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by

Juri Marcucci and Mario Quagliariello

Department of Economics and Related Studies
University of York
Heslington
York, YO10 5DD

IS BANK PORTFOLIO RISKINESS PROCYCLICAL? EVIDENCE FROM ITALY USING A VECTOR AUTOREGRESSION*

Juri Marcucci[a, b] and Mario Quagliariello[a, c, ♦]

[a] Bank of Italy, *Banking and Financial Supervision*, Via Milano 53, 00184 Rome, Italy
[b] University of California, San Diego, *Department of Economics*, 9500 Gilman Dr, La Jolla, CA 92093-0508, USA
[c] University of York, *Department of Economics and Related Studies*, Heslington, York, YO10 5DD, UK.

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♦ Corresponding author: Email: mario.quagliariello@bancaditalia.it; Ph. +39-06-4792-3980; fax. +39-06-4792-4460.

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Abstract

This study analyzes the cyclical behaviour of the default rates of Italian bank borrowers over the last two decades. A vector autoregression (VAR) modelling technique is employed to assess the extent to which macroeconomic shocks affect the banking sector (first round effect). The VAR also helps to disentangle the feedback effects from the financial system to the real side of the economy. We find evidence of the first round effect and some support for the feedback effect which operates via the bank capital channel.

JEL Classification: C32, E30, E32, E44, G28

Keywords: First-round effect, procyclicality, feedback effects, VAR, banks, default rate

1. Introduction

A large empirical literature has focused on the analysis of the effects of macroeconomic disturbances on the banking system. In fact, there is an increasing consensus on the fact that bank fragility is the result of both systemic and idiosyncratic factors. These studies generally confirm that banks' balance sheets are affected, simultaneously or with some delay, by the business cycle. Much less attention has been paid on the possible feedback effects of bank instability on real economic activity that could amplify the fluctuations especially during recessions.

This paper is an attempt to analyze both the effects using a vector autoregression (VAR) approach. With respect to cross-sectional or panel techniques, VAR's allow to fully capture the interactions among micro and macroeconomic variables, providing an ideal framework for financial stability purposes. As in the existing literature, we start with a simple open economy model in which we introduce the default rate equation to catch the direct effect of the business cycle on banks' portfolio riskiness. To evaluate the possible existence of a feedback effect, we add an equation linking credit supply and bank capital. This allows us to test whether banks' portfolio riskiness affects, in turn, the real economy and the nature of the transmission mechanism. Following the capital crunch hypothesis, we use some measures of capital adequacy as indicators of banks' ability to keep sufficient loan supply in recessionary conditions. The empirical results are quite supportive of both a first round effect and some feedback effects over the last two decades in the Italian economy.

The estimated relations may be easily employed for carrying out stress testing exercises, i.e., for assessing the resilience of the banking system in the presence of sudden unfavorable macroeconomic shocks, thus strengthening supervisory authorities' capability to forecast and, possibly, prevent financial crises.

The paper is organized as follows. Section 2 gives both the theoretical underpinnings and the empirical evidence of (pro)cyclicality of banks' operations previously found in the literature. Section 3 presents the economic model while Section 4 describes the estimation method employed and illustrates the empirical evidence on Italian data. Section 5 sketches some conclusions and directions for further research.

2. Cyclicality and procyclicality of banks' behavior

2.1 Theory...

There are a number of possible explanations to the procyclicality of banks' behavior: disaster myopia, over-optimism, herd behaviors, and insufficient market discipline. A possible pattern is as follows. At the beginning of the expansionary phase, firms' profits tend to increase, asset prices rise and customers' expectations are optimistic. Expansion of aggregate demand leads to a remarkable growth in bank lending and in economy's indebtedness. In such a boom, banks may underestimate their risk exposure and relax their standards; this process causes the deterioration of borrowers' creditworthiness. When an exogenous shock occurs, customers' profitability worsens and over-optimism is likely to become over-pessimism which, in turn, can trigger the fall of asset prices that further affects customers' financial wealth and depresses the value of collaterals. Furthermore, the rise of unemployment reduces households' disposable income and their ability to repay their debts. An accumulation of non-performing assets tends to emerge and the number of firm failures increases, causing losses in banks' balance sheets (cyclicality). We define the impact of the business cycle on the banking system as the first round effect.

Consequently, banks' profitability and capital adequacy deteriorate. Banks may, then, react by tightening credit supply, especially if they have thin capital buffers above the minimum capital requirement. If banks' credit can not be easily substituted by other sources of financing, firms can deal with insufficient funding for their investment projects. This amplifies the effects of the downturn determining procyclicality. Such feedback from the banking system to the real economy is the feedback effect.

According to the lending channel theory, reserve requirements on demand deposits are the main explanation of the role of banks in monetary policy transmission. In fact, aggregate bank deposit and asset expansions are constrained on the supply side by reserve requirements. The impact of external disturbances, either real or monetary shocks, is therefore affected by the level of banks' reserves.

Moreover, banks deal with another constraint since they have to comply with minimum capital requirements[1] (Bliss and Kaufman, 2002). Under a binding risk-based capital requirement, in normal times, banks can not expand lending without raising additional capital. Even when the minimum requirement is not binding, a low-capitalized bank may optimally forgo profitable loans in order to reduce the risk of future capital inadequacy[2] (Van den Heuvel, 2002). During recessions, loan losses can cause banks to contract credit supply in order to restore minimum capital ratios in response to the pressure of the supervisory authorities and the financial markets. If the banking system as a whole has the excess capital needed to absorb the adverse shocks, the overall effect on bank credit will be limited and the feedback impact negligible. By contrast, if banks have too thin capital buffers, they will prefer reducing lending rather than raising capital, which is far more costly in recessions. The presence of asymmetric information and the lemons problem are important in explaining why banks prefer contracting credit supply rather than issuing new equity (Peek and Rosengren, 1995). For this reason, Bernanke and Lown (1991) argue that the credit crunch should be better named capital crunch since the shortage of equity capital is the most important factor reducing banks' ability to lend.

Therefore, the actual relevance of the feedback effect depends on: 1) the role banks play in firms' financing; 2) the borrowers' access to the capital markets (i.e., the degree of substitutability of loans and bonds); 3) the adequacy of bank capital buffers. These factors influence the magnitude of banks' reaction to external shocks and the ability of the borrowers to find alternative financial sources if banks reduce their credit supply.

In fact, the lending channel is particularly relevant in countries where financial markets are relatively less developed and firms, especially small and medium-sized ones, largely depend on banks' loans. The speed of the transmission mechanism is affected by the maturity of loans and the nature (fixed/floating) of interest rates: banks that predominantly lend on a short term basis may change credit policies faster than those with long-term contracts.

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[1] Under 1988 Capital Accord, intermediaries are required to keep a level of capital no less than 8 percent of their risk-weighted assets (solvency ratio). Banks belonging to banking groups are required to keep a lower solvency ratio (7 percent) provided that the group is compliant with the 8 percent requirement. In the presence of provisions against expected losses, supervisory capital should cover unexpected losses. Non-compliant banks have to meet the regulatory solvency ratio by either raising additional capital or contracting their assets.

[2] Banks tend to keep their capital levels above the regulatory minimum to avoid incurring extra costs related to market discipline and supervisory intervention. For details on the capital buffer theory, see Furfine (2001).

The decline in banks' willingness to lend affects bank-dependent borrowers either reducing financial resources at their disposal or making the cost of external financing higher. In either case, the net return of investments falls, reducing the demand for investment and reinforcing the recession. Bank-dependent borrowers may not be rationed, but they are certain to incur extra costs associated with the search for new lenders and the establishment of new credit relationships (Bernanke and Gertler, 1995). This extra cost is particularly evident for small and medium-sized firms, where the role of private and soft information is more important and the costs of acquiring information and monitoring borrowers' credit worthiness are larger. The quantitative impact of a reduction in bank loans is however not certain, since it depends on the size of the credit reduction, on the effects of such reduction on credit costs, and on the share of output accounted for by bank-dependent firms (Bernanke and Lown, 1991). This is largely an empirical matter.

2.2 ...and empirical evidence

There is a huge literature supporting the existence of a first round impact from the economy to the banking sector.

Salas and Saurina (2002) observe that macroeconomic shocks are quickly transmitted to Spanish banks' balance sheets. In fact, during economic booms, intermediaries tend to expand their lending activity, often relaxing their selection criteria. As a consequence, during downturns, bad loans remarkably increase. Using a panel of Italian banks, Quagliariello (2004) finds that loan loss provisions and bad debts increase in bad macroeconomic times. Pesola (2001) shows that the high level of both corporate and households' indebtedness along with a GDP growth below the forecasts contributed to the banking crises in the Nordic countries. Similar evidence is provided in cross-country comparisons by Bikker and Hu (2002), Laeven and Majoni (2003) and Valckx (2003).

Using aggregated data, Gambera (2000), and Meyer and Yeager (2001) document that a small number of macroeconomic variables are good predictors for non-performing loan ratio in the US. Similarly, Hoggarth and Zicchino (2004) provide evidence of a clear link between the state of the UK business cycle and banks' write-offs.

Much less effort has been devoted to analyzing the feedback effect from the banking sector to the real side of the economy. From an empirical perspective, the bank-dependence of the non-financial sector is signaled by several factors such as the importance of small firms and the structure of capital markets.

The evidence on a feedback effect in the US is somewhat mixed. Bernanke and Lown (1991) agree that credit crunch imposes costs on some borrowers, but do not find any significant support that it plays a major role in worsening the recessionary conditions. Conversely, Peek et al. (2003) find that loan supply shocks affect the real macroeconomic variables and, in particular, those components of GDP more dependent on banks loans, such as inventories. On the role of bank capital, Peek and Rosengren (1995) show that in the US, during downturns, poorly capitalized banks tend to shrink credit more than well-capitalized intermediaries. Similarly, Kishan and Opiela (2000) confirm that the small low-capitalized banks have the largest response to monetary policy. Bernanke and Lown (1991) document that the capital constraint leads to unwillingness to lend, while falling capital ratios have a small but significant impact on banks' loans, even after controlling for macroeconomic conditions.

Market financing of the corporate sector is less developed in Europe than in the US and the effects of a capital crunch might be more pronounced. As reported by Ehrmann et al. (2001) and Gambacorta (2001), in France, only the largest companies can issue debt securities. In 1998, bonds represented only 1% of the corporate sector's total financial liabilities in Italy and Germany, 4% in France and Spain, 7% in the UK. Accordingly, in Italy and Germany, the stock market capitalization is rather low. Therefore, European firms are heavily dependent on banks' credit to finance their investments.

Table 1 contains some indicators that summarize the role of the banking system as a source of external financing.

[Insert Table 1 here]

In Italy, the relevance of bank credit as a source of financing for non-financial firms is witnessed by the share of monetary financial institutions' (MFI) loans to total lending, which is higher than the average for the euro area. Further, the weight of bonds with respect to total liabilities is rather small (1.7% against 8.9% in the euro area). Moreover, the fact that most borrowers rely on short-term loans suggests that the transmission mechanism may be relatively rapid. Finally, as far as the structure of the corporate sector is concerned, we note that the smallest firms, those with 1-9 employees, represent almost 43% of the total and absorb more than one-third of total employment.

