10.438*** (0.000)	-10.595*** (0.000)
PE	-1.349 (0.871)	-1.557 (0.805)
ΔPE	-7.999*** (0.000)	-8.235*** (0.000)
D4PE	-4.200*** (0.000)	-4.588*** (0.000)
HPI	-1.935* (0.051)	0.493 (0.820)
ΔHPI	-2.616*** (0.009)	-4.259*** (0.000)
D4HPI	-2.268** (0.023)	-1.129 (0.234)

ADF is the Augmented Dickey-Fuller test. PP is the Phillips-Perron test. H0: the series has a unit root.  
\*, \*\*, \*\*\* Indicate significance at 10%, 5% and 1% respectively. Sample: 1975Q1-2008Q4

Variables in levels

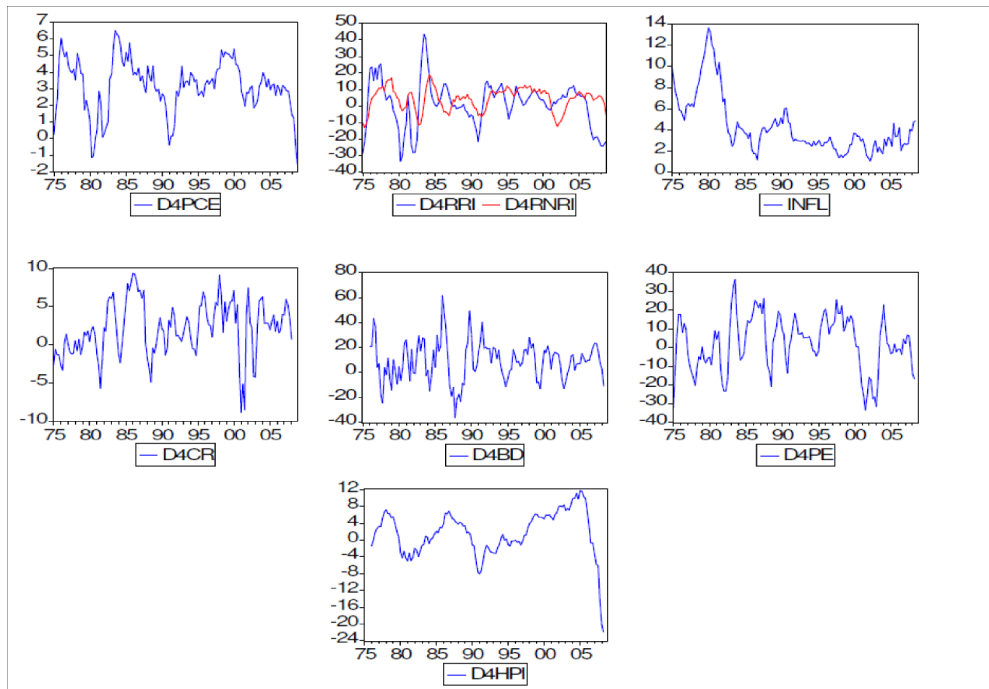


DESCRIPTIVE STATISTICS

	PCE	RI	NRI	INT	CPI	CR	BD	SPR	PE	HPI
<b>Mean</b>	5158.730	357.1779	739.7196	6.816165	133.1589	1.582430	0.071005	1.092256	19.64378	126.9331
<b>Median</b>	4795.900	337.4010	593.4780	6.060000	137.0000	1.522185	0.051052	0.960000	18.32496	115.0651
<b>Maximum</b>	8316.100	601.9770	1423.095	18.39000	213.3010	2.358872	0.230722	2.690000	43.06147	207.8386
<b>Minimum</b>	2814.600	175.4830	291.7310	1.070000	52.80000	1.090855	0.010384	0.550000	6.893638	99.49390
<b>Std. Dev.</b>	1625.685	104.5431	332.4811	3.624906	44.84991	0.386205	0.059441	0.435133	9.697599	28.80151
<b>Skewness</b>	0.407600	0.531534	0.534111	1.005169	-0.126484	0.338578	0.992477	1.250871	0.669499	1.618348
<b>Kurtosis</b>	1.944018	2.689028	1.866795	4.142747	1.954038	1.851243	3.024427	4.308339	2.634360	4.442311
<b>Jarque-Bera Probability</b>	9.862211	6.798616	13.43993	29.63313	6.417417	9.854089	21.83771	44.16967	10.67663	69.58372
	0.007219	0.033396	0.001207	0.000000	0.040409	0.007248	0.000018	0.000000	0.004804	0.000000
<b>Sum</b>	686111.1	47504.66	98382.71	906.5500	17710.13	210.4632	9.443618	145.2700	2612.623	16882.10
<b>Sum Sq. Dev.</b>	3.49E+08	1442662.	14591769	1734.473	265519.9	19.68834	0.466384	24.99292	12413.73	109497.6
<b>Observations</b>	133	133	133	133	133	133	133	133	133	133



Variables in differences



DESCRIPTIVE STATISTICS

	D4PCE	D4RI	D4NRI	INFL	D4CR	D4BD	D4PE	D4HPI
<b>Mean</b>	3.279182	2.389048	4.829288	4.207177	2.245189	9.299429	2.879668	1.817753
<b>Median</b>	3.277919	3.567594	6.126815	3.334497	2.207346	9.732217	5.125796	1.820756
<b>Maximum</b>	6.505520	43.41448	18.72291	13.62102	9.348847	61.76972	36.28356	11.72675
<b>Minimum</b>	-1.142050	-33.46683	-12.42104	1.063542	-8.857615	-36.33989	-33.49221	-20.10005
<b>Std. Dev.</b>	1.499183	13.12224	6.582523	2.679017	3.561632	15.69935	14.22949	5.099864
<b>Skewness</b>	-0.564653	-0.132779	-0.623134	1.736797	-0.420209	0.113701	-0.357993	-0.749878
<b>Kurtosis</b>	3.533413	4.145197	2.981846	5.632663	3.285229	3.746486	2.729124	4.883584
<b>Jarque-Bera Probability</b>	8.384249	7.428232	8.350133	102.1076	4.233658	3.273120	3.149806	31.15971
	0.015114	0.024377	0.015374	0.000000	0.120413	0.194648	0.207028	0.000000
<b>Sum</b>	423.0145	308.1872	622.9781	542.7259	289.6294	1199.626	371.4772	234.4901
<b>Sum Sq. Dev.</b>	287.6862	22040.73	5546.190	918.6731	1623.709	31548.13	25917.25	3329.102
<b>Observations</b>	129	129	129	129	129	129	129	129