While Kashyap and Stein (1997) observe that Italy is a country in which the lending channel is very likely to operate, the existence of a credit channel is well documented for Italy by Buttiglione and Ferri (1994), Angeloni et al. (1995), Chiades and Gambacorta (2000), and Gambacorta (2001).

As far as the capital crunch is concerned, analyzing the influence of Italian banks' capital on the response of lending to monetary and GDP shocks, Gambacorta and Mistrulli (2003) document that well-capitalized banks are better in shielding their credit supply from monetary shocks and their lending policies are less procyclical. Moreover, they find that banks with capital in excess of the regulatory minimum can more easily deal with temporary borrowers' difficulties, thus preserving long-term relations.

In sum, while there is a huge and unequivocal empirical support to the existence of a first round effect, there is much less evidence on the actual relevance of the feedback effect.

3. The economic model

We assume that the economy is described by the following structural form equation

$$\Gamma(L)\, y_t = \varepsilon_t \tag{1}$$

where $\Gamma(L)$ is a matrix polynomial in the lag operator L, y_t is an $n \times 1$ data vector, and ε_t is an $n \times 1$ vector of structural disturbances. These disturbances are serially uncorrelated and $Var(\varepsilon_t) = \Lambda$, where Λ is a diagonal matrix with the variances on its main diagonal. We can thus estimate a reduced-form VAR

$$y_t = \mathrm{A}(L)\, y_{t-1} + e_t \tag{2}$$

where $\mathrm{A}(L)$ is a matrix polynomial in the lag operator L, and $Var(e_t) = \Sigma$. Several identification methods can be used to recover the parameters of the structural-form equation from the estimated parameters in the reduced-form VAR. The identification schemes under consideration impose restrictions only on the contemporaneous structural parameters. Letting

Γ_0 be the matrix of contemporaneous coefficients in the structural form, and $\Gamma^0(L)$ be the coefficient matrix in $\Gamma(L)$ without the contemporaneous coefficients, we have

$$\Gamma(L) = \Gamma_0 + \Gamma^0(L) \tag{3}$$

Therefore, the parameters and the residuals in the structural-form equation and those in the reduced-form equation are related by the following equations

$$\mathrm{A}(L) = -\Gamma_0^{-1}\Gamma^0(L), \quad \text{and} \quad \varepsilon_t = \Gamma_0 e_t \tag{4}$$

which implies that

$$\Sigma = \Gamma_0^{-1}\Lambda\Gamma_0^{-1} \tag{5}$$

In the method proposed by Sims (1980), identification is achieved by Cholesky decomposition of the reduced-form residuals' covariance matrix. Consequently, Γ_0 becomes triangular so that a recursive structure, i.e. the Wold-causal chain, is assumed. In the general non-recursive modeling strategy suggested by Blanchard and Watson (1986), Bernanke (1986), and Sims (1986), maximum likelihood estimates of Λ and Γ_0 can be obtained only through the sample estimate $\hat{\Sigma}$. The right-hand side of (5) has $n(n+1)$ free parameters to be estimated. However, since Σ contains $n(n+1)/2$ parameters, even normalizing the n diagonal elements of Γ_0 to 1, we need at least $n(n-1)/2$ restrictions on Γ_0 to achieve identification. In this generalized structural VAR approach, Γ_0 can be any non-recursive structure.

For our analysis, we select a recursive identification scheme with a Cholesky decomposition. As a robustness check we also use the procedure suggested by Pesaran and Shin (1998), which provides results that do not depend on the ordering of the variables.

3.1 Aggregate Model

Hoggarth and Zicchino (2004) start selecting a narrow set of variables to be included in their VAR, motivating their choice with the previous literature on reduced-form macroeconomic models, such as Ball (1998), Blake and Westaway (1996) or Garratt et al. (2003). Hoggarth and Zicchino (2004) adopt a macroeconomic model enriched with a micro equation that describes the behavior of UK banks' loan write-offs. Loan write-offs are related to both the real interest rate and the output gap. The other four macroeconomic relationships consist of an IS curve, a backward looking AS curve which corresponds to a Phillips curve, an uncovered interest rate parity (UIP), and a modified Taylor rule. Following this small-scale macroeconomic model, their baseline VAR consists of four macro variables (output gap, nominal short-term interest rate, real exchange rate and annual inflation rate) and the micro variable banks' loan write-offs.

For our baseline VAR we build on a similar small-scale macroeconomic model. Thus, the baseline VAR includes the following variables: 1) bank borrowers' default rate, 2) output gap, 3) inflation rate, 4) three-month interbank interest rate, 5) real exchange rate. Certainly there are many other potential business cycle indicators, but a preliminary analysis suggested that the output gap is the most powerful one.

The identification scheme we adopt is recursive. The default rate is assumed to be contemporaneously exogenous to the output gap and all the other variables included. In the following, we order contemporaneously exogenous variables first, so that variables at the front are assumed to affect the following variables contemporaneously, but to be affected by shocks to the following variables only after a lag. On the other hand, those variables that are at the end are assumed to affect the preceding variables only after a lag, but are very reactive to shocks that hit the preceding variables. In the VAR, the financial variables are ordered at the end, since they respond immediately to shocks to the real side of the economy, whereas the real variables (default rate and output gap) are ordered at the beginning, because of their sluggish reaction to financial and monetary shocks. Furthermore, the output gap is ordered after the default rate reflecting the prior belief that business cycles affect bank losses only after a substantial lag, as shown by Bikker and Hu (2002), Pain (2003) and Quagliariello (2004).

We expect the default rate to be negatively affected by the output gap, since good macroeconomic conditions should make it easier for borrowers to honor their obligations. Higher interest rates entail an increasing debt burden for banks' borrowers. The rate of inflation, which is usually considered a signal of macroeconomic mismanagement and a source of uncertainty, should exhibit a positive relation with the default rate, even though one may also argue that inflation reduces the debt burden in real terms. Finally, we note that if there is a feedback effect, output gap might, in turn, be affected by a rise in the default rate.

3.2 Sectoral Models

Along with the aggregate model, we consider two sectoral models, in order to assess whether, and to what extent, the corporate and household sectors react to different macroeconomic shocks.

For our corporate specification we include the same aggregate variables of our baseline model, but for inflation and real exchange rate. In particular, we simply consider a model with the default rate for the corporate businesses and a measure of financial leverage. In detail, the corporate model includes the default rate for corporate business, the output gap, the leverage, and the interest rate, in this exact order. Along with the measure for the general aggregate activity, we add the level of the interest rates and non-financial firms' leverage. In fact, interest rates and indebtedness represent proxies for corporate sector's financial fragility. When interest rates are high, firms face greater difficulties in paying their loans back, especially if they are hugely indebted (Benito et al. 2001).

We also consider a model for the household sector, in which we try to identify the effects of macroeconomic shocks on households' default rates. Our VAR model for the household sector includes five variables: the default rate for the household sector, the output gap, the ratio of households' indebtedness to nominal GDP, the annual inflation rate, and the nominal interest rate. We excluded EXRATE since its impact on households' default rates should not be particularly relevant.

As for the corporate sector, the equations try to summarize the effects on the households' default rate of the macroeconomic conditions and the corresponding fragility of the household sector.

3.3 Feedback Model

Finally, to test for the existence of feedback effects, we include in the model a proxy for bank disposable capital and one for credit supply. With respect to the baseline model, this extended specification should be better suited for capturing the potential effects of banks' behavior on the real sector.

Our preferred proxy for disposable capital is the ratio of negative free capital to supervisory capital, where the free capital is the share of capital free from fixed assets (total supervisory capital minus net bad loans, real and financial fixed assets), and indicate if banks have adequate capital buffers for undertaking new investments. We prefer this variable to excess capital, i.e., the share of supervisory capital above the minimum regulatory requirement, since the former is not provided for by banking regulations. Therefore, it should be less sticky and better able to convey signals on capital constraint.

The spread between the average interest rate on short-term loans and the interest rate paid by the most creditworthy borrowers (10^{th} percentile of the distribution of short-term loans with respect to the interest rate) constitutes a good proxy for the overall credit supply conditions of the financial system (see Bonaccorsi di Patti et al., 2003). The widening of the spread should indicate a tightening of credit supply. This variable is thus introduced in the VAR to analyze the effects of loan market on the real side of the economy. In our view, credit supply conditions depend on macroeconomic variables as well as on banks' capital buffers.

Hence, this model includes the default rate, the output gap, the proxy for bank disposable capital, the inflation rate, and the proxy for credit supply.

4. Data and results

With respect to other methods, VAR's allow us to simulate the response over time of all the variables included in the system to either a disturbance to itself or to any other variable. In other words, the fact that all the variables are endogenously determined can be used to assess the feedback effects of the banking variables on the real economy.

4.1 Data

In Italy, credit exposures are to be valued at their estimated realizable value. In particular, bad debts are defined as all exposures to insolvent borrowers, regardless of any collateral received[3].

Notwithstanding the lack of an objective definition of bad loans, Italian banks tend to correctly classify their exposures with appropriate timing (Moody's 2003), making them a good ex-post indicator of the riskiness of banks' debtors. Since the stock indicators for bank riskiness are typically too sticky to promptly reflect the evolution of the business cycle, we use a flow measure, i.e., the ratio of the amount of loans classified as bad debts in the reference quarter to the performing loans outstanding at the end of the previous one. This ratio can be interpreted as a default rate.

For each variable, Table 2 provides a description of the variables, the method adopted for their computation, the sample availability, and their source. The top panel shows the microeconomic variables, while the bottom panel gives the macroeconomic ones.

[Insert Table 2 here]

Table 3 provides some descriptive statistics of all the variables andtheir correlations.

Some comments are needed for the correlations. All default rates are significantly highly correlated, with an almost unity correlation between ADR and ADR_C. This is not surprising since performing loans granted to the corporate sector represent more than 85% of total debts with peaks of 95% at the beginning of our sample. The alternative output gap measures are significantly correlated each other, with a higher correlation between GAP_T and the others.

[Insert Table 3 here]

Figure 1 depicts the main variables used in our analyses. The behavior of GAP provides a reliable picture of the evolution of the business cycle in Italy. It identifies four main downturns: in the aftermath of the European Monetary System crisis in 1992-93; in

[3] A borrower is considered insolvent if she is globally unable to cover her financial obligations and is not expected to recover, even if it does not necessarily result in legally ascertained bankruptcy.

1996 and 1999; and since end-2001. The plots of interest rate and spread confirm the severity of the 1992-1993 recession. In particular, the dramatic increase of the spread suggests that banks contracted their credit supply.

[Insert Figure 1 here]

The negative trend of interest rates and inflation since the mid-nineties witnesses the efforts of Italy in order to comply with the Maastricht Treaty provisions.