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## TABLES AND FIGURES

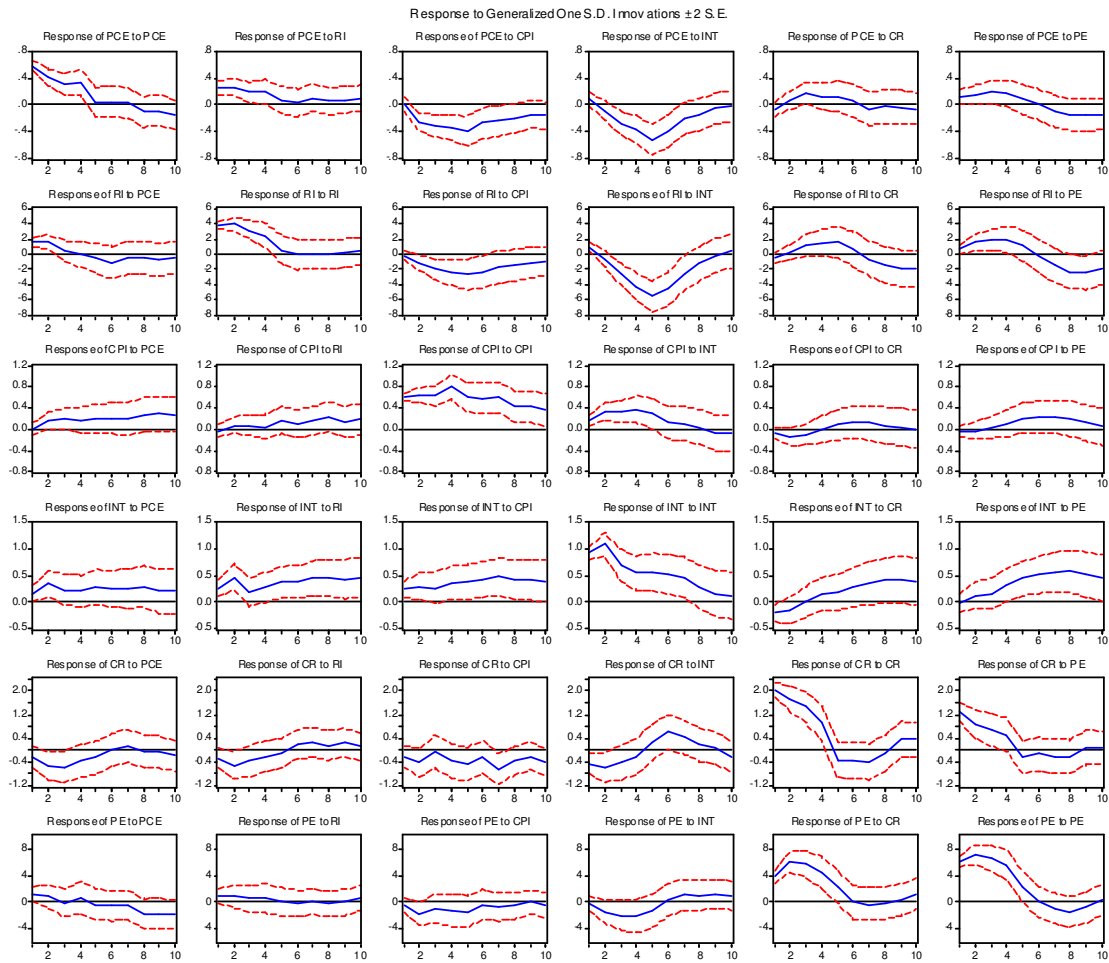
**Table 1 - Tests for Granger non-causality of CR, BD and SPR**

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).

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

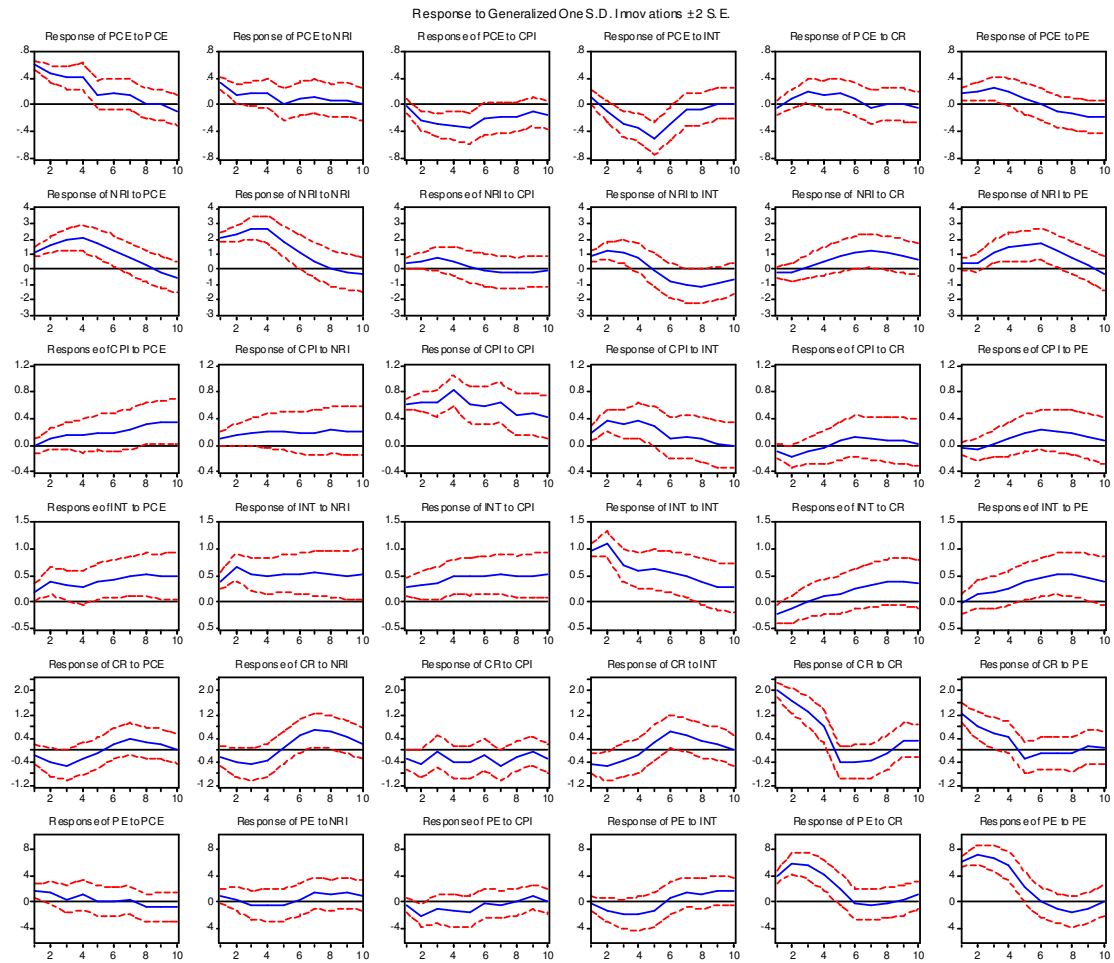
**Figure 1 - Impulse responses from VAR with PE and RI**

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).



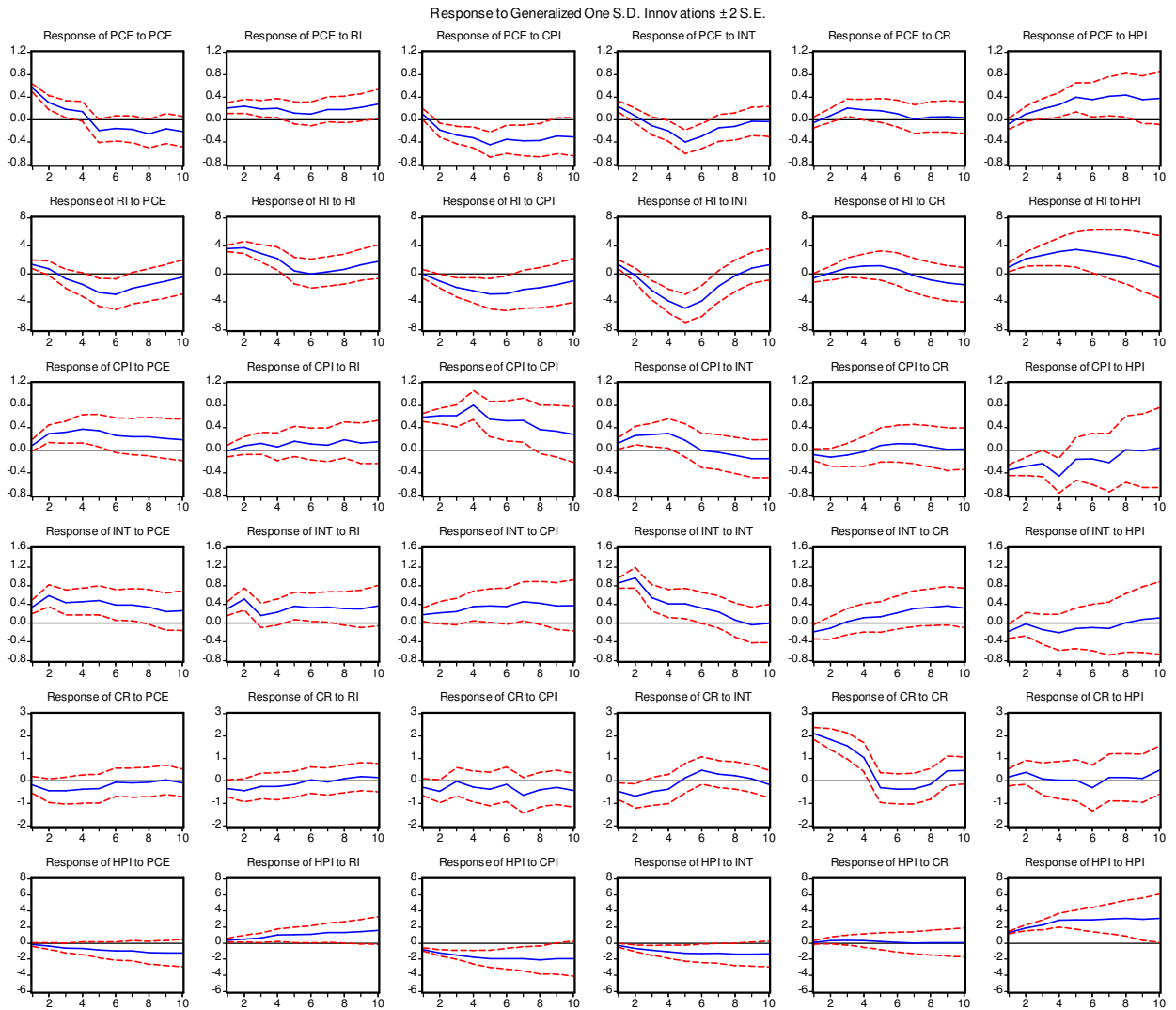
**Figure 2 - Impulse responses from VAR with PE and NRI**