As far as the default rate is concerned, we note that the indicator tends to follow a cyclical pattern, but it is also affected by bank-specific factors. For instance, the peak in 1993-1994 is clearly the outcome of the unfavorable economic conditions, but the peak in 1995 reflects the crisis of the Southern banking system. Furthermore, we observe that in 2001 and 2002, despite the severe downturn, the default rate does not show any significant increase. In principle, the default rate series may show a seasonal pattern since banks tend to revise their evaluation on loan quality mainly at the year-end. However, we note that seasonal-adjusted series are very similar to the non-adjusted ones and the correlation is close to unity. Furthermore, the raw series does not present any particular seasonal patterns over the years and, therefore, we prefer using raw data[4].

The ratio of negative free capital to supervisory capital seems to be led mostly by bank-specific factors. For instance, the increase of the indicator in the second half of the nineties is the consequence of the remarkable expansion of financial fixed assets, due to the consolidation process of the Italian banking system.

To understand the statistical properties of the variables used in the present paper, and to characterize the nature of their trend and cycle components, a series of unit root tests are conducted (table 3). First of all, the Augmented Dickey-Fuller (ADF) test with a constant and with constant and trend, together with the Phillips-Perron (PP) test for the null of non-stationarity are employed[5]. We use a lag length of five quarters for the ADF tests and a bandwidth of eight quarters for the PP tests. The ADF test with constant rejects the null of non-stationarity only for GAP_HP, while the ADF test with constant and trend rejects the null of a unit root only for GAP at a significance level of 5%. The PP test rejects the null of non-stationarity only for all the default rates and for EXCRATIO at 5%.

Since these tests are generally unable to distinguish clearly between integrated and highly autocorrelated series, and have low power in small samples, their results must be interpreted in the light of economic theory. To gain additional insights, the KPSS test is also computed. This test swaps the roles of the null and the alternative hypotheses in such a way that the null of stationarity is tested[6].

The KPSS tests for both level and trend stationarity fail to reject the null of stationarity for all the series. Therefore, in the following analysis, the variables included in the VAR are all in levels, also because we are interested in tracing out their comovements and interrelationships, and this would somehow be biased, if first differences were adopted (Enders, 1995).

To take into account either structural breaks in the default rate series or particular events, we also introduce some intercept dummies. In both the baseline and the feedback models, we add two dummy variables: one for the fourth quarter of 1995, and the other for the period from the first quarter of 2001 to the first quarter of 2004. For the corporate sector, along with these dummies, we also include a dummy for the third quarter of 1991. Finally, for the household model, we only introduce a dummy for the first quarter of 2002.

All the dummies correspond to peaks of the default rate, generally due to specific factors or events. The dummy 2001:I-2004:I tries to control for a possible structural break in the default rate series. In fact, since 2001 credit quality seems to be, *ceteris paribus*, better than in the past, probably as a consequence of the adoption of more severe credit standards

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[4] The results provided in the following sections are generally robust to seasonal-adjustments.

[5] This set of tests is not reported and the table is available from the authors upon request.

[6] The KPSS test for the null of level or trend stationarity is computed as $\xi = \sum_{t=1}^{T}\left(\sum_{j=1}^{t} y_t\right)^2 \Big/ T^2\hat{\sigma}_{LR}^2$, where T is the sample size, $\hat{\sigma}_{LR}^2$ is the long-run variance of y_t, and y_t is the residual from the regression of the series on a constant or on a constant plus trend according to the particular null hypothesis being tested. The null of stationarity will be rejected for high values of ξ. The long-run variance of y_t is evaluated using a non-parametric estimator of the spectral density at frequency zero, $\hat{\sigma}_{LR}^2 = \hat{\gamma}_0 + 2\sum_{\tau=1}^{m} w(\tau,m)\hat{\gamma}_\tau$, where $\hat{\gamma}_\tau$ is the sample autocovariance of y_t at lag τ. If the Newey-West estimator is adopted, $w(\tau,m)$ is the Bartlett kernel. For the bandwidth m, the truncated automatic bandwidth selector suggested by Stock (1994) is implemented, so that $m = \min\{\hat{m}_T, 12(T/100)^{2/10}\}$, where $\hat{m}_T$ is Andrews' (1991) automatic selector based on an estimated AR(1) model.

and more sophisticated risk management techniques. The dummy also controls for the introduction of the European single currency.

4.2 Empirical Evidence from VARs

4.2.1 Baseline models

The sample for the baseline VAR covers the period 1990:I-2004:I. We start with a reasonably general lag structure and select the most parsimonious specification according to several information criteria. The left panel of Table 4 summarizes the results for lag selection. Several information criteria are reported, together with the sequential likelihood ratio test and the final prediction error. Numbers in boldface indicate the minimum along each column and, accordingly, select the lag to be chosen. Among the different criteria, we concentrate our attention to the Schwartz (SC) and to the Hannan and Quinn (HQ) Information Criteria. We do not consider the sequential likelihood ratio test because, in general, one can not control for the overall size of this test. The final prediction error is more important when a researcher is interested in forecasting, whereas the Akaike information criterion (AIC) is well known to be extremely insensitive to the addition of more lags which are not sufficiently penalized. Most criteria suggest a very parsimonious representation. We adopt the lag structure consistent with the Schwarz criterion and choose one as the optimal number of lags. This is consistent with previous works on quarterly data (Hoggarth and Zicchino, 2004).

[Insert Table 4 here]

Preliminary indications on the interactions among the variables are provided by the results of the Granger pairwise causality tests. The *p*-values for these tests are reported in the right panel of Table 4. Apart from the real exchange rate, all the other variables help to predict the default rate at the 5% significance level. By contrast, there is no evidence of the existence of a feedback effect from the banking system to the real economy, since ADR does not help to predict the output gap at usual significance levels.

When estimating a reduced-form VAR, the error term can be interpreted as surprise movements in each variable after taking its past values into account. If the different variables in the model are correlated with each other, then the error terms are likely to be also correlated across equations. On the other hand, if reduced-form residuals show a low degree of correlation across equations, then the ordering of the variables becomes almost unimportant and, therefore, they get close to the structural shocks. This seems to happen in our baseline VAR, where the highest correlations among the residuals are those between INFL and GAP, and INFL and REXR[7].

Table 5 shows the percentage of the variance of the error made in forecasting a variable due to a specific shock at a given horizon. Looking at the variance decomposition of ADR and GAP, we can see that at twelfth-quarter horizon, less than 5% of the error in the forecast of ADR can be attributed to GAP. The output gap seems to be a highly persistent variable since twelve quarters ahead only 20% of the error in its forecast is due to all the other variables in the system. Most importantly, we can hardly attribute to ADR 2% of the error in the forecast of GAP at the same horizon.

[Insert Table 5 here]

The impulse response functions provide a more detailed picture of the dynamics of the variables. Figure 2 shows the impulse responses of each variable to one standard deviation shocks of the others.

[Insert Figure 2 here]

The response of the default rate to a positive one-standard deviation shock of the output gap is significant in the subsequent four quarters. This means that in expansionary phases the default rate tends to diminish and the effect lasts for almost one year. The responses are similar in magnitude in all quarters. The cumulative impact is about –0.05. As expected, the rise of interest rates increases the probability that borrowers become insolvent and the effect of this shock is significant and very persistent (6 quarters). The same holds also for the inflation rate.

The evidence provided so far is very supportive of the hypothesis that the default rate follows the business cycle. To assess the robustness of our results, we re-estimate the baseline model in two ways: i) we extend the sample by including the period 1985-1989, where, since the default rate is available only on an annual frequency, quarterly data are

[7] Residual correlations are not reported. The tables are available upon request.

interpolated[8]. ii) We use different indicators of the phase of the business cycle, including the output gap computed as deviations from its trend (GAP_T) and from the Hodrick-Prescott filtered series (GAP_HP).

The first robustness check consists in re-estimating the baseline VAR over the period 1985:I-2004:I. Overall the previous findings still hold. GAP does Granger cause ADR at 5% significance level, together with R3M. The correlations between reduced-form residuals show that now only the linear relationship between INFL and REXR is quite strong, suggesting that variable ordering might not be an issue here. Regarding the variance decomposition, at twelfth-quarter horizon, more than 16% of the error in the forecast of ADR can now be attributed to GAP, whereas at the same horizon 8% of the error of GAP is attributable to ADR.

Figure 3 depicts the impulse response functions for the VAR with longer sample.

[Insert Figure 3 here]

The impulse responses confirm the main findings of the previous model, even though the response of ADR to inflation is no longer significant. The response of ADR to output gap is conversely much more persistent (7 quarters). The response of the output gap to a positive shock in the default rate goes in the expected direction, but it is not significant.

We also compared our starting results with those obtained using alternative business cycle indicators. Many results from previous models still hold. When GAP_HP is employed, the lag length selected by the Schwartz criterion is 1, and all the variables in the ADR equation do Granger cause the dependent variable, except the annual inflation rate. The residuals show the highest correlations not only between INFL and REXR, but also between ADR and GAP_HP. At twelfth-quarter horizon, 15% of the error in the forecast of ADR can be attributed to GAP_HP, whilst at the same horizon almost 12% of the error of GAP_HP is attributable to ADR[9].

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[8] Data are interpolated by calculating the average weight of each quarterly datum on the corresponding year, for the sample period where quarterly data are available (1990:I-2004:I). Then, the final quarterly weight applied to annual data before 1990:I is the average of the weights over each single quarter for the sample 1990:I-2004:I.

[9] The tables of the variance decomposition for the robustness models are not reported. They are available upon request.

As far as GAP_T is concerned, the selected lag is still 1, and both GAP_T and R3M do Granger cause the default rate. In addition, the residuals show the highest correlations between INFL and REXR, and also between ADR and GAP_T. At twelfth-quarter horizon, 14% of the error in the forecast of ADR can be attributed to GAP_T, but at the same horizon only 3% of the error of GAP_T is attributable to ADR. Since in the ADR equations both indicators do Granger cause the dependent variable at any conventional level of significance, our results on the cyclicality of the Italian default rate seem to be robust to different specifications. The relative impulse response functions are illustrated in Figure 4.

Figure 4 compares the impulse responses of the default rate to shocks to the different measures of the output gap. The impulse response of ADR to the corresponding measure of output gap is significant for 4 quarters. Therefore, even with different measures of the output gap the previous results are still valid.

[Insert Figure 4 here]

As a further robustness check, along with the standard IRF's computed with the Cholesky decomposition, we also use the responses calculated using the procedure suggested by Pesaran and Shin (1998), which gives results that are independent on the order of the variables. In all cases, the response of ADR to a shock to the real economy is significantly negative, at least for the first few quarters.

4.2.2 Corporate model

Table 6 and 7 report the results for the Corporate Sector VAR.

[Insert Table 6 and 7 here]

The lag length selected by SC and HQ is 1. Both GAP and LEVERAGE do Granger cause ADR_C, confirming the findings for other countries in the literature. The only residual correlation with a high value is the one between R3M and LEVERAGE. At the twelfth quarter ahead, only 5% of the error in the forecast of ADR can be linked to GAP, whereas at the same horizon ADR_C takes only into account 8% of the error in the forecasts of GAP (Table 7).