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**

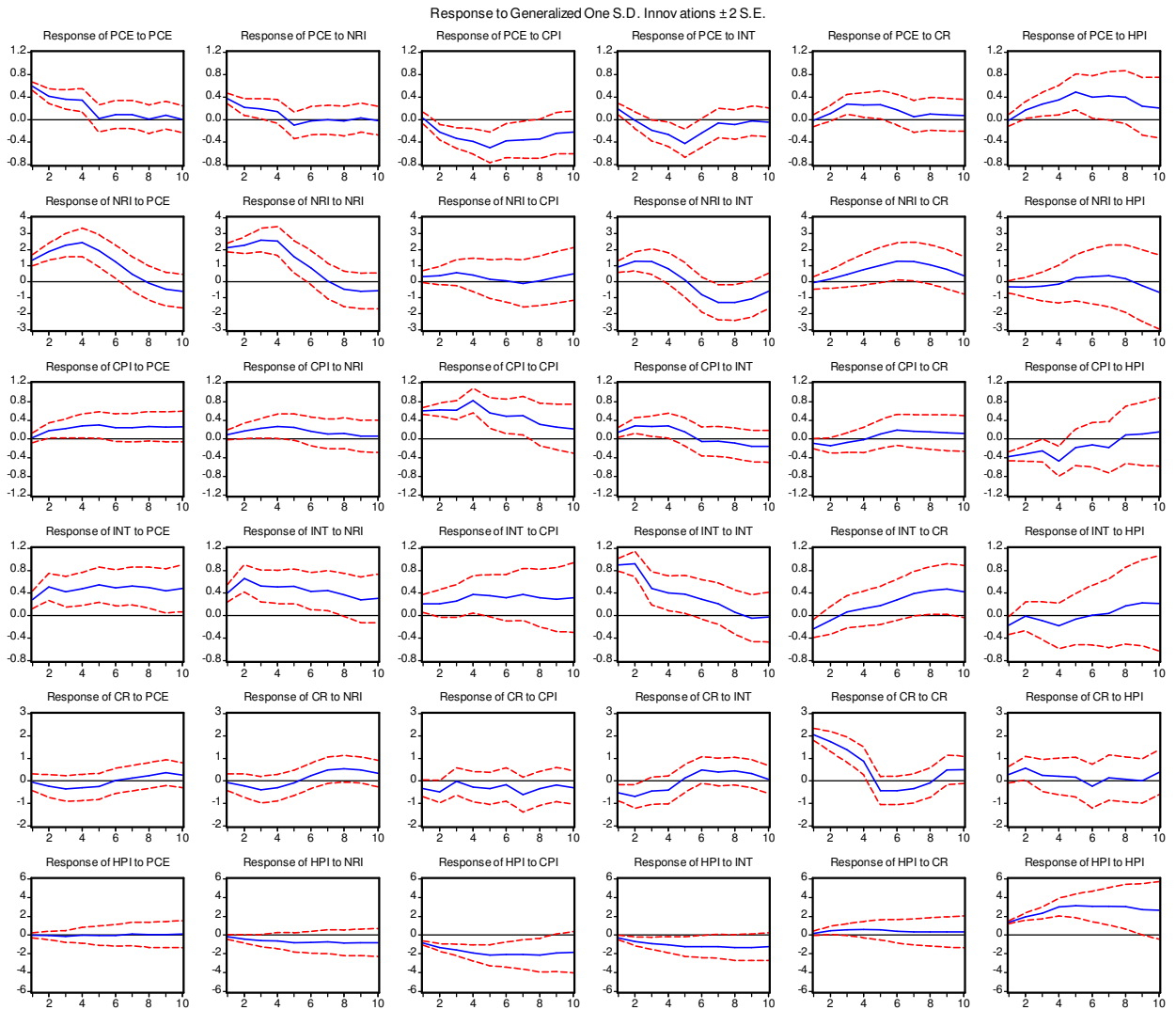
Generalized impulse responses to a one-standard deviation shock,  $\pm$  two standard errors bands. The VAR lag length is 5, and it includes the variables  $X_t' = (\Delta PCE, \Delta INV, \Delta CPI, INT, \Delta CR, \Delta ASP)$ , where  $INV$  is residential investment ( $RI$ ) and  $ASP$  is the log 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).





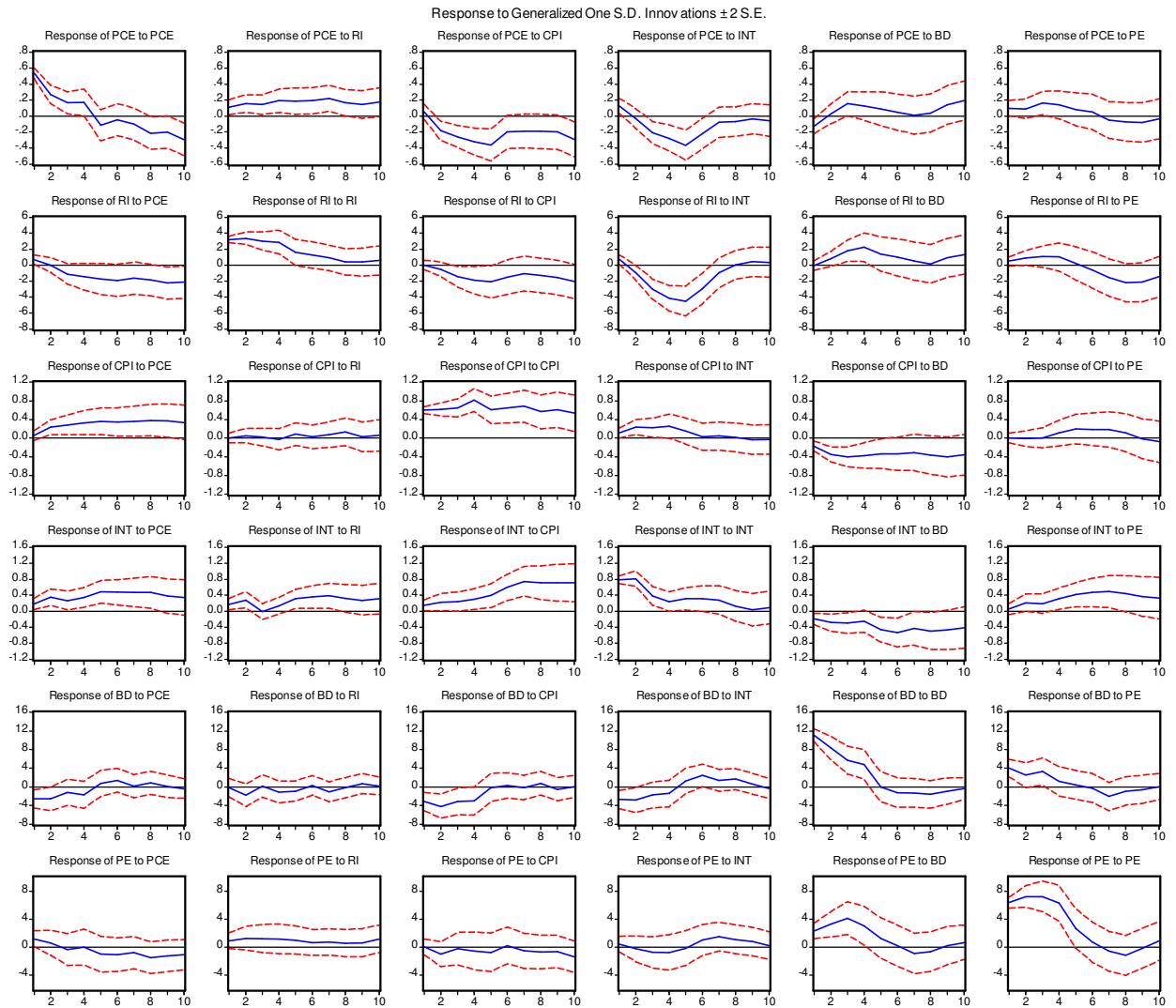
**Figure 4 - Impulse responses from VAR with HPI and NRI**

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).



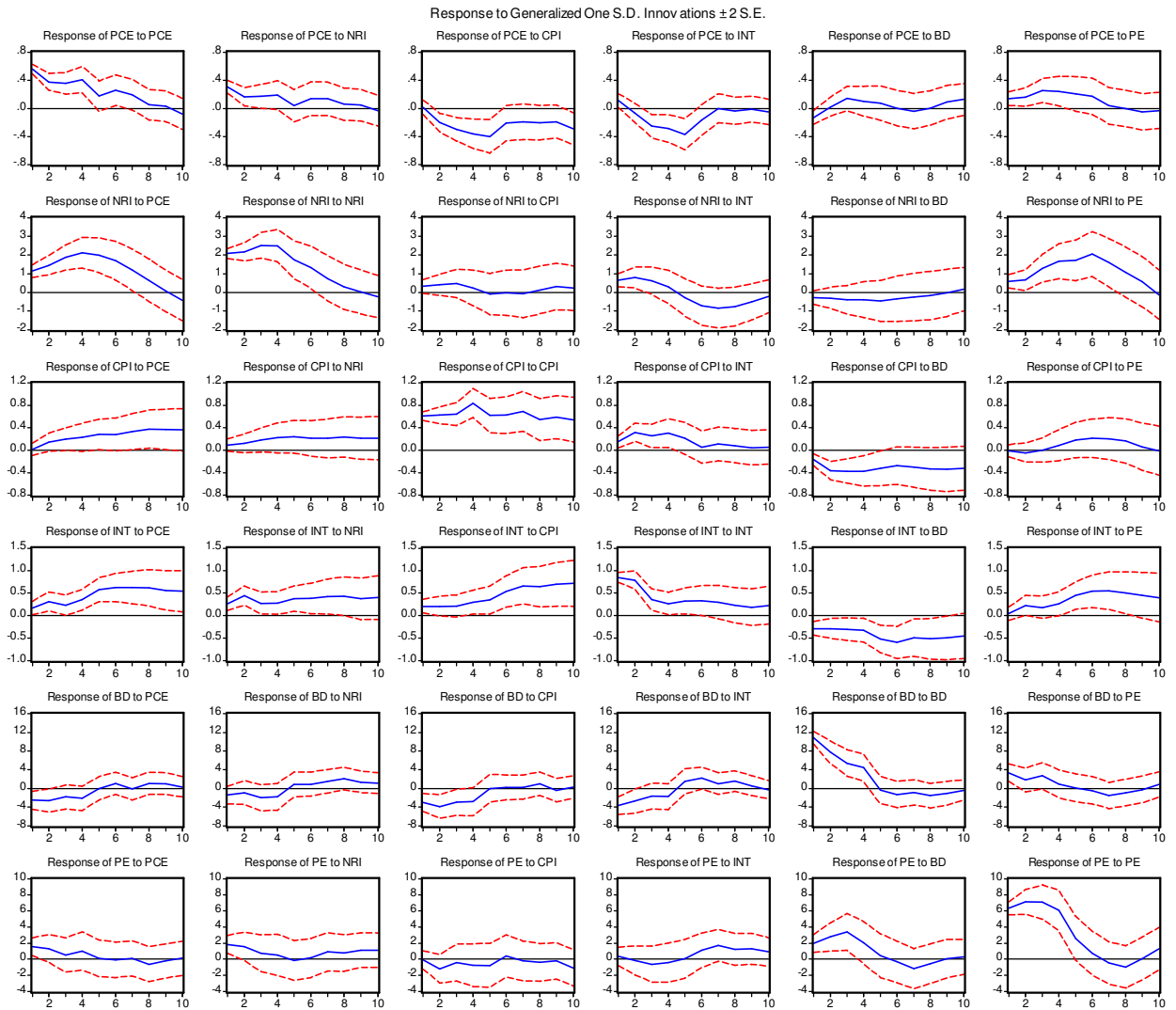
**Figure 5 - Impulse responses from VAR with PE and RI**

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).