The impulse response functions for this model are plotted in Figure 5. They clearly show that a positive shock on GAP has a significant negative impact on ADR for the subsequent 4 quarters and such an impact does not significantly vary across quarters.

[Insert Figure 5 here]

Furthermore, the response of ADR to LEVERAGE is positive and very persistent. By contrast, the interest rate level does not appear to be very significant, confirming the results of Granger causality.

4.2.3 Household model

Table 8 and 9 illustrate the results from the household VAR. The Schwarz and HQ information criteria advise to employ one lag.

[Insert Table 8 and 9 here]

The Granger causality tests shows that, as expected, the default rate for the household sector is Granger caused by the output gap, the level of indebtedness and the inflation rate. The residuals are not highly correlated, but for the relationship between INFL and GAP, indicating that the ordering might not be an issue here. Twelve quarters ahead only 9% of the error in the forecast of the default rate can be attributed to GAP, while ADR_H explains only 1% of the error in the forecast of the output gap (Table 9).

However, looking at the impulse response functions in Figure 6, we note a puzzling result for the ratio of households' financial debts to GDP. A positive shock on the latter negatively affects the former. This outcome seems to indicate that increasing levels of debt reduce the default rate, which is counterintuitive. We believe that such result is due to the indicator, which is probably a rough proxy for indebtedness. Indeed, there is not clear-cut evidence on the expected effects of this variable (see also Salas and Saurina, 2002, and Pain, 2003). The response of ADR to GAP is significant for the first four quarters and the impact is particularly large in the second and the third quarters.

[Insert Figure 6 here]

4.2.4 Is there a feedback effect?

The results obtained in the previous paragraphs are very supportive of the idea that the default rate is cyclical, i.e., that banks' portfolio quality tends to deteriorate during downturns. By contrast, we did not find any significant evidence of procyclicality, i.e., of a feedback effect from the banking sector to the real economy.

In this section, we explore the issue of procyclicality by discussing our VAR model that explicitly takes into account the variables that may act as a transmission mechanism of the feedback effect.

Table 10 gives the results of the lag selection criteria and Granger causality tests for this reduced-form VAR. According to the Schwarz information criterion, we include one lag of the selected variables. Also, the table provides the results of the Granger causality tests. The output gap does Granger cause ADR at 10% significance level. In addition, INFL and SPREAD help to predict ADR at the usual significance levels. More interestingly, there seems to be a significant feedback effect as witnessed by the fact that ADR and SPREAD do Granger cause GAP. Unfortunately, our findings do not document a relevant role of capital buffers in the transmission mechanism. The residuals are not highly correlated, but for the relationship between INFL and GAP, and that of SPREAD and GAP, indicating that the ordering might not be an issue here.

[Insert Table 10 here]

Tables 11 reports the variance decomposition for the feedback model. Twelve quarters ahead, only 8% of the error in the forecast of the default rate can be attributed to GAP, while ADR_H explains only 2% of the error in the forecast of the output gap. Moreover, at the same horizon only 1% of the forecast error in NEG_CAP can be attributed to ADR, while almost 9% of the error in SPREAD is explained by NEG_CAP. Eventually, SPREAD explains more than 12% of the forecast error of GAP three years ahead. These results give substantial evidence of a feedback effect.

[Insert Table 11 here]

The impulse response functions depicted in Figure 7 partially confirm the results of the Granger causality tests. There is still clear evidence of a first round effect and some signals that a feedback mechanism operates at least in the first two quarters. In particular, we do not find evidence of a direct effect of ADR on NEG_CAP, which is not surprising if banks are able to cover loan losses using profits, without depleting their capital. Furthermore, the response of SPREAD to NEG_CAP shows that credit supply is also partially affected by capital constraints and the significant reaction of the output gap to SPREAD confirms that the contraction of loan supply may reinforce the recessionary conditions.

[Insert Figure 7 here]

5. Conclusions

The aim of this paper is to shed some light on relation between business cycle and banks' behavior for the Italian banking system. Previous studies mainly focused on the issue of cyclicality of banks operations, whereas the analysis of the feedback effect has been largely neglected so far.

We employ a reduced-form VAR to assess the relevance of both the effect of the business cycle on banks' borrowers default rates and the possible impact of bank problems on the real economy. The VAR systems allow to fully capture the interactions among the relevant variables and to analyze their simultaneous responses to shocks of different nature.

Following the existing literature, we start with a simple open economy model in which we introduce the default rate equation to capture the effect of the economy on credit quality. Then, following the capital crunch hypothesis, we add an equation linking credit supply and bank capital to test whether the deterioration of credit quality affects, in turn, the real economy.

We find a rather convincing evidence on the first round effect and some support to the idea that a feedback effect operates via the bank capital channel.

In particular, our results confirm that the default rates follow a cyclical pattern. They fall in good macroeconomic times and increase during downturns. This evidence is robust to different measures of the output gap and holds for the household and corporate sectors as well as for the non-financial sector as a whole. Furthermore, our findings seem to suggest that, when capital surpluses over regulatory minimum are low, banks may reduce lending, which, in turn, negatively affects the output levels.

Although based on a relatively short time period and a single country, our results confirm the importance for banks to keep sufficient capital buffers in order to maintain an adequate credit supply also during contractions, thus reducing the possibility of procyclicality.

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Table 1: The importance of the credit channel

FACTORS AFFECTING THE FEEDBACK EFFECT					
	Loans from MFIs/Total liabilities (1)	**Short-term loans/total loans (1)**	**Bond/Total liabilities (1)**	**No. small firms/total (2)**	**Employment in small firms/total (2)**
Italy	22.0	57.7	1.7	42.9	34.8
France	7.3	30.1	16.3	42.5	22.9
Germany	22.9	28.8	2.6	53.0	24.0
Spain	15.1	35.1	3.5	n.a.	n.a.
UK	n.a.	n.a.	n.a.	31.4	16.9
Euro Area	19.7	37.6	8.9	n.a.	n.a.

Notes: (1) Financing of non financial corporations; end-2000; source ECB, Report on financial structures, 2002. (2) Small firms are those with 1-9 employees; end-1996 for Italy, France and Spain, end-1997 for Germany and the UK; source Eurostat, Enterprises in Europe, 2001.

Table 2: Data Description

Name	*Description*	*Formula*	*Sample*	*Source*
Microeconomic Variables				
ADR	Default Rate (Amount)	100*[Flow of New Bad Debts (t)] / [Performing Loans (t-1)]	1985:I-2004:I	Credit Register
ADR_C	Default Rate for the Corporate Sector	100*[Flow of New Bad Debts for Coporate Sector (t)] / [Performing Loans (t-1)]	1990:I-2004:I	Credit Register
ADR_H	Default Rate for the Households Sector	100*[Flow of New Bad Debts for Household Sector (t)] / [Performing Loans (t-1)]	1990:I-2004:I	Credit Register
NEG_CAP	Disposable Capital	([Negative Free Capital] / [Total Supervisory Capital])*100	1985:I-2004:I	Supervisory Reports
Macroeconomic Variables				
GAP	Output Gap from Bank of Italy - Quarterly Model (BIQM)	([Actual Output] / [Potential Output]-1)*100	1985:I-2004:I	R.D. database
GAP_HP	Output Gap as Deviations of GDP from HP filtered series	[Actual Output] - [HP-filtered series]	1985:I-2004:I	-
GAP_T	Output Gap as Deviations of GDP from a trend	[Actual Output] – [Trend]	1985:I-2004:I	-
INFL	Annual Inflation rate	100*(CPI(t)-CPI(t-4)) / CPI(t-4)	1985:I-2004:I	R.D. database
R3M	Three Month Interbank interest rate		1985:I-2004:I	
REXR	Real exchange rate	[Real Exchange Rate Index]/100	1985:I-2004:I	R.D. database
SPREAD	Spread	[Average interest rate on short-term loans] - [minimum interest rate on short term loans (10th percentile)]	1989:I-2004:I	R.D. database
LEVERAGE	Firms' leverage	Debt / ([Equity Capital]+Debt)	1990:I-2004:I	Financial accounts
DEBT_H	Households' indebtedness	[Household Indebtedness] / GDP	1989:I-2004:I	Financial accounts

Notes: Actual Output is the Italian nominal GDP at constant market prices. The data are seasonally adjusted and corrected for the number of working days. CPI is the Consumer Price General Index (year base 1995). The Real Exchange Rate Index is an indicator of competitiveness with respect to 25 countries. Such indicator is a weighted average of bilateral exchange rates evaluated at a common currency.

Table 3: Descriptive Statistics and Correlations

	ADR	ADR_C	ADR_H	GAP	GAP_HP	GAP_T	INFL	R3M	SPREAD	REXR	LEVERAGE	DEBT_H	NEG_CAP
Mean	0.531	0.722	0.832	0.998	0.000	0.196	3.670	7.376	2.697	1.053	47.706	14.642	7.064
Median	0.504	0.656	0.884	0.706	0.108	0.078	2.832	7.219	2.629	1.037	48.948	13.202	5.381
Maximum	1.121	1.444	1.545	11.250	1.627	3.743	6.730	16.500	4.306	1.209	57.818	20.223	16.308
Minimum	0.217	0.322	0.243	-5.232	-2.331	-2.594	1.297	2.078	1.990	0.881	34.244	11.986	1.317
Std. Dev.	0.227	0.295	0.352	3.674	0.928	1.538	1.621	3.793	0.425	0.080	7.144	2.397	4.612
Skewness	0.720	0.774	-0.197	0.647	-0.327	0.469	0.439	0.262	1.135	0.581	-0.296	0.850	0.674
Kurtosis	2.771	2.777	1.944	3.442	2.386	2.708	1.839	1.925	5.231	2.676	1.688	2.265	2.079
Jarque-Bera	5.054	5.813	3.019	4.439	1.913	2.292	5.034	3.395	24.051	3.457	4.926	8.150	6.327
***p*-value**	(0.080)	(0.055)	(0.221)	(0.109)	(0.384)	(0.318)	(0.081)	(0.183)	(0.000)	(0.178)	(0.085)	(0.017)	(0.042)
Observations	57	57	57	57	57	57	57	57	57	57	57	57	57
KPSS Level	**0.293**	**0.360**	**0.387**	**0.457**	**0.133**	**0.024**	**0.174**	**0.300**	**0.420**	**0.311**	**0.438**	**0.123**	**0.171**
KPSS Trend	**0.095**	**0.036**	**0.066**	**0.021**	**0.074**	**0.025**	**0.045**	**0.109**	**0.056**	**0.109**	**0.117**	**0.099**	**0.056**

Correlations	ADR	ADR_C	ADR_H	GAP	GAP_HP	GAP_T	INFL	R3M	SPREAD	REXR	LEVERAGE	DEBT_H	NEG_CAP
ADR	1	*	*	*	*		*	*	*		*	*	
ADR_C	0.99	1	*	*	*		*	*	*	*	*	*	
ADR_H	0.80	0.81	1	*	*		*	*	*		*	*	*
GAP	0.52	0.50	0.57	1	*	*	*	*	*	*	*	*	*
GAP_HP	-0.46	-0.46	-0.39	0.31	1	*			*		*		
GAP_T	-0.10	-0.11	0.00	0.70	0.80	1							
INFL	0.66	0.58	0.39	0.56	-0.08	0.17	1	*	*		*	*	
R3M	0.74	0.66	0.64	0.72	-0.18	0.26	0.81	1	*		*	*	
SPREAD	0.66	0.61	0.67	0.45	-0.50	-0.08	0.50	0.80	1		*	*	
REXR	-0.26	-0.27	-0.22	-0.35	-0.11	-0.17	-0.25	-0.10	0.12	1			
LEVERAGE	0.80	0.75	0.67	0.48	-0.46	-0.15	0.78	0.86	0.80	-0.06	1	*	
DEBT_H	-0.74	-0.73	-0.85	-0.81	0.21	-0.26	-0.46	-0.77	-0.73	0.24	-0.70	1	*
NEG_CAP	0.12	0.16	0.35	0.33	0.23	0.15	-0.12	0.08	0.11	-0.15	0.06	-0.43	1

Notes: The sample is 1990:I-2004:I. KPSS is the Kwiatkowski, Phillips, Schmidt, and Shin (1992) test for the null hypothesis of stationarity. The numbers in boldface for the KPSS tests represent those tests which are not significant at 5%. The 5% critical values of the KPSS tests are 0.463 and 0.146 for the level and the trend version respectively. A '*' indicates those correlation coefficients that are significant at 5%.

Table 4: Lag Selection and Granger Causality for Baseline VAR. Sample 1990:I-2004:I

Lag Length Selection						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-212.60	NA	2.02E-03	7.99	8.52	8.19
1	41.40	436.70	6.61E-07	-0.05	**1.38**	0.51
2	79.52	58.85	**4.31E-07**	-0.51	1.82	**0.40**
3	97.67	24.84	5.88E-07	-0.27	2.96	0.98
4	134.53	**43.97**	4.42E-07	**-0.69**	3.44	0.92
5	154.58	20.40	6.56E-07	-0.51	4.51	1.44
6	183.61	24.45	8.12E-07	-0.65	5.26	1.65

Granger pairwise Causality tests					
	Dependent Variable in Regression (Regressand)				
Regressor	ADR	GAP	INFL	R3M	REXR
ADR		0.13	0.42	0.33	0.67
GAP	**0.00**		0.09	0.88	0.14
INFL	**0.05**	0.41		**0.03**	0.10
R3M	**0.00**	**0.02**	0.62		**0.01**
REXR	0.06	0.22	**0.04**	0.71	
All	**0.00**	**0.03**	**0.05**	**0.03**	**0.01**

Notes: In the lag selection table (left panel), the numbers in boldface select the best model according to the criterion in each column. LR is the sequential likelihood ratio test, FPE is the final prediction error, AIC, SC and HQ are the Akaike, Bayesian Schwarz and Hannan-Quinn information criteria respectively. In the Granger-causality tests (right panel), the *p*-values in boldface represent the regressors (or row variables) that help to predict each regressand in the column at 5%.

Table 5: Variance Decomposition for Baseline VAR

Baseline VAR: 1990.1-2004.1

Variance Decomposition of ADR:

Period	S.E.	ADR	GAP	INFL	R3M	REXR
1	0.117	100.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4	0.144	68.396	4.163	9.610	15.789	2.041
		(8.944)	(3.221)	(6.043)	(6.896)	(2.225)
8	0.160	56.396	3.864	16.058	21.003	2.679
		(11.740)	(3.567)	(9.888)	(10.222)	(3.704)
12	0.168	51.668	4.173	20.040	20.692	3.426
		(13.190)	(3.561)	(12.023)	(11.784)	(5.150)

Variance Decomposition of GAP:

Period	S.E.	ADR	GAP	INFL	R3M	REXR
1	0.686	0.465	99.535	0.000	0.000	0.000
		(3.324)	(3.324)	(0.000)	(0.000)	(0.000)
4	1.326	1.224	91.232	1.109	4.459	1.975
		(5.985)	(8.464)	(2.189)	(4.511)	(2.053)
8	1.676	1.076	82.943	2.424	5.814	7.743
		(5.649)	(12.147)	(5.314)	(8.581)	(6.609)
12	1.791	0.960	78.670	2.569	5.273	12.528
		(5.154)	(14.323)	(7.519)	(10.104)	(9.568)

Variance Decomposition of INFL:

Period	S.E.	ADR	GAP	INFL	R3M	REXR
1	0.346	0.070	6.297	93.633	0.000	0.000
		(3.266)	(5.427)	(5.930)	(0.000)	(0.000)
4	0.713	1.519	14.539	80.540	0.347	3.054
		(5.136)	(9.152)	(9.457)	(2.792)	(2.464)
8	0.989	1.302	22.056	66.451	0.574	9.617
		(5.287)	(12.813)	(13.946)	(6.157)	(6.498)
12	1.137	1.189	24.349	58.520	0.503	15.439
		(5.387)	(13.849)	(15.711)	(7.799)	(9.376)

Variance Decomposition of R3M:

Period	S.E.	ADR	GAP	INFL	R3M	REXR
1	0.886	0.115	0.343	1.600	97.941	0.000
		(2.299)	(2.513)	(5.115)	(6.298)	(0.000)
4	1.454	1.465	3.233	13.004	82.059	0.240
		(4.476)	(3.952)	(10.306)	(11.289)	(1.419)
8	1.819	1.669	12.290	26.512	57.024	2.505
		(4.969)	(8.566)	(14.954)	(15.444)	(4.380)
12	2.116	1.479	18.720	30.662	42.294	6.846
		(5.075)	(11.004)	(16.487)	(16.513)	(7.118)

Variance Decomposition of REXR:

Period	S.E.	ADR	GAP	INFL	R3M	REXR
1	0.027	1.013	0.908	10.088	0.718	87.272
		(3.336)	(3.029)	(6.714)	(2.212)	(7.897)
4	0.046	1.876	1.925	4.738	15.588	75.873
		(6.210)	(2.585)	(5.219)	(9.220)	(11.623)
8	0.058	2.062	7.514	3.459	32.379	54.585
		(6.305)	(6.093)	(6.101)	(14.284)	(13.689)
12	0.064	2.082	10.832	3.211	37.885	45.990
		(6.087)	(8.326)	(7.708)	(15.808)	(13.461)

Notes: Standard errors in parentheses.

Table 6: Lag Selection and Granger Causality for Corporate VAR. Sample 1990:I-2004:I

Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-328.68	NA	8.73E+00	13.52	14.12	13.75
1	-158.36	287.21	**2.07E-02**	7.46	**8.68**	**7.93**
2	-142.35	24.48	2.13E-02	7.46	9.28	8.16
3	-129.35	17.84	2.52E-02	7.58	10.01	8.51
4	-118.52	13.16	3.37E-02	7.79	10.82	8.94
5	-104.80	14.53	4.26E-02	7.87	11.51	9.26
6	-75.37	**26.54**	3.14E-02	**7.35**	11.59	8.97

Granger pairwise Causality tests

	Dependent Variable in Regression (Regressand)			
Regressor	ADR_C	GAP	LEVERAGE	R3M
ADR_C		0.06	0.41	0.23
GAP	**0.00**		0.50	**0.05**
LEVERAGE	**0.00**	0.92		**0.05**
R3M	0.57	0.13	0.09	
All	**0.00**	0.11	**0.01**	**0.03**

Notes: In the lag selection table (left panel), the numbers in boldface select the best model according to the criterion in each column. LR is the sequential likelihood ratio test, FPE is the final prediction error, AIC, SC and HQ are the Akaike, Bayesian Schwarz and Hannan-Quinn information criteria respectively. In the Granger-causality tests (right panel), the *p*-values in boldface represent the regressors (or row variables) that help to predict each regressand in the column at 5%.

Table 7: Variance Decomposition for Corporate VAR

Corporate Sector VAR: 1990.1-2004.1

Variance Decomposition of ADR_C:

Period	S.E.	ADR_C	GAP	LEVERAGE	R3M
1	0.155	100.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
4	0.169	85.492	4.120	8.365	2.023
		(5.074)	(2.872)	(3.765)	(3.471)
8	0.184	74.409	3.931	15.376	6.283
		(7.414)	(2.730)	(6.667)	(6.466)
12	0.194	67.235	4.964	19.762	8.039
		(9.172)	(3.146)	(8.616)	(8.535)

Variance Decomposition of GAP:

Period	S.E.	ADR_C	GAP	LEVERAGE	R3M
1	0.714	0.219	99.781	0.000	0.000
		(2.153)	(2.153)	(0.000)	(0.000)
4	1.326	6.588	89.422	0.022	3.968
		(7.441)	(9.980)	(1.059)	(5.401)
8	1.586	8.412	82.725	0.016	8.847
		(8.837)	(14.749)	(3.043)	(10.144)
12	1.652	8.844	80.204	0.015	10.937
		(8.793)	(16.537)	(5.153)	(11.915)

Variance Decomposition of LEVERAGE:

Period	S.E.	ADR_C	GAP	LEVERAGE	R3M
1	1.209	1.021	2.116	96.863	0.000
		(4.021)	(5.119)	(6.540)	(0.000)
4	2.427	3.380	5.270	87.115	4.235
		(6.240)	(7.734)	(9.196)	(6.043)
8	3.442	2.977	13.157	76.627	7.239
		(6.395)	(11.441)	(12.757)	(10.988)
12	4.198	2.225	21.212	69.548	7.014
		(6.032)	(13.731)	(14.241)	(12.544)

Variance Decomposition of R3M:

Period	S.E.	ADR_C	GAP	LEVERAGE	R3M
1	0.899	0.555	0.952	3.877	94.617
		(2.984)	(3.565)	(4.741)	(6.142)
4	1.432	3.108	8.790	10.012	78.090
		(6.067)	(7.872)	(7.243)	(11.114)
8	1.714	2.299	22.489	15.553	59.659
		(5.600)	(12.495)	(9.887)	(15.335)
12	1.904	1.919	30.600	18.876	48.604
		(5.332)	(13.930)	(11.501)	(16.617)

Notes: Standard errors in parentheses.

Table 8: Lag Selection and Granger Causality for Household VAR. Sample 1990:I-2004:I

Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-349.92	NA	9.28E-01	14.11	14.49	14.26
1	-82.34	461.71	6.92E-05	4.60	**5.93**	**5.11**
2	-55.19	41.53	6.59E-05	4.52	6.79	5.39
3	-21.63	**44.74**	**5.14E-05**	4.18	7.40	5.41
4	1.80	26.65	6.48E-05	4.24	8.41	5.84
5	29.89	26.44	7.73E-05	4.12	9.24	6.08
6	64.30	25.64	8.79E-05	**3.75**	9.81	6.07

Granger pairwise Causality tests

	Dependent Variable in Regression (Regressand)				
Regressor	ADR_H	GAP	DEBT_H	INFL	R3M
ADR_H		0.62	0.64	0.41	0.91
GAP	**0.00**		0.93	**0.01**	0.48
DEBT_H	**0.00**	0.10		0.13	0.73
INFL	**0.01**	0.24	0.90		0.13
R3M	0.26	**0.03**	0.07	0.83	
All	**0.00**	**0.05**	**0.05**	0.14	0.09

Notes: In the lag selection table (left panel), the numbers in boldface select the best model according to the criterion in each column. LR is the sequential likelihood ratio test, FPE is the final prediction error, AIC, SC and HQ are the Akaike, Bayesian Schwarz and Hannan-Quinn information criteria respectively. In the Granger-causality tests (right panel), the *p*-values in boldface represent the regressors (or row variables) that help to predict each regressand in the column at 5%.