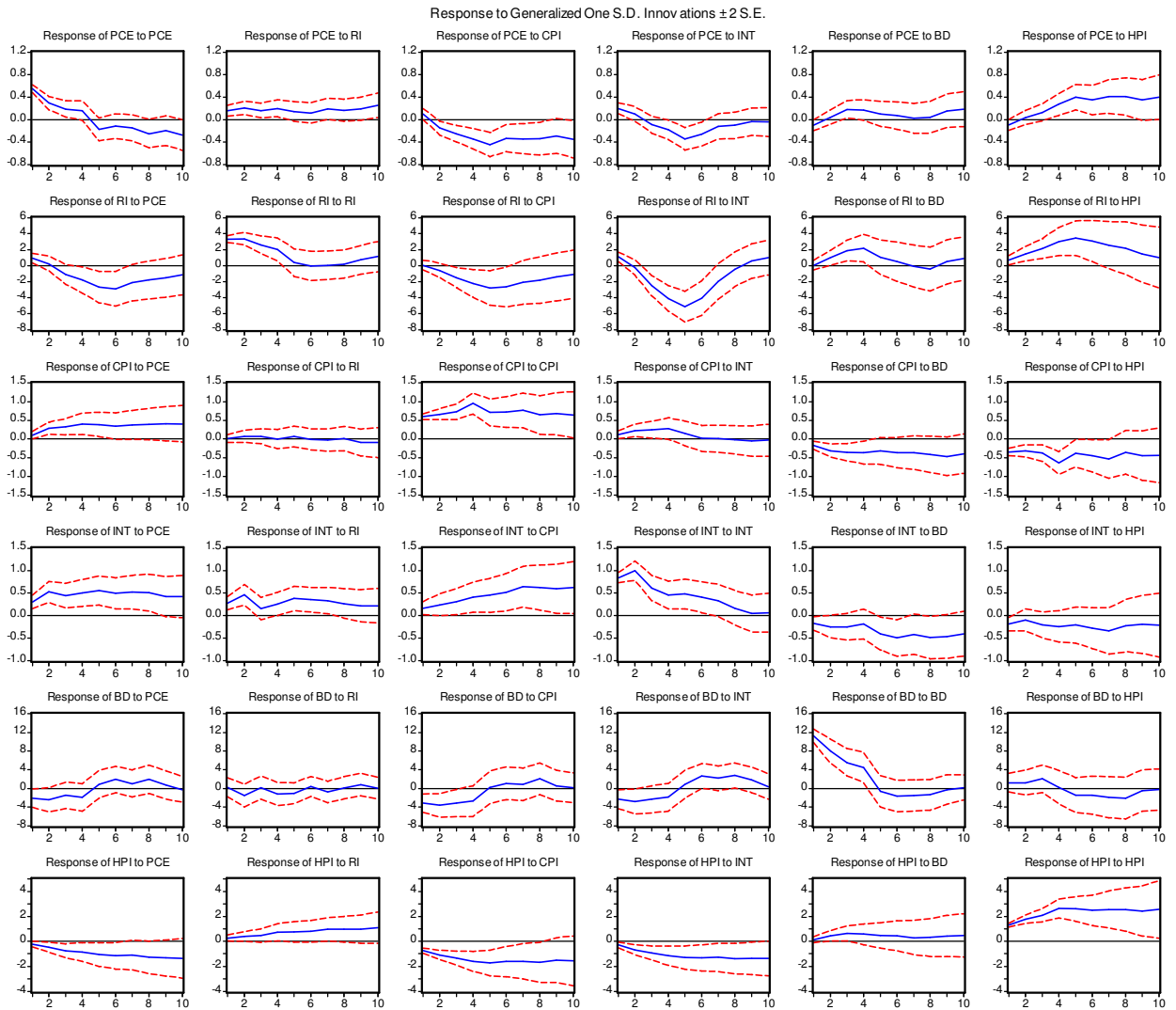
**Figure 6 - Impulse responses from VAR with PE and NRI**

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).



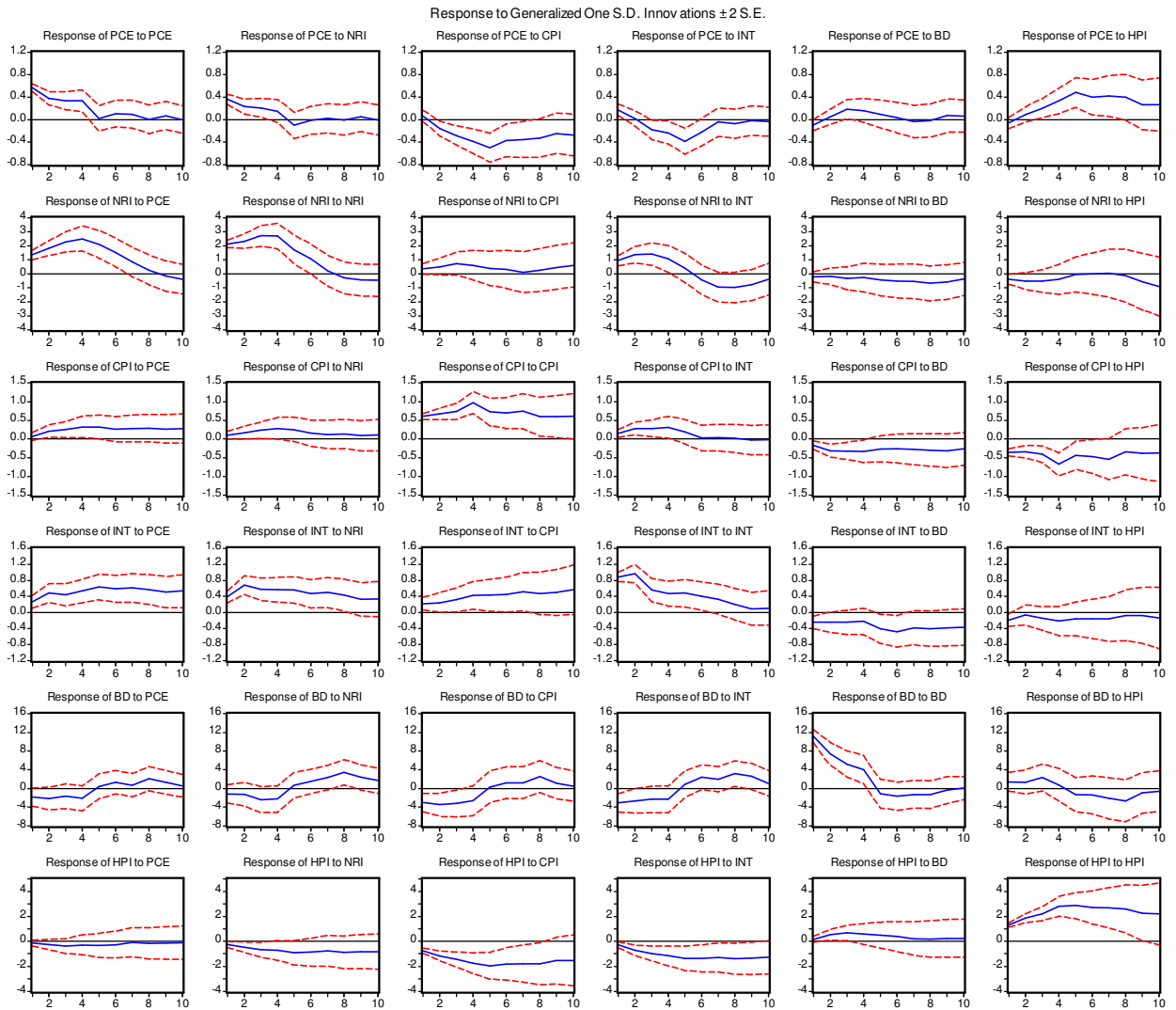
**Figure 7 - Impulse responses from VAR with HPI and RI**

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).