Table 9: Variance Decomposition for Household VAR

Household Sector VAR: 1990.1-2004.1

Variance Decomposition of ADR_H:

Period	S.E.	ADR_H	GAP	DEBT_H	INFL	R3M
1	0.148	100.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4	0.176	71.622	10.672	13.054	2.839	1.813
		(7.409)	(4.514)	(3.766)	(2.805)	(1.994)
8	0.196	58.352	9.850	17.732	4.141	9.925
		(9.009)	(4.216)	(6.107)	(5.385)	(8.049)
12	0.213	50.270	9.192	19.214	6.540	14.784
		(9.671)	(4.159)	(8.043)	(8.015)	(11.561)

Variance Decomposition of GAP:

Period	S.E.	ADR_H	GAP	DEBT_H	INFL	R3M
1	0.749	0.715	99.285	0.000	0.000	0.000
		(3.508)	(3.508)	(0.000)	(0.000)	(0.000)
4	1.311	1.048	88.584	1.456	0.767	8.145
		(4.671)	(9.510)	(1.820)	(2.044)	(6.857)
8	1.601	0.941	75.851	6.334	1.395	15.479
		(4.237)	(15.326)	(6.043)	(4.532)	(12.017)
12	1.726	0.962	68.782	12.980	1.670	15.606
		(4.066)	(16.951)	(10.185)	(6.470)	(12.806)

Variance Decomposition of DEBT_H:

Period	S.E.	ADR_H	GAP	DEBT_H	INFL	R3M
1	0.206	0.011	0.041	99.948	0.000	0.000
		(2.169)	(1.890)	(2.950)	(0.000)	(0.000)
4	0.421	1.002	0.126	92.594	0.490	5.788
		(3.299)	(3.217)	(7.385)	(1.581)	(6.135)
8	0.635	2.238	1.234	79.094	3.151	14.283
		(4.463)	(5.621)	(13.891)	(5.302)	(13.471)
12	0.829	3.428	4.399	67.632	7.346	17.194
		(5.269)	(8.882)	(17.522)	(9.254)	(16.615)

Variance Decomposition of INFL:

Period	S.E.	ADR_H	GAP	DEBT_H	INFL	R3M
1	0.351	3.120	10.281	0.109	86.491	0.000
		(3.885)	(7.072)	(2.038)	(7.497)	(0.000)
4	0.671	5.663	23.798	0.812	69.590	0.137
		(6.921)	(10.936)	(2.081)	(11.997)	(2.750)
8	0.893	5.142	34.067	0.952	57.352	2.487
		(6.766)	(13.795)	(2.405)	(13.556)	(7.300)
12	1.017	4.543	37.925	0.803	50.242	6.487
		(6.346)	(14.724)	(2.952)	(13.917)	(11.347)

Variance Decomposition of R3M:

Period	S.E.	ADR_H	GAP	DEBT_H	INFL	R3M
1	0.905	3.354	0.441	0.044	1.186	94.974
		(5.775)	(2.945)	(2.281)	(3.308)	(6.952)
4	1.459	4.264	4.983	0.091	7.099	83.564
		(6.418)	(6.302)	(2.127)	(7.386)	(10.528)
8	1.764	5.301	15.454	0.188	15.368	63.689
		(6.318)	(10.727)	(2.630)	(11.683)	(14.732)
12	1.981	5.466	23.730	0.500	19.633	50.672
		(5.947)	(12.514)	(3.587)	(13.654)	(16.204)

Notes: Standard errors in parentheses.

Table 10: Lag Selection and Granger Causality for Feedback VAR. Sample 1990:I-2004:I

Lag Length Selection						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-322.37	NA	1.46E-01	12.27	12.82	12.48
1	-124.96	337.40	2.80E-04	6.00	**7.46**	**6.56**
2	-101.50	35.83	3.07E-04	6.05	8.43	6.97
3	-79.73	29.29	3.74E-04	6.17	9.46	7.44
4	-53.99	29.96	4.22E-04	6.14	10.34	7.77
5	-23.99	29.45	4.52E-04	5.96	11.07	7.94
6	25.51	**39.60**	**2.79E-04**	**5.07**	11.09	7.40

Granger pairwise Causality tests					
	Dependent Variable in Regression (Regressand)				
Regressor	ADR	GAP	NEG_CAP	INFL	SPREAD
ADR		**0.02**	0.72	0.56	0.98
GAP	0.12		0.97	**0.02**	0.51
NEG_CAP	0.76	0.17		**0.00**	0.55
INFL	**0.03**	0.38	0.77		0.25
SPREAD	**0.01**	**0.01**	0.97	0.46	
All	**0.00**	**0.02**	0.97	**0.01**	0.63

Notes: In the lag selection table (left panel), the numbers in boldface select the best model according to the criterion in each column. LR is the sequential likelihood ratio test, FPE is the final prediction error, AIC, SC and HQ are the Akaike, Bayesian Schwarz and Hannan-Quinn information criteria respectively. In the Granger-causality tests (right panel), the *p*-values in boldface represent the regressors (or row variables) that help to predict each regressand in the column at 5%.

Table 11: Variance Decomposition for Feedback VAR

Prociclicality VAR: 1990.1-2004.1

Variance Decomposition of ADR:

Period	S.E.	ADR	GAP	NEG_CAP	INFL	SPREAD
1	0.123	100.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4	0.153	71.550	7.376	0.878	4.626	15.570
		(10.976)	(4.810)	(2.903)	(3.905)	(8.048)
8	0.163	63.218	7.967	1.124	8.323	19.368
		(13.101)	(5.684)	(4.342)	(6.224)	(9.836)
12	0.167	60.567	7.681	3.206	9.396	19.151
		(13.676)	(5.462)	(6.441)	(6.890)	(10.035)

Variance Decomposition of GAP:

Period	S.E.	ADR	GAP	NEG_CAP	INFL	SPREAD
1	0.681	0.187	99.813	0.000	0.000	0.000
		(3.218)	(3.218)	(0.000)	(0.000)	(0.000)
4	1.344	2.706	82.657	6.398	0.250	7.988
		(7.048)	(11.040)	(6.208)	(1.858)	(6.964)
8	1.639	2.332	71.771	14.053	0.552	11.291
		(7.807)	(15.666)	(11.841)	(4.012)	(10.039)
12	1.738	2.092	67.086	17.764	0.793	12.265
		(7.813)	(17.478)	(14.336)	(5.457)	(11.040)

Variance Decomposition of NEG_CAP:

Period	S.E.	ADR	GAP	NEG_CAP	INFL	SPREAD
1	1.984	0.512	3.468	96.020	0.000	0.000
		(2.591)	(6.136)	(6.274)	(0.000)	(0.000)
4	3.228	1.348	2.749	95.790	0.071	0.042
		(6.813)	(6.031)	(9.292)	(1.568)	(2.159)
8	3.698	1.470	2.171	96.034	0.098	0.227
		(8.150)	(6.283)	(11.334)	(3.538)	(3.758)
12	3.853	1.457	2.027	96.024	0.096	0.395
		(8.250)	(6.562)	(12.228)	(4.929)	(4.805)

Variance Decomposition of INFL:

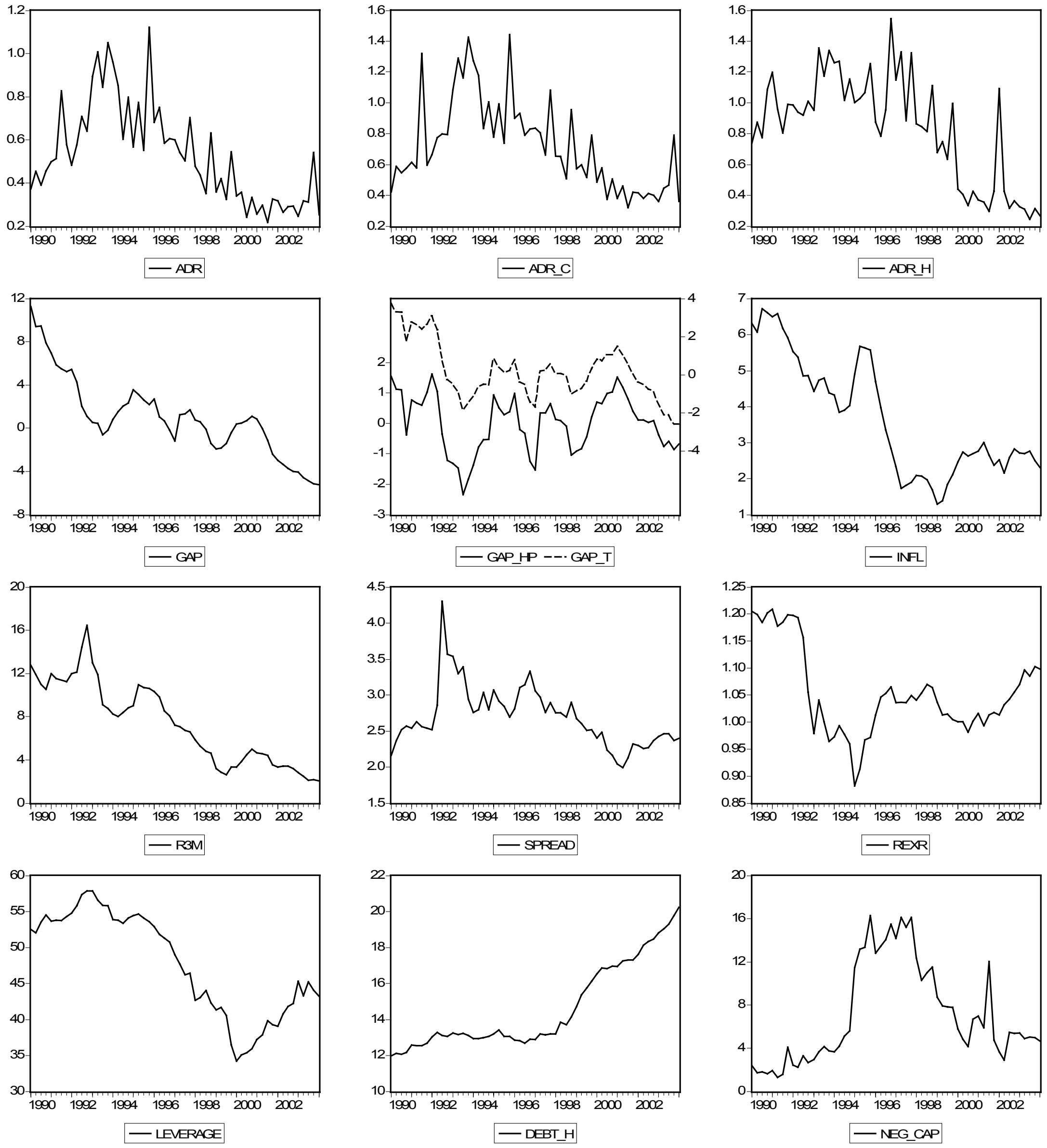
Period	S.E.	ADR	GAP	NEG_CAP	INFL	SPREAD
1	0.330	0.181	8.881	0.835	90.103	0.000
		(3.147)	(6.887)	(2.915)	(7.750)	(0.000)
4	0.538	0.420	13.279	11.687	73.843	0.771
		(5.817)	(8.197)	(8.586)	(10.382)	(2.456)
8	0.714	0.449	14.528	35.455	49.030	0.538
		(7.255)	(9.806)	(15.680)	(12.750)	(3.659)
12	0.838	0.339	14.041	48.141	36.595	0.884
		(7.720)	(10.246)	(17.398)	(12.538)	(4.462)

Variance Decomposition of SPREAD:

Period	S.E.	ADR	GAP	NEG_CAP	INFL	SPREAD
1	0.257	2.898	18.426	6.661	0.252	71.762
		(4.750)	(8.732)	(6.229)	(1.720)	(9.797)
4	0.352	2.806	18.065	9.214	1.346	68.569
		(5.646)	(8.397)	(9.446)	(3.790)	(10.952)
8	0.368	2.725	17.324	9.210	3.334	67.407
		(5.856)	(8.401)	(10.689)	(6.364)	(11.535)
12	0.371	2.706	17.043	9.380	4.125	66.746
		(6.102)	(8.234)	(10.681)	(7.179)	(11.734)

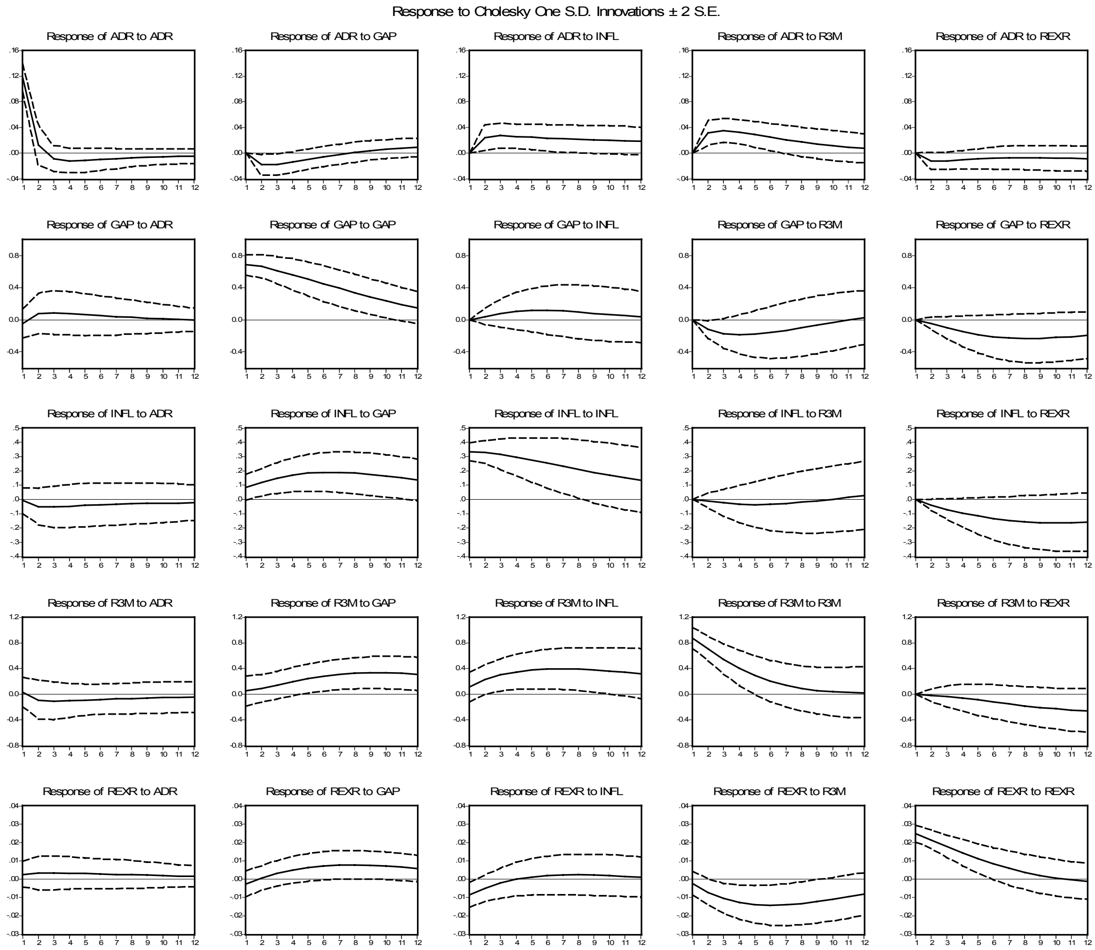
Notes: Standard errors in parentheses.

Figure 1: Data



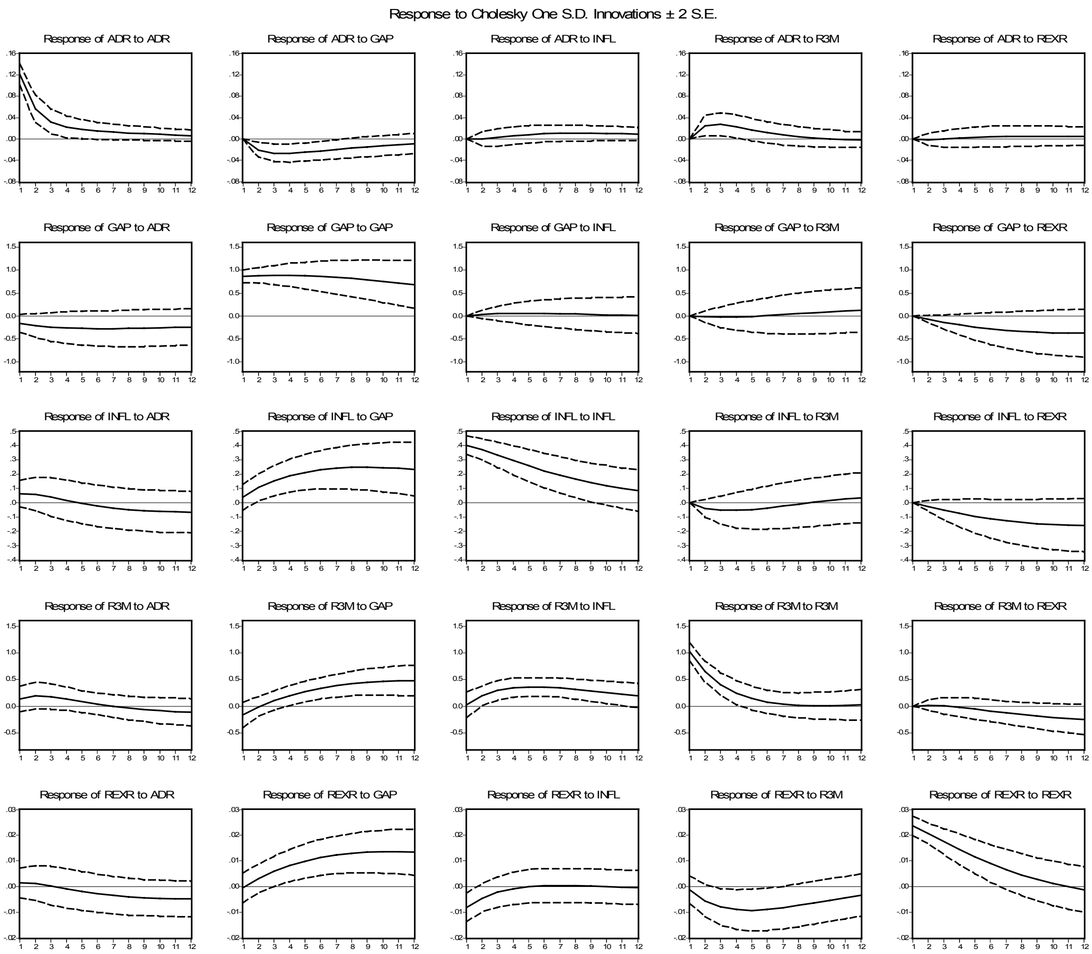
Notes: The figure depicts all the variables used in the paper and described in Table 2 for the sample 1990:I-2004:I. For the graph in the middle of the second row, the left-hand scale is referred to GAP_HP, while the right-hand scale is referred to GAP_T.

Figure 2: Impulse Response Functions for the Baseline VAR. Sample: 1990:I-2004:I



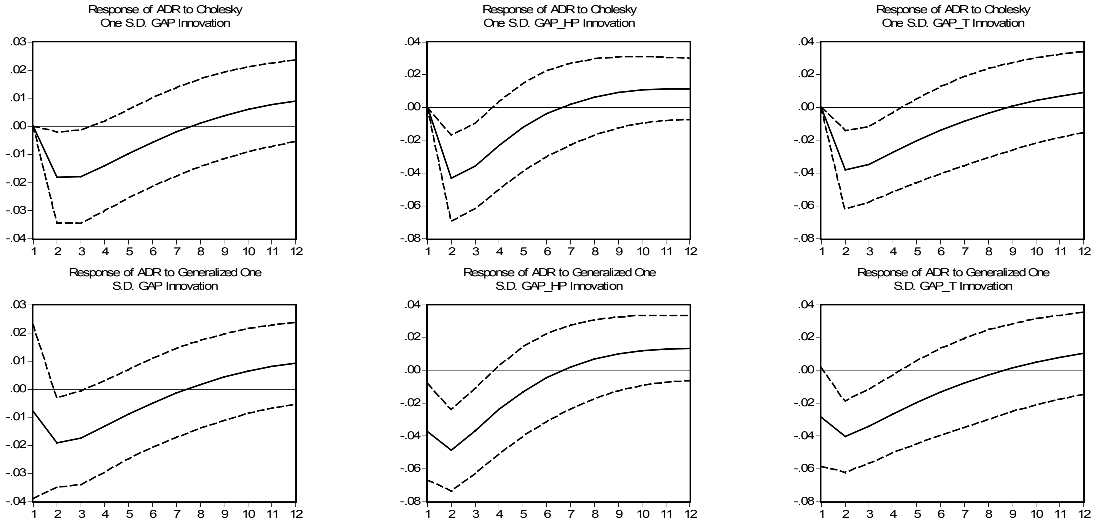
Notes: The IRF's are computed with Cholesky factorization and two standard error bands.