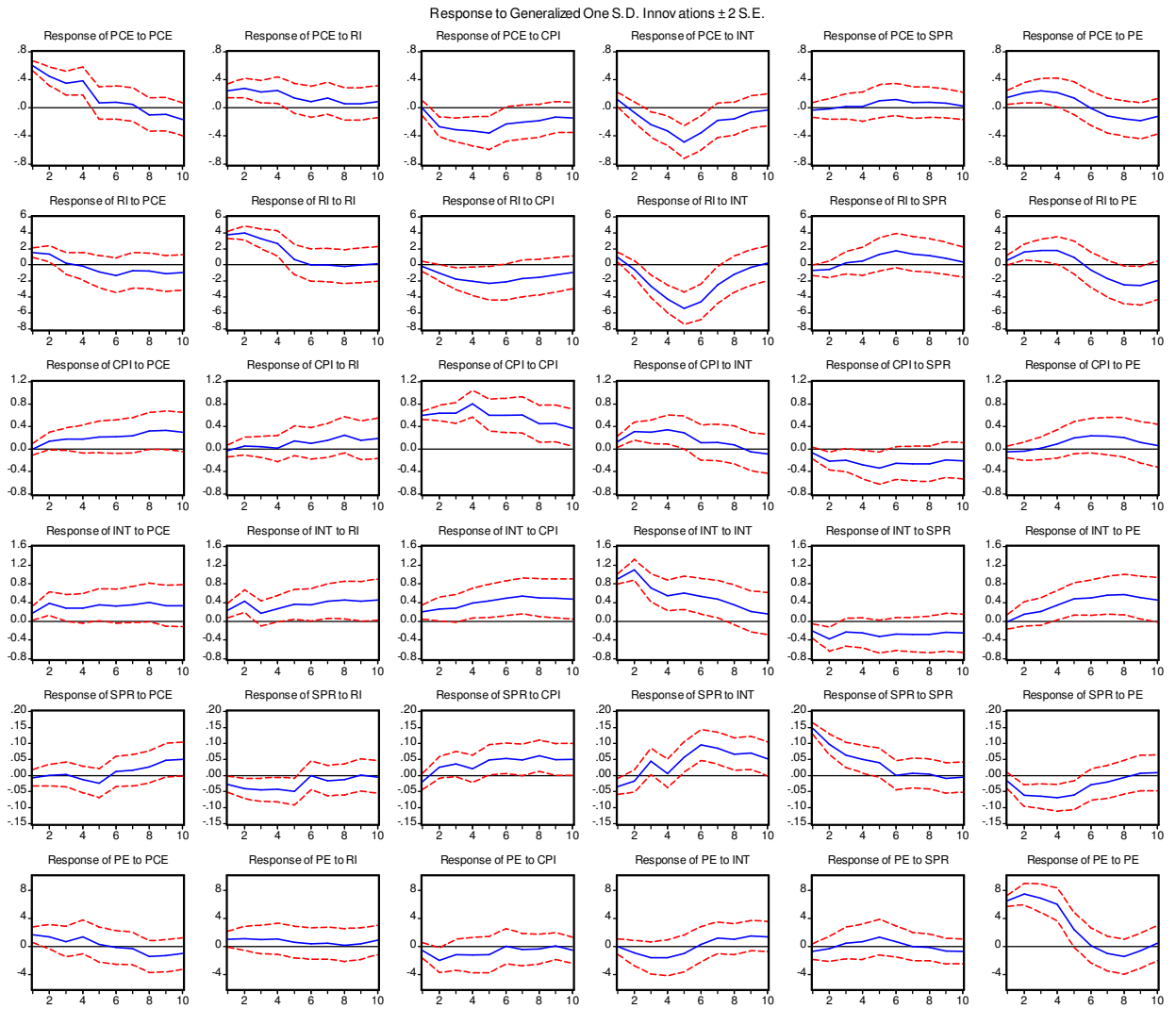
**Figure 8 - Impulse responses from VAR with HPI and NRI**

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).