Figure 3: Impulse Response Functions for the Baseline VAR. Sample: 1985:I-2004:I



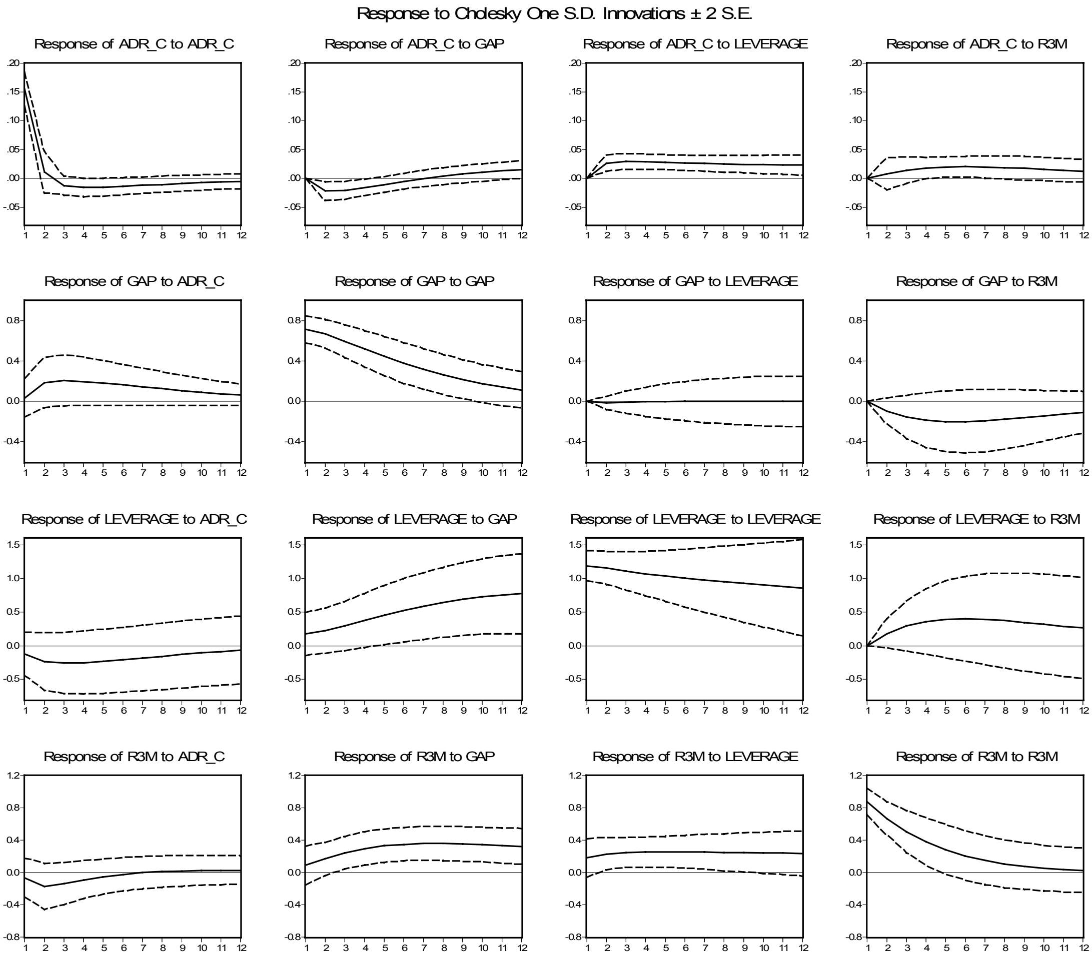
Notes: The IRF's are computed with Cholesky factorization and two standard error bands.

Figure 4: Comparison of IRF's of ADR with respect to different measures of Output Gap.



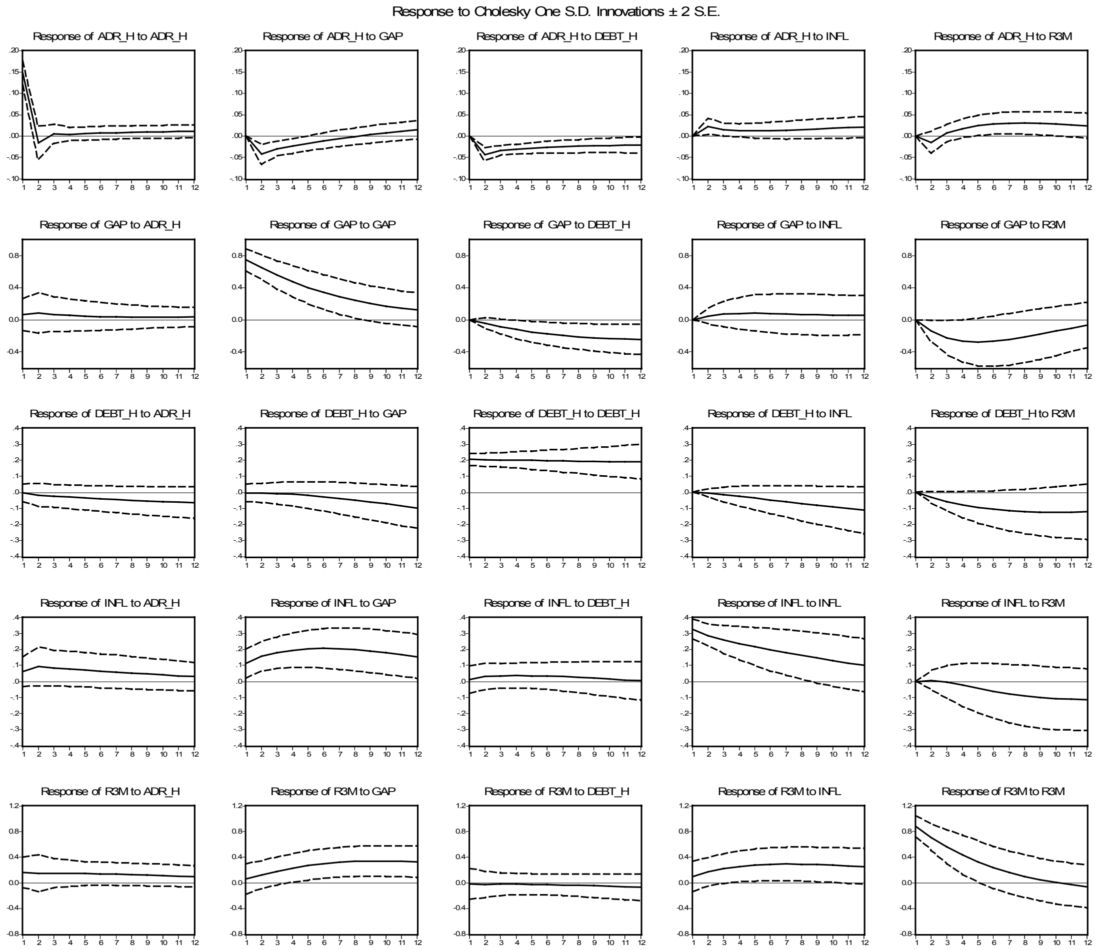
Notes: In the top panel the IRF's are computed with Cholesky factorization. The bottom panel depicts the generalized IRF's calculated using the procedure by Pesaran and Shin (1998). In both panels, two standard error bands are shown.

Figure 5: Impulse Response Functions of the VAR for the Corporate Sector. Sample: 1990:I-2004:I



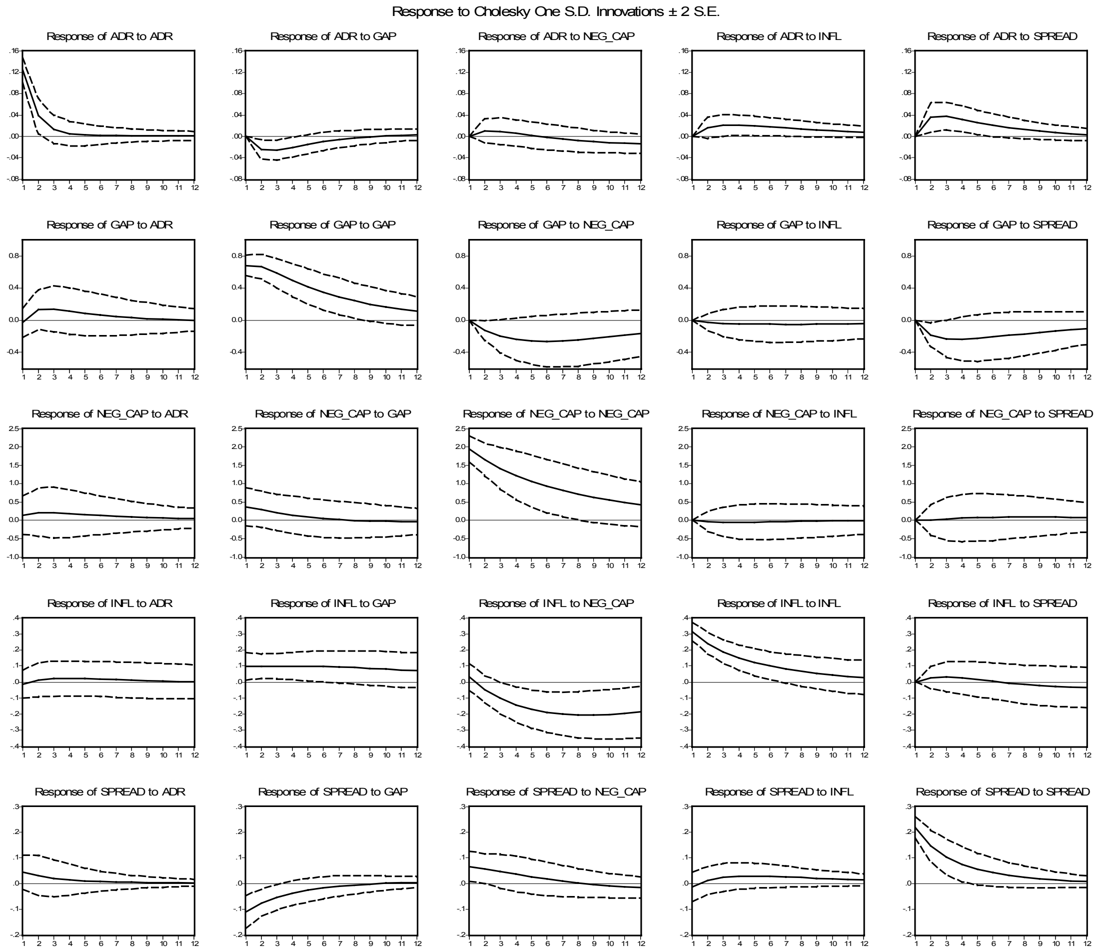
Notes: The IRF's are computed with Cholesky factorization and two standard error bands.

Figure 6: Impulse Response Functions of the VAR for the Household sector. Sample: 1990:I-2004:I



Notes: The IRF's are computed with Cholesky factorization and two standard error bands.

Figure 7: Impulse Response Functions of the Feedback VAR. Sample: 1990:I-2004:I



Notes: The IRF's are computed with Cholesky factorization and two standard error bands.