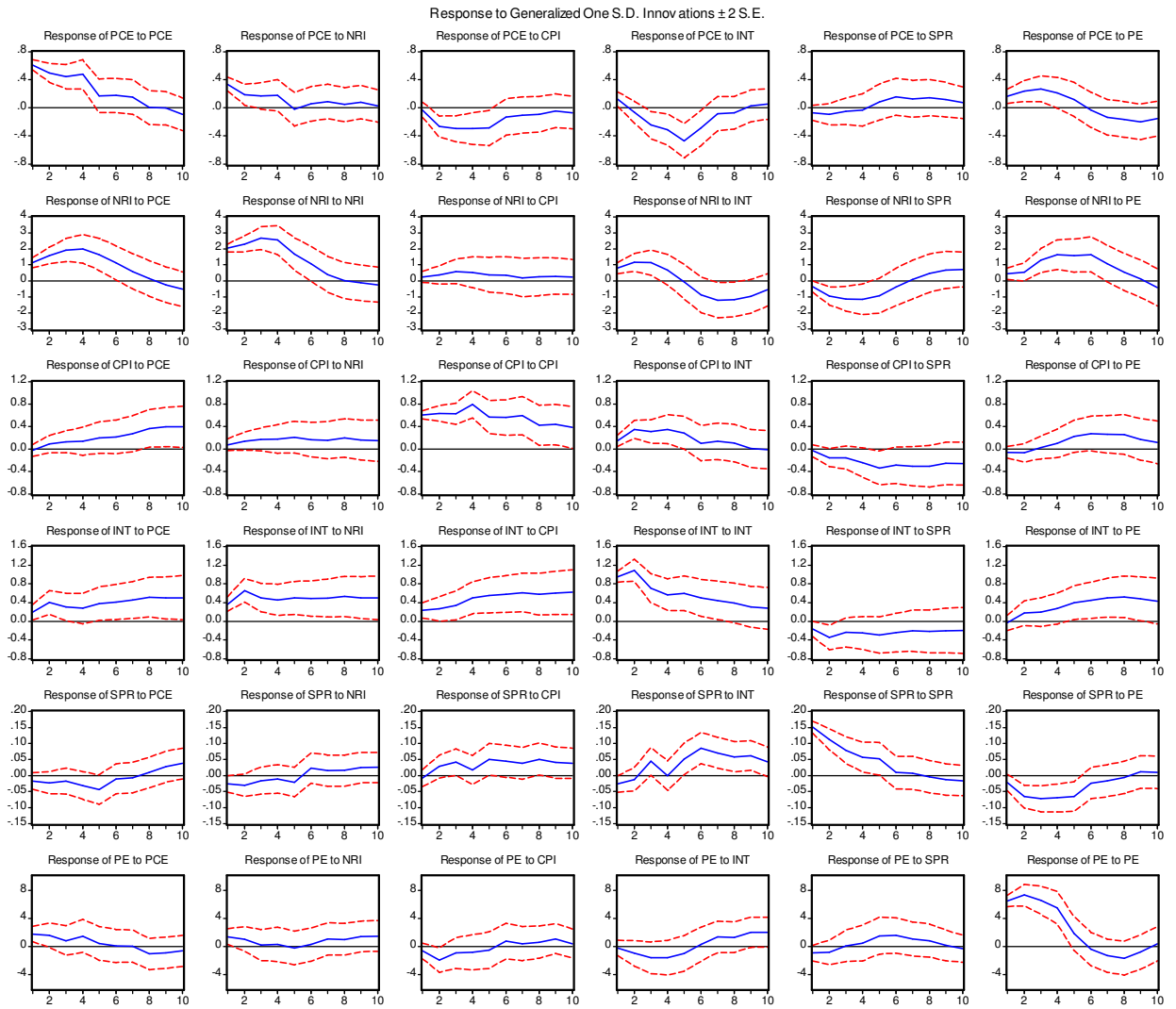
**Figure 9 - Impulse responses from VAR with PE and RI**

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).



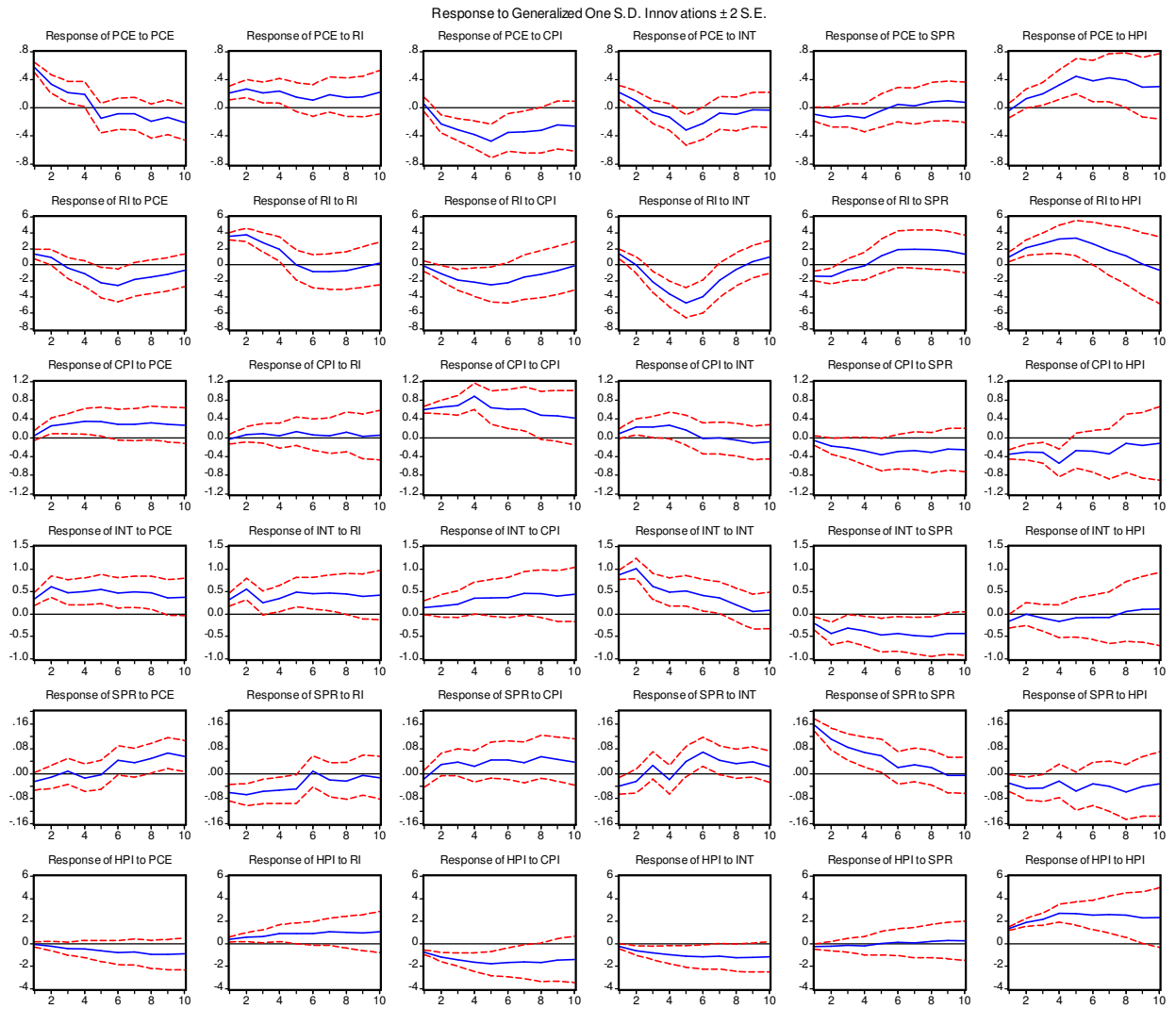
**Figure 10 - Impulse responses from VAR with PE and NRI**

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 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 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).





**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).